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Automatic Monitoring of Class A Pan Evaporation using the Internet of Things (IoT)

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ABSTRACT

This study aimed to assess suitable water level sensor types and implement the automated monitoring of water levels within a Class A pan evaporation system using the Internet of Things (IoT). Both analogue and ultrasonic water level sensors underwent testing in controlled laboratory conditions for performance analysis. The results showed that the analogue water level sensor exhibited suboptimal output sensor responses compared to the ultrasonic sensor, primarily due to its susceptibility to variations in solution types and immersion depths. In contrast, ultrasonic sensors demonstrated strong performance with acceptable error rates, as evidenced by the Mean Absolute Error (MAE) of 1.03, Root Mean Squared Error (RMSE) of 1.42, and Coefficient of Determination (R^2) of 0.94 during laboratory testing. However, the ultrasonic sensor's performance was somewhat reduced during field testing, exhibiting accuracy levels ranging from 6.7% to 51.2% within a greenhouse environment during rock melon cultivation. These discoveries highlight the feasibility of using ultrasonic sensors with environmental calibration to automate real-time evaporation measurements towards precision irrigation practices.

Keywords: Ultrasonic sensor, Water level, Internet of Things, Precision irrigation, Evaporation

1. INTRODUCTION

The spread of the Internet of Things (IoT) into agricultural fields has received the most excellent attention from scholars and farmers. IoT is a system that relates computing devices that connect sensors with unique identifiers and can communicate data over a network independently[1] IoT has been used in various applications such as crop growth monitoring, plant disease detection [2], [3], and irrigation management [4]–[8]. Sensors play a pivotal role in enabling the functionality and capabilities of IoT systems. One of the vital sensors for precision irrigation is the water level sensor, which has different mechanisms and functions. Sensors enable real-time data collection, transforming into actionable insights such as automation, device control, and decision support systems [9], [10].

The ultrasonic sensor is explicitly designed for measuring the distance between two points. Among the applications of ultrasonic sensors in precision irrigation are measuring water levels and object detection[11]. Ultrasonic sensors emit short bursts of high-frequency sound waves and measure the time it takes to bounce off an object and return to the sensor. The sensor consists of a transmitter that sends sound waves and a receiver that detects the echoes. By detecting the duration of wave travel to the object and the subsequent return trip, the sensor can determine the distance to the object [12]. Factors like the speed of sound and signal processing techniques play a crucial role in achieving accurate distance calculations. Ultrasonic sensors offer the ability to measure distances accurately using sound waves, making them suitable for various

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applications such as object detection, obstacle avoidance, and liquid-level monitoring [11], [13]–[15]. Precision irrigation leverages water level data to deliver precise amounts of water where needed, conserving resources and enhancing crop health. Deep learning, combined with water level sensors, enables the creation of predictive models that optimize irrigation schedules based on historical data and real-time sensor inputs. By embedding these intelligent systems into agricultural practices, the farmer can enhance the efficiency of water usage in agriculture.

Class A pan evaporation is a simple and widely used method to evaluate evaporation from open water surfaces. The evaporation and evapotranspiration concept is crucial in irrigation management since it depends on seasonal variation and real-time weather conditions. The evaporation data from the pan needs to be measured daily for irrigation management and crop surveillance. However, monitoring the water level in Class A pan evaporation is quite tiresome since the water level inside the pan needs to be monitored daily. Therefore, the present study aims to assess the effectiveness and potential of the water level sensor attached to Class A pan evaporation using the Internet of Things (IoT) approach. This study is specifically designed to achieve the following aims: (1) To assess the impact of analogue water level sensors on various solution types and immersion depths, (2) To estimate the performance of ultrasonic sensors at different water depth levels, and (3) To evaluate the performance of ultrasonic sensors under field conditions.

2. MATERIAL AND METHODS

This study used low-cost water level sensors to measure water levels inside Class A pan evaporation. Low-cost sensors refer to sensors or devices that are relatively cheap to produce compared to conventional sensors. These sensors are more widely available and appropriate for a variety of applications because they are made to deliver crucial data and measurements. This study was divided into laboratory experiments and field testing at the Institut of Sustainable Agrotechnology (INSAT), Universiti Malaysia Perlis (UNIMAP).

2.1 Laboratory Experiment

In the laboratory stage, two water level sensors were evaluated and tested before being selected for the water level monitoring system. The first is an analogue water level sensor, and the second is an ultrasonic water level sensor (Figure 1). The analogue and ultrasonic water level sensors were obtained from local online platforms. The analogue water level sensor has three pins: the analogue signal pin, the power pin, and the ground pin. The analogue pin, power pin and ground pin of the water level sensor were connected to the analogue pin (A0), 5 V power supply, and ground pin of the Arduino Uno microcontroller, respectively. Both sensor data were displayed via a serial monitor of the Arduino Uno Integrated Development Environment (IDE) version 1.8.19.

The working mechanism of the analogue water level sensor was based on sensor depth immersed in the solution. The tip of the water level sensor was inserted into a 100 mL beaker with different solutions at different depths beginning from 10, 20, 30, and 40 mm. The depth selection was based on the allowable sensor exposure. The tested solutions used are tap water, distilled water, rainwater, lake water, solution with 2.0 electrical conductivity (EC), solution with 4.0 EC, solution with 8.0 EC, calibration solution of pH 4.01, calibration solution of pH 6.86 and calibration solution of pH 9.18. Tab water and distilled water were obtained from the INSAT laboratory. Lake water was obtained from a retained pond in INSAT, while rainwater used was harvested and collected one hour before the experiment began. A solution with EC 2.0, 4.0, and 8.0 mS/cm was prepared by mixing rock melon fertilizer A and B solutions. After being submerged for about 2 minutes and achieving equilibrium, the data was recorded every 10 seconds for 2 minutes. Before moving to the next solution, the sensor tip was washed with distilled water.

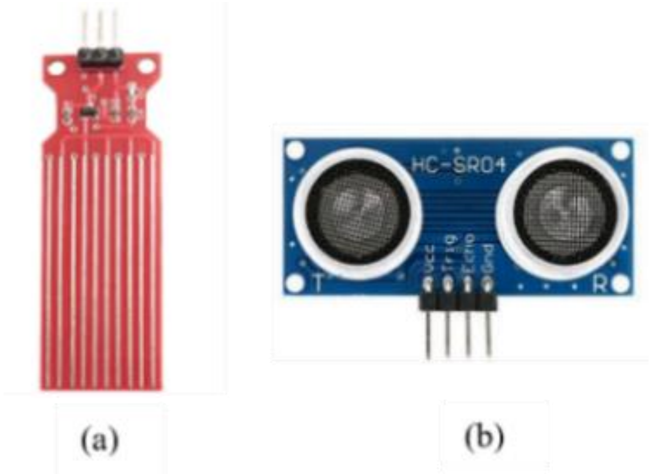

Figure 1: Analogue (a) and ultrasonic water level sensor (b).

The ultrasonic sensor (HC-SR04) was tested at the various heights of the sensor to the tap water column surface by using a 1000 mL measuring cylinder and measuring tape. The ultrasonic sensor data was collected every 4 seconds for 5 minutes for every testing number. The detailed setting of the experiment is shown in Table 1 and Figure 2. In this experiment, the original height of the ultrasonic sensor was fixed at a constant position throughout the experiment. The range of depth selected was based on the maximum and minimum height of the experimental setup. The tap water was added until it reached the required depth. Later, the water depth in the measuring cylinder and the volume of water added to the measuring cylinder were measured. The ultrasonic sensor has four pins: power pin, ground pin, trigger pin, and echo pin. The power pin, ground pin, trigger pin, and echo pin of the ultrasonic sensor were connected to the 5V power pin, ground pin, digital pin 9, and digital pin 10 of the Arduino Uno Microcontroller, respectively. The trigger pin initiates and triggers ultrasonic sound pulses by setting it as high for 10μs. Upon transmission of the ultrasonic burst, the echo pin becomes high and stays that way until the sensor gets an echo, which turns low. The distance can be determined by timing how long the Echo pin remains high.

Table 1: The detailed setting of the ultrasonic sensor.

Test No.	Depth of Ultrasonic Sensor to Water Surface (cm)	Depth of Water (cm)	The volume of Water in the Measuring Cylinder (mL)
1	43.4	0.0	0.0
2	42.0	1.4	47.0
3	39.0	4.4	149.0
4	35.0	8.4	260
5	30	13.4	400
6	20	23.4	690
7	5	38.4	1137
8	3	40.4	1197
9	2	41.4	1227
10	1	42.4	1257

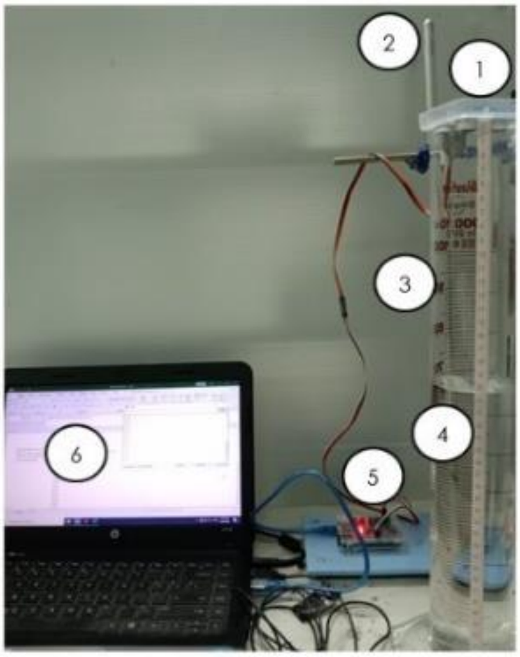

Figure 2: Ultrasonic sensor testing at the laboratory. The components are (1) Ultrasonic sensor, no (2) Retort stand, (3) Measuring cylinder, (4) Measuring tape, (5) Arduino Uno microcontroller, and (6) Serial monitor.

2.2 Water Level Measurement in Greenhouse

The sensors were attached to the Class A pan evaporation in the field test, as shown in Figure 3. The Class A pan evaporation was installed inside a greenhouse at the Institute of Sustainable Agriculture (INSAT), Universiti Malaysia Perlis, Padang Besar, Malaysia (6°39’15.78” N, 100°15’51.21” E). Before the experimental setting, the ground surface was levelled using an aluminium water level. Class A pan evaporation with a standardized container (stainless steel, 1207 mm diameter, 250 mm height) was placed on the wooden pallet at a height of 50 mm from the ground surface. The data was taken during rock melon var Glamour (*Cucumis melo*) cultivation between March and May 2023. The Class A pan is positioned at the frontal edge inside the greenhouse, adjacent to the rock melon cultivation area.

The system monitored and collected the water level, water temperature, indoor ambient relative humidity, outdoor ambient relative humidity, indoor ambient temperature, outdoor ambient temperature, and light intensity (LDR) data. Water level, water temperature, and LDR data were measured by ultrasonic sensor, DS18B20 temperature sensor, and LDR sensor, respectively, while ambient temperature and relative humidity were measured by DHT22 sensor. Later, the data is stored on the ThingSpeak™ IoT platform via the ESP8266 Wi-Fi module attached to the Arduino Uno Microcontroller. The internet connectivity was based on an Umobile sim card connected to the wireless router. The water level data inside the Class A pan was manually measured using J-Hook daily at 10:00 a.m. The water level was allowed to fluctuate between 50 mm (minimum level) and 70 mm (maximum level) depth from the pan top. If the water level drops below the maximum level, the water from the storage tank is filled into the Class A pan until it reaches the minimum level.

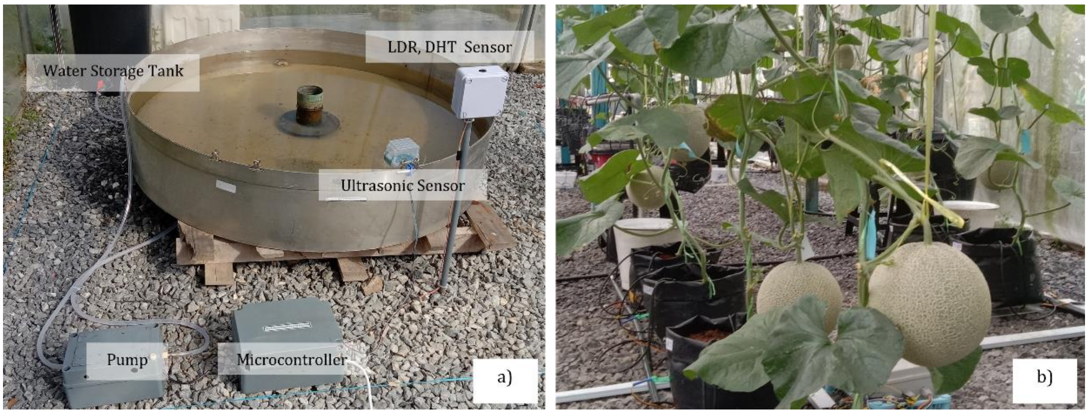

Figure 3: Class A pan evaporation with IoT devices (a) and rock melon plant at 50 days of planting (b).

2.3 Statistical Analysis and Data Visualization

The data on water level was subjected to a non-parametric test (IBM SPSS Statistic Version 25) using the Kruskal-Wallis test since the normality assumptions were not met[16]. A pairwise comparison analysis between groups was performed if significant differences were detected. The significant level was set at a 95% confidence level (p=0.05). The data was plotted using Microsoft Excel and R programming language.

3. RESULTS AND DISCUSSION

3.1 Effect of Immersion Depth and Type of Solution on Analog Sensor Output

Figure 4 shows the trends of analogue sensor reading on different solution types. The solution tested can be classified into three classes. Class I as fresh water (tap water, distilled water, rainwater, and lake water), Class II as fertilizer solution (Solution with 2.0, 4.0, and 6.0EC) and Class III as acidity water (solution with pH 4.01, 6.86, and 9.18). The analogue sensor gives a positive sensor reading response when immersed in distilled water at different depths. The variation of sensor reading can be seen clearly with a significant increasing trend from 10 mm to 40 mm. Although tap water showed an increasing reading trend with increasing immersion sensor depth, the sensor reading is insignificant from each depth setting. Other Class I of the freshwater category majority showed insignificant fluctuation of sensor reading for each depth setting (see Table 2).

The analogue water level reading on Class II of fertilizer solution reveals that electrical conductivity concentrations influenced the sensor reading. The analogue sensor values for three fertilizer solutions vary between 600 and 650 mV when tested at 4 different depths. The result also discloses that the hydrogen ion concentration in a solution influences the analogue sensor reading. Interestingly, the sensor reading showed the lowest value (400 mV) compared to other water classes but the highest at approximately 600 mV. Table 3 represents the correlation matrix for different solutions. In general, different types of solutions will influence the sensor reading. This experimental testing shows that the chemical properties of water and the immersion depth influenced the output of the analogue sensor. The analogue water level sensor has five exposed copper and five exposed sense traces. When immersed in the solution, power and sense traces are connected. The sensor's conductivity improves, and resistance decreases with increased water immersion. Conversely, reduced water immersion leads to decreased conductivity and increased resistance. We suggested that for water level reading in the class A pan, the water level sensor selected and used in the water level monitoring system is the contactless water level sensor type since the water used in the class A pan is tap water or rainwater for ease of handling by the practitioner.

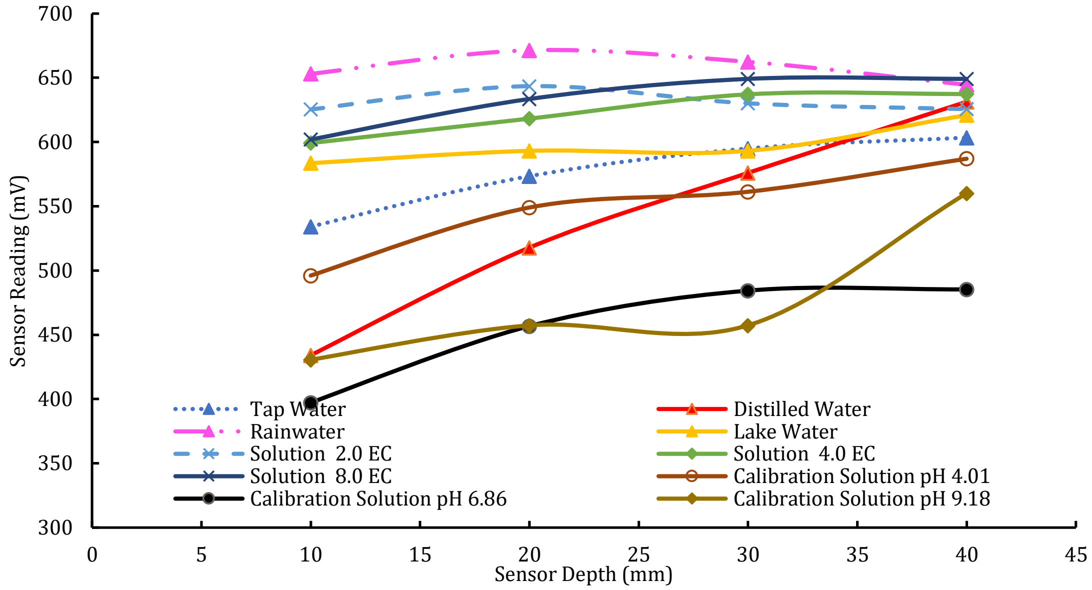

Figure 4: Sensor reading trends on different solution types

3.2 Performance of Ultrasonic Sensor

Figure 5 presents the ultrasonic sensor's estimated and actual reading with the 1:1 line. The plotting point between both readings demonstrated good fitting with the coefficient of determination (R^2) of 0.94, suggesting that the estimated readings can explain about 94.0% of the variance in the actual readings. However, the last reading shows poor fitting to the straight line. The mean absolute error (MAE) is approximately 1.03 from the performance parameter. This means, on average, the estimated readings are off by about 1.03 units from the actual readings. The absolute error percentage (AEP) ranges from approximately 0.00% to 360.00%. A percentage above 100% indicates that the estimated reading was off by more than the actual reading. The root means squared error (RMSE) is 1.42, which shows the average magnitude of errors between estimated and actual readings. The estimated readings have an average percentage error of about 39.69% compared to the actual readings based on mean absolute percentage error (MAPE).

The mean percentage error (MPE) for this data set is approximately -34.31%. This indicates that, on average, the estimated readings have a negative percentage error of about 34.31% compared to the actual readings. A negative MPE suggests that the model tends to underestimate the actual values on average. Although the coefficient of variation (CV) indicates that the standard deviation is about 99.96% of the mean, which suggests a relatively high degree of variability in the data, it only consists of one point of the data set (at 10 mm). A mean signed deviation (MSD) of 0.25 represents the average signed difference between the estimated and actual readings. Positive values indicate that the estimates are, on average, higher than the actual readings, while negative values indicate that the estimates are lower. The median absolute deviation (MAD) indicates the dispersion or spread of the errors. A smaller MAD shows lower variability, while a larger MAD suggests greater variability. In this study, a MAD of 0.85 indicates that the average absolute difference between the estimated and actual readings is around 0.85 units. Overall, the results showed that the ultrasonic sensor excellently performs and gives accurate readings in laboratory conditions. The position of the ultrasonic sensor should be kept in mind so that it is not placed too close or approximately 10 mm or 20 mm [17] from the water level surface.

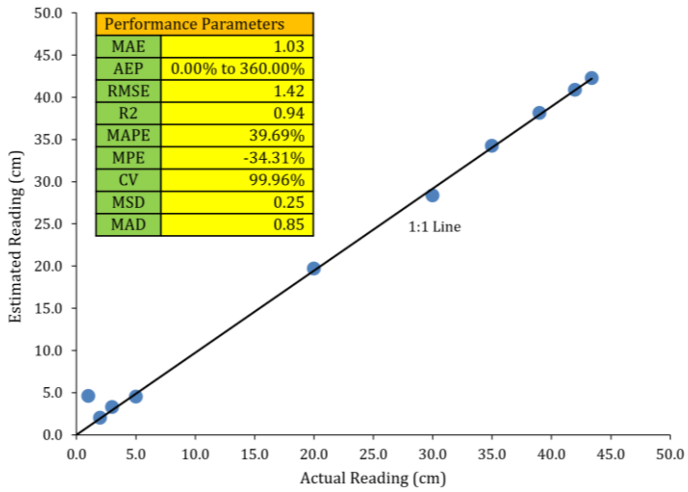

Figure 5: Estimated and actual reading from the ultrasonic sensor with a 1:1 line. MAE is mean absolute error, AEP is absolute error percentage, RMSE is the root mean squared error, R^2 is coefficient of determination, MAPE is mean absolute percentage error, MEP is mean percentage error, CV is coefficient of variation, MSD is mean signed deviation, and MAD is a median absolute deviation.

3.3 Real-time Data Monitoring by Using IoT

Figure 6 displays the real-time data on water level and environmental parameters on the selected date. The IoT approach can monitor the water level data, including environmental parameters, in real-time. The greenhouse's indoor temperature (maximum 49.4 ^{o}C, minimum 20.2 ^{o}C) is higher than the outdoor temperature (maximum 46.8 ^{o}C, minimum 18.9 ^{o}C). The greenhouse's mean relative humidity (69.9%) is lower than the mean outside relative humidity (77.5%). The greenhouse structure causes the inside temperature to be higher and relative humidity to be lower than the outside temperature and relative humidity. The changes in inside and outside environmental parameters influence the evaporation rate of water inside Class A pan. The water temperature shows the pattern of temperature changes at daylight and night. Water temperature increases steadily at around 8:00 a.m. and peaks at about 5:00 p.m. Then, the water temperature decreases steadily until approximately 7:00 a.m. the next day. The LDR values represent the daylight and night changes during the growing season. The LDR sensor can also be attached to the plant to sense the leaf growth performance in the different growing stages [18].

The water level data inside the Class A pan indicates the changes over time. Water level data is converted to the drawdown values to reflect the amount of evaporated water. By considering the actual daily values recorded from J-hook, it was found that the percentage error of the system varied between 6.7% and 51.2% based on the dates of 31 March 2023, 02 April 2023, and 14 April 2023. The accuracy of the ultrasonic sensor can be increased if the view angles can be considered during data collection[19]. Although the use of ultrasonic sensors in the laboratory is accurate, the performance of ultrasonic sensors in an open environment could be considered moderate. The result is acceptable since the use of ultrasonic sensors in the open field is influenced by obstacles such as wind speed, temperature, and relative humidity, which could affect the response of ultrasonic waves. Correcting water level data with ambient temperature gives more accurate results [13], [20]. This study provided valuable information on the fundamental understanding of low-cost sensors to monitor water levels inside a Class A pan for evaporation measurement. The proposed monitoring system can observe water levels and environmental parameters in real time. However, the result of this study is confined to greenhouse conditions and low-cost ultrasonic sensors (HC-SR04) during the dry season.

4. CONCLUSION

In this study, an effort was made to monitor the water level inside Class A pan evaporation through IoT. The developed system could detect the water level and capture the environmental data for further analysis. The direct contact distance sensor type immersed in liquid should consider the liquid properties that may influence the sensor reading. Although the performance of the ultrasonic sensor in the controlled environmental setting is excellent (coefficient of determination (R^2) is 0.94, Mean Absolute Error (MAE) is 1.03, and Root Mean Squared Error (RMSE) is 1.42), the application of ultrasonic sensors in the open field or greenhouse needs to consider the factors that disturb ultrasonic waves, such as wind speed, ambient temperature, humidity changes, water temperature, water surface conditions, and interference. An ignorance of the mentioned factors reported in this study caused the accuracy of using the tested sensor to vary from 6.7% to 51.2%. The user must also note the ultrasonic sensor's working distance range since the specific sensor has a limited effective range. This study suggests that the ultrasonic sensor deployment at the field crop required environmental calibration specifically for the tested environment. Appropriate calibration and signal processing techniques ensure accurate and reliable water level measurements, influencing the strength of transmitted and returning signals. Water contamination, maintenance issues, and electrical safety significantly affect contact water level sensors. However, selecting the suitable sensor for smart farming projects depends on specific sensor limitations and considerations.

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Table 2: Effect of analogue sensor reading on the different depths of submerged sensor tip on the same solution.

Solution	Depth (mm)				Chi-Square (df)	p*
	10	20	30	40		
Tap water	535.00(2.00)[a]	573.50(7.00)[ae]	594.50(2.00)[be]	603.00(1)[cbd]	29.36(3)	< 0.001
Distilled water	440.50 (47.50)[a]	514.50 (18.00)[abd]	568.00 (34.5)[bc]	633.00(5.25)[ce]	29.12(3)	< 0.001
Rainwater	657.00(16.00)[a]	672.50(5.50)[b]	663.50(7.00)[abc]	637.50(13.50)[ac]	17.87(3)	< 0.001
Lake water	584.50(22.25)[ab]	593.00(22.25)[bd]	593.00(1.75)[ad]	612.00(5.25)[bc]	20.00(3)	< 0.001
Solution with 2.0 EC	625.50(10.00)[a]	643.00(13.00)[bd]	628.00(8.50)[acd]	625.50(4.50)[ac]	17.74(3)	< 0.001
Solution with 4.0 EC	599.50(5.25)[a]	617.00(7.25)[ab]	635.5(7.25)[b]	635.5(5.25)[cb]	26.31(3)	< 0.001
Solution with 8.0 EC	600.50(8.00)[a]	633.00(6.50)[ab]	649.00(4.25)[b]	649.00(4.25)[cb]	26.34(3)	< 0.001
Calibration solution of pH 4.01	493.50(9.00)[a]	546.5(12.00)[ad]	559.00(7.00)[cbd]	587.00(2.00)[c]	28.08(3)	< 0.001
Calibration solution of pH 6.86	392.00(11.25)[a]	447.50(27.75)[abc]	476.00(30.75)[bc]	481.50(18.50)[c]	22.57(3)	< 0.001
Calibration solution of pH 9.18	429.00(2.75)[ac]	452.50(10.00)[cb]	452.50(10.00)[cb]	556.00(45.50)[b]	26.62(3)	< 0.001

The sensor values are represented by median and interquartile range values in brackets. The sensor values with the same alphabet in the row are insignificant. p* was obtained from the Kruskal-Wallis test. df is the degree of freedom.

Table 3: Correlation matrix for different solutions

Solution Types	TW	DW	RW	LW	2EC	4EC	8EC	4pH	6pH	9pH
Tap Water (TW)	1									
Distilled Water (DW)	.920**	1								
Rainwater (RW)	-0.117	-0.241	1							
Lake Water (LW)	.731**	.757**	-0.126	1						
Solution 2EC (2EC)	-0.167	-0.158	.509**	-0.225	1					
Solution 4EC (4EC)	.811**	.889**	-0.134	.502**	0.093	1				
Solution 8EC (8EC)	.854**	.802**	-0.191	.489**	-0.15	.763**	1			
Solution 4pH (4pH)	.890**	.947**	-0.243	.726**	-0.049	.885**	.789**	1		
Solution 6pH (6pH)	.726**	.862**	-0.137	.551**	0.185	.952**	.697**	.888**	1	
Solution 9pH (9pH)	.805**	.903**	-0.168	.758**	0.105	.820**	.669**	.912**	.873**	1

** Correlation is significant at the 0.01 level (2-tailed)

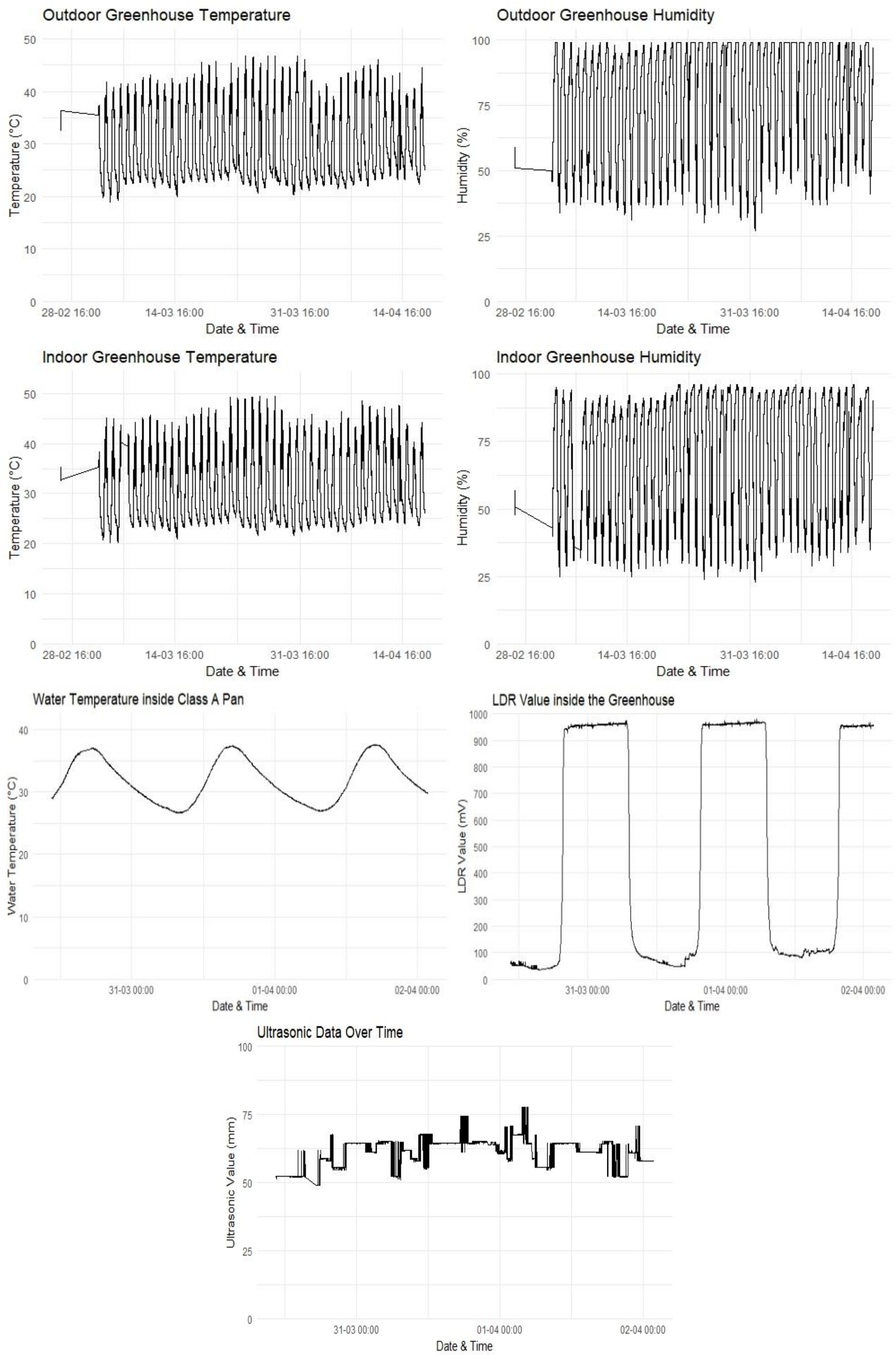

Figure 6: Trends of water level and environmental parameters on selected dates.

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