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Internet of Things (IoT)-Based Precision Irrigation With LoRaWAN Technology Applied to Vegetable Production

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ABSTRACT. ***Precision irrigation with sensors has proven to be effective for water saving in crop production. Internet of things (IoT) system is necessary for monitoring real-time data from sensors and automating irrigation systems. Long-range wide-area network (LoRaWAN) is low-cost and easy to be implemented in IoT systems that can be used for precision crop irrigation. In this study, an IoT-based precision irrigation system with LoRaWAN technology was developed and evaluated as a precision management tool on fresh-market tomato production in an open field. Four irrigation scheduling treatments were designed and tested, including ET (ETc), MP60 (Watermark 200SS-5 soil matric potential sensors, -60 kPa), MP40 (-40 kPa), and GesCoN (decision support system). The treatments were arranged based on a randomized complete block design (RCBD) with four replications. System feasibility, yield, and irrigation water use efficiency (iWUE) were evaluated during the experiment. The results indicated that treatment MP60 and GesCoN had a marketable yield 15.2% and 22.1% higher than ET, respectively. MP40 had a marketable yield 12.5% lower than ET. GesCoN had a significantly higher yield than ET and MP40. However, MP60 did not produce significantly different results from GesCoN and ET but had higher yield than MP40. MP40 received relatively low water via irrigation because of unproper installation and positioning of the soil moisture sensors, which caused a higher incidence of blossom end-rot and thus lower marketable yield. Nevertheless, the LoRaWAN-based IoT system worked well in terms of power consumption, communication, sensors reading and valve control. It can be potentially implemented for precision and automatic irrigation operation in vegetable fields.***

Keywords. IoT, LoRaWAN, precision irrigation, vegetables.

1. Introduction

In the United States, agriculture is a major consumer of ground and surface water, accounting for approximately 80% of the nation's consumptive water use, and this percentage can be higher in the western states characterized by a dryer climate (USDA-ERS, 2019). As the global population continues to increase, food-crop production is expected to increase dramatically while water resources are increasingly limited (Howell, 2001; Di Gioia, 2018). Therefore, it is very important to use water efficiently, especially for crops such as vegetables, characterized by shallow roots and relatively high water content, and thus very sensitive to water stress. Water can be in excess or deficit, and thus irrigation water management can substantially impact vegetable yield and quality (Shock, 2007; Poh, 2011). Conventionally, farm managers determine when and how much to irrigate vegetable crops based on their experiences and often varies by their time availability, which may not be optimal leading to inefficient water usage and crop yield and quality reduction either by over-irrigating or under-irrigating. Precision irrigation is defined as a modern irrigation management strategy that allows growers to avoid plant water stress at critical growth stages by applying only the necessary amount of water directly to the crop, varying rate and duration as needed based on site-specific conditions (Casadesus, 2012). By applying precision irrigation on agricultural crops, farmers are expected to benefit from lower cost of irrigation water and manpower, and improvement of crop yield and quality. Adoption of precision irrigation for crop production systems requires the development of integrated sensing, decision-making strategies, and control systems, eventually to precisely control the timing, rate and distribution of water as needed (Smith and Baillie, 2009).

The application of irrigation can be related to soil, plant, or weather (Romero et al., 2012). Different sensor systems and technologies have been investigated and tested for precision irrigation, including evapotranspiration (ET)-based, plant-based, and soil moisture-based systems (Pardossi and Incrocci, 2011). ET-based irrigation requires a complete set of weather parameters from a nearby weather station or a Class A pan evaporimeter to estimate the ET rate (FAO, 1998; Di Gioia et al. 2009). For plant-based irrigation, canopy temperature is usually used as an indicator to schedule irrigation based on plant infrared thermal response to water status (Conaty et al., 2012). Sap flow, as a plant parameter, is also used to schedule irrigation (Fernandez et al., 2008). Among these methods, soil moisture sensor-based precision irrigation has been widely tested and used in vegetable fields and protected culture systems. Soil volumetric water content (VWC) and soil matric potential (MP) are two indicators for available water in the soil which can be used to implement soil moisture-based irrigation systems (Osroosh et al., 2016). VWC is the ratio of water volume and soil volume with a unit of percentage or m^3/m^3. MP describes the force with which soil matrix holds water (Bianchi et al., 2017). MP measures the required energy for water movement in the soil which is always a negative number with a unit of kPa. In this study, the soil moisture-based irrigation method was used throughout the experiments. Based on preliminary study, the soil MP sensors can fit the IoT systems better and showed sensitivity to variations of soil moisture for vegetable irrigation. Thus, MP sensors were selected over VWC sensors in this study.

Wired or wireless sensor network is one of the key technologies for precision and automated irrigation systems. Vellidis et al. (2008) developed and evaluated a real-time smart sensor array which measured soil moisture and temperature for scheduling cotton irrigation. In similar research, a microcontroller was used to provide real-time feedback control for a drip-irrigation system, toggling system control valves to apply water under the appropriate conditions (Prathyusha and Suman, 2012). Different embedded control technologies have been applied for automated irrigation systems, such as Xbee-PRO technology (Ramya et al., 2012), GSM Bluetooth-based remote-control systems (Gautam and Reddy, 2012), and Dual Tone Multiple Frequency (DTMF) signaling (Dubey et al., 2011). Coates and Delwiche (2009) developed a mesh network system for wireless valve controllers and sensors to limit power consumption in addition to controlling water usage. Applications for mobile phones and wireless personal digital assistants (PDAs and "tablets") have been developed to enable access to remote sensor data and control over physical irrigation systems from a distance (Ahmed and Ladhake, 2011; Sumeetha and Sharmila, 2012).

Internet of Things (IoT), which was coined as a term in 1999 by Kevin Ashton, is a combination of networked sensors and machines for capturing, transmitting, managing, and analyzing data. Firstly, the data from sensors are uploaded wirelessly to a server. Then data are available on the internet for analysis and computing. Finally, the server sends commands wirelessly to the actuators for executing tasks. A project called SWAMP tested the effect of their IoT-based irrigation system at four pilot locations in Brazil, Italy and Spain (Kamienski et al., 2019). Goap et al. (2018) developed an IoT-based smart irrigation management system with machine learning algorithm to improve irrigation control.

Various wireless technologies in IoT systems have been investigated for crop irrigation management, such as Wi-Fi, cellular network (GPRS, LTE), ZigBee, and LoRaWAN. Zhao et al. (2017) compared the performance of Wi-Fi, ZigBee, GPRS, and LoRaWAN for irrigation systems. The results indicated that Wi-Fi and ZigBee had low coverage and only worked for the vegetable fields near to the gateway. GPRS is good for long-distance communication, but it has high-power consumption, and high cost of maintenance and deployment. LoRaWAN technology has a maximum range of 10 km with low power consumption and low-cost, which could allow for affordable precision irrigation systems for small farms. This technology was originally published in 2015 by LoRa Alliance, a non-profit association supporting the LoRaWAN protocol (LoRa Alliance, 2015); however, it is still not widely used in precision irrigation systems. To the best of knowledge, the LoRaWAN based system has been proposed for vegetables, but has not been tested under field conditions.

Therefore, the primary goal of the present study was to develop an effective IoT-based precision irrigation system using LoRaWAN technology for vegetable production. Different irrigation treatments were established to evaluate the performance of the soil moisture sensor-based irrigation strategies, and the functionality and robustness of the IoT system.

Specific objectives were:

1. to develop a LoRaWAN technology-based IoT wireless sensing network system for precision irrigation for vegetable irrigation,
2. to conduct the functionality evaluation on the irrigation system in terms of data communication, irrigation execution and power consumption, and
3. to evaluate the efficacy of the developed IoT-based precision irrigation system at field scale using fresh-market tomato as a test crop and comparing the MP sensor-based, ET_c-based, decision support system-based irrigation scheduling.

It is hypothesized that for vegetable fields often located at distance from the farm center, and thus far away from an internet connection-point such as a gateway, LoRaWAN could be a good choice for the wireless technology in IoT-based irrigation. By using a LoRaWAN IoT-based precision irrigation system, vegetable farmers will rationalize and optimize the irrigation management saving water and improving crop yield, and irrigation water use efficiency (iWUE).

2. Methodology

2.1 Experimental setup

To achieve the proposed goal and objectives, an open field irrigation management study was conducted at the Horticultural Research Farm of the Penn State Russell E. Larson Agricultural Research Center (Furnace, PA) during 5/21/2020 – 9/23/2020. The soil type in the experiment field was silty clay loam with 13.5% of sand, 47.8% of silt, and 38.8% of clay. The soil pH was 6.5. Contents of phosphate, potash, magnesium, and calcium were 156, 266, 521, and 3203 lb/A, respectively. Total nitrogen and carbon soil content were 0.13% and 1.13%, respectively. The content of ammonium nitrogen was 2.34 mg/kg.

Fresh-market tomatoes (*Solanum lvcopersicum* L.) cv. Red Deuce F1 (HM Clause, Davis, CA) were used as the test crop. Seedlings were planted at the 4th true-leaf stage on May 21st, 2020 on raised beds mulched with black polyethylene film served by a single drip tape per bed. Beds were 0.91 m wide and 2.13 m away from each other, and plants were planted at in-row distance of 0.46 m, establishing a density of 1.03 plants m^{-2}. The 16 mm in diameter drip tape had emitters spaced 0.30 m and had a flow rate of 1 L/h per emitter at 55 kPa (T-Tape, Rivulis Irrigation Ltd. San Diego, CA). Plants were trellised using the stake and Florida weave method (Di Gioia et al., 2016) and the crop was managed according to local practices using an integrated pest management approach. A view of the open field experiment is shown in Figure 1.

Figure 1. View of the open field irrigation experiment.

Four treatments using different irrigation scheduling were designed and tested. Between 0 and 34 days after transplanting (DAT), the whole irrigation system and IoT system were tested, and the irrigation was the same for four treatments during this period. The treatments started on 36 DAT. Treatment 1 (standard control, denoted ET) was based on crop evapotranspiration (ET_c) and consisted of irrigating the crop with a volume equivalent to 100% of the ET_c estimated on daily basis using a dual crop coefficient model according to FAO Paper 56 (FAO, 1998). Irrigation was applied after reaching 12 mm of cumulative water deficit on average. Treatment 2 and 3 were based on soil matric potential (MP) sensors (Watermark 200SS-5, Irrometer company, Inc., Riverside, CA) at different setpoints of -60 kPa (denoted MP60) and -40 kPa (denoted MP40), respectively. Once the average sensor readings at 20 cm depth reached the thresholds, the IoT system would send a notification and valves were manually controlled through the IoT system interface. The irrigation durations for the MP60 and MP40 were determined by monitoring the sensor readings in the pre-tests, and some adjustments were made during the experiment according to the response of the sensors at 20 and 40 cm soil depth, which were on average 114 and 117 min between 36 and 66 DAT, 177 and 151 min between 67 and 83 DAT, and 285 and 241 min between 84 and 125 DAT, respectively. Treatment 4 (denoted GesCoN) was based on recommendations provided by a decision support system (DSS) named GesCoN. When irrigation was needed, the system would send the suggestion of irrigation volume and time. GesCoN is a model based DSS developed by researchers at the University of Foggia (Italy) to estimate crop N and water requirements and manage fertigation in open field grown vegetables (Elia and Conversa, 2015) and calibrated on tomatoes (Conversa et al. 2015). Using the real-time, historic, and forecasted local weather data, the basic information on soil (soil texture and mineral content), the specific crop (species, variety, planting date, planting density, estimated production), on the area of the field and on the irrigation system (drip tape flow rate and distance between drippers) the GesCoN integrates water balance, plant growth, and nitrogen uptake sub-models to estimate crop dry matter production, crop yield, evapotranspiration, soil moisture, drainage flow, soil nitrogen dynamics, and nitrate leaching and provides recommendations on irrigation and N fertigation. The DSS GesCoN has been integrated with the web-application Ecofert (www.ecofert.it) and an Android App (Ecofert). The DSS can be connected to weather stations using the RESTful API method to automatically retrieve real-time on-site or location specific climate data (Gallardo et al. 2020).

All treatments received N fertilizer via fertigation at the same time, in the same form and amount according to the recommendations provided by GesCoN as reported in Table 1.

Table 1. Fertigation dates, fertilizer and application rates recommended through GesCoN over the entire growing season.

Date	GesCoN suggested fertilizer	N%	Applied N (kg ha^{-1})
6/26/2020	Urea	46	18
6/30/2020	Urea	46	30
7/15/2020	Urea	46	30
7/21/2020	Urea	46	19
	Calcium nitrate	15.5	8
7/31/2020	Urea	46	14.5
	Calcium nitrate	15.5	9.5
Total N applied			129

The layout of the field is shown in Figure 2. The overall field (planting area) was 27.74 m × 42.67 m in dimension. The field was constituted by 12 raised beds 42.7 m long. Three beds constitute a block, and each block was divided into 4 sections, each hosting an irrigation strategy treatment. Overall, the field was divided into 16 experimental units of the same size. Each experimental unit was constituted by three beds about 9.14 m long. Twenty plants were placed in each bed, for a total of 60 plants per experimental unit. Treatments were arranged in a randomized complete block design (RCBD) with four replicates for each. Four treatments were randomly distributed in each block.

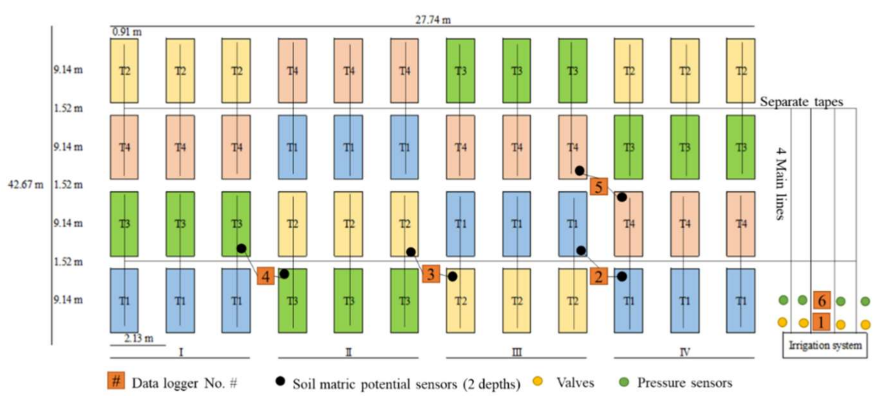


Figure 2. Experimental setup and the locations of the sensors and dataloggers.

An irrigation system was setup in the field, connecting irrigation pipelines, solenoid valves, pressure sensors, soil MP sensors and data loggers (DL). Six data loggers were used to connect the sensors and valves, including one for valves (DL 1), four for soil MP sensors (DL 2~5), and one for pressure sensors (DL 6). DL 1 connected to four valves. DL 2, 3, 4, and 5 connected to four soil MP sensors of treatment ET, MP60, MP40, and GesCoN, respectively. DL 6 connected to four pressure sensors. The detail of sensors, datalogger, and valves are introduced in the following sections.

2.2 Irrigation system setup

Figure 3 shows the structure of the irrigation system, including pipelines, valves, pressure sensors, flow meters, and other accessories. The water was supplied from the main water line of the farm. The main irrigation line after a screen filter was divided into four pipelines, one for each treatment. Four latching DC solenoid valves (PGV Series 2.54 cm, Hunter Inc., San Marcos, CA) were installed at the beginning of each line, followed by the pressure sensors (0.64 cm 5V 0-1.2 MPa) installed one per line behind the solenoid valves to measure the water pressure. The pressure indicated the status of the valves. The pressure regulators (241 kPa) behind the pressure sensors limited the water pressure reaching the following components. The flow meters measured the cumulative flow volume during the experiment. The fertigation system constituted by a by-pass with a Venturi injector was used to apply fertilizers when recommended by the DSS GesCoN. When fertigation started, the injector was opened first, then the switch in the pipeline was closed. When fertigation ended, the switch in the pipeline was opened first, then the injector was closed. The pressure gauges were used to measure the real-time water pressure and calibrate pressure sensors. The last components were pressure regulators at 103 kPa, which is the suggested pressure for the irrigation drip-tape lines used. Drip tapes were placed underneath the mulch for each section. Then the drip lines on the same treatment were connected to the pipes in the field pathway. Finally, these pathway pipes were connected to the corresponding pipelines (2.54 cm) for each treatment.

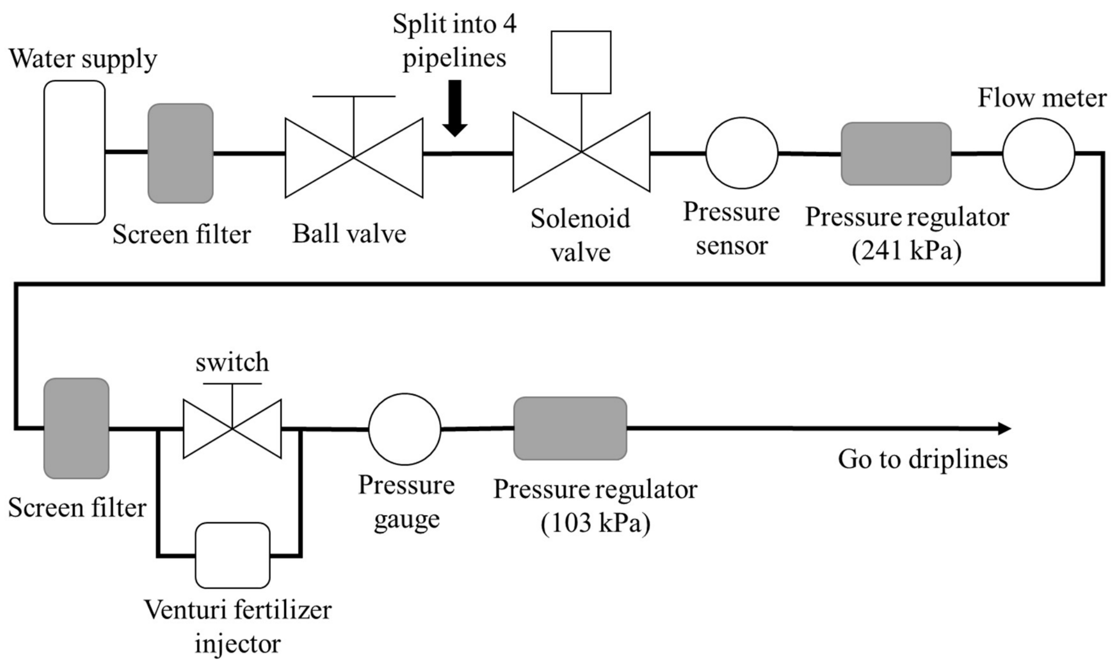


Figure 3. The schematic of the overall irrigation system setup with one treatment irrigation pipeline as an example.

2.3 Sensor system setup

As indicated earlier, in total six data loggers were used in the system. The major components of the data loggers included a base control board (Vinduino LLC, Temecula, CA) and a LoRaWAN wireless communication unit with antenna (LM130-H1, GlobalSat WorldCom Corp., New Taipei City, Taiwan). Each data logger was powered by 3.7 V lithium-ion polymer (LiPo) battery, and a solar panel (70 mm × 70 mm) was connected to charge the battery. DL 1 and 6 used 10000 mAh batteries and Data loggers 2~5 used 5000 mAh batteries. In each treatment, four soil MP sensors (Watermark 200SS-5, Irrometer company, Inc., Riverside, CA) were used. Figure 4 shows the connection of the soil MP sensors to the data loggers.

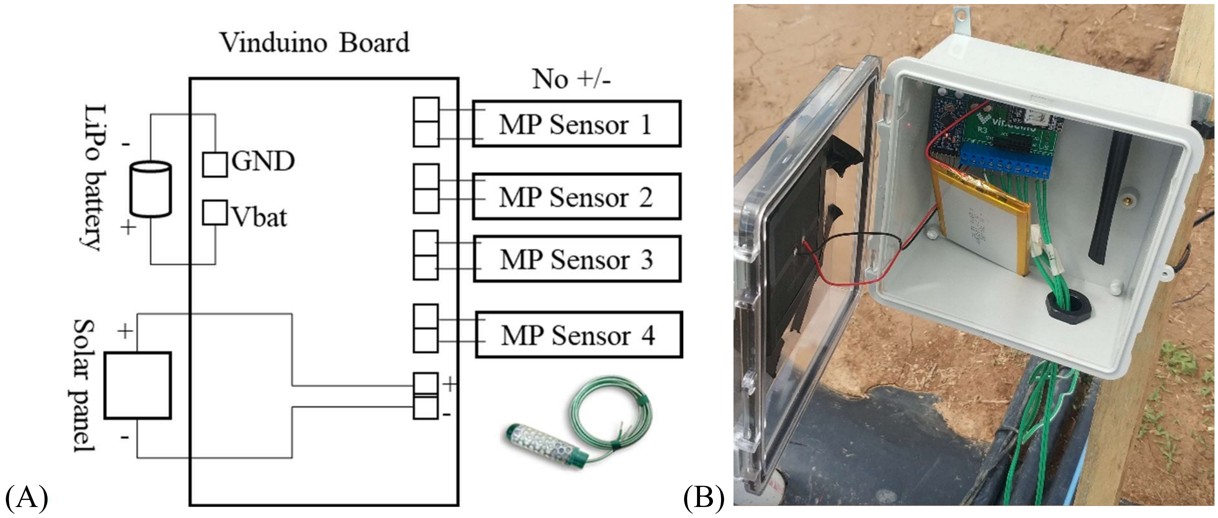


Figure 4. Connection of soil MP sensors with the data logger. (A) schematic illustration. (B) connection with the datalogger

In each treatment, the sensors were installed in two experimental units and at two depths (20 cm, 40 cm). During the installation, a soil sampler was used to dig a cylinder hole at 40 cm depth. Then, two soil MP sensors, which were soaked in water for 24 hours before installation, were placed in the hole. The original soil was back filled, and water was added to ensure the close contact between the sensors and soil. The average soil MP of two experiment units at 20 cm was used for starting the irrigation in the treatments MP60 and MP40. The sensors at 40 cm were used as a reference to check whether the water went down to the depth when the irrigation ended. The sensors installed in treatments ET and GesCoN were used only for monitoring the soil moisture levels.

In each treatment pipeline, a pressure sensor was installed behind the solenoid valve to indicate the valve status (on or off). The sensors were calibrated with the pressure gauges installed on the same line. By adjusting the opening of the ball valve, eleven pairs of pressure sensor readings and pressure gauge readings from 0 to 207 kPa were used to calibrate the pressure sensor. Figure 5 shows the connection of the pressure sensors to the data loggers.

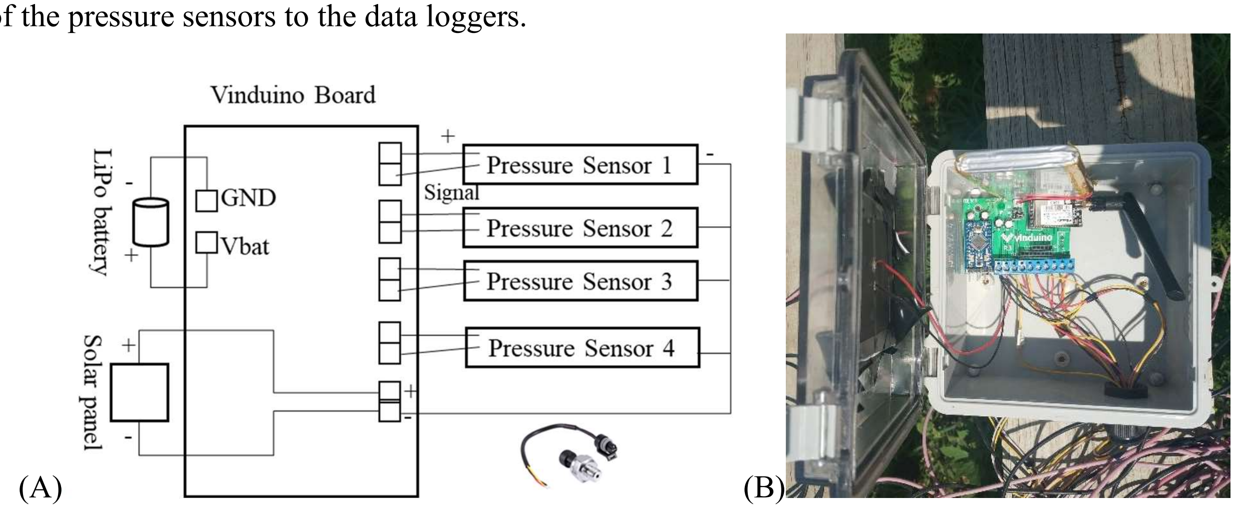
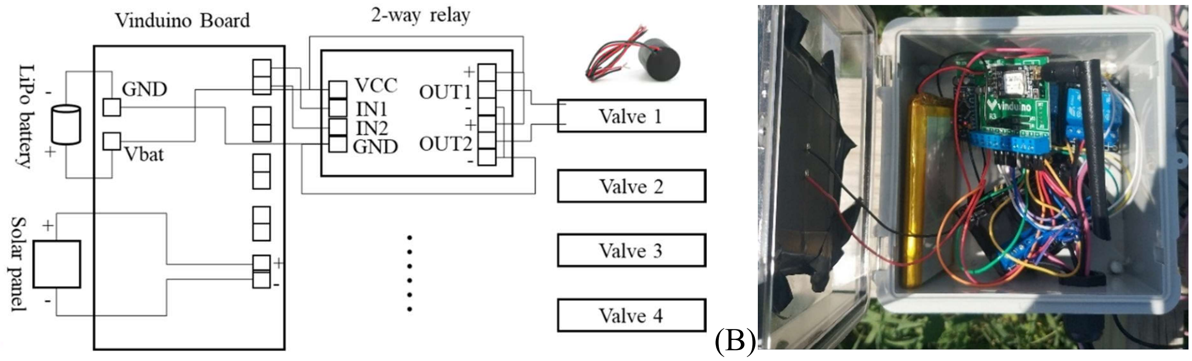


Figure 5. Connection of pressure sensors with the data logger. (A) schematic illustration. (B) connection with the datalogger

2.4 Valve control

DC latching solenoid valves were used to control irrigation by connecting and disconnecting the water supply. Figure 6 shows the connection of valves and the data logger. The Vinduino board originally supports only one valve. For using it to control four valves, the sensor ports on the board were used to extend the capability. Sensor ports can send high/low signal at 3.3/0 V, but the current is not enough for executing the valves. To use the battery voltage (Vbat, 3.7 ~ 4.2 V) as power of the valves, four 2-way relays were added for the valve control. Two sensor ports send high/low signals to the IN1 and IN2 port of the 2-way relay to change electric potential at OUT1 and OUT2. High or low of IN corresponds to Vbat or 0V of OUT. OUT1 and OUT2 connect to the positive and negative electrode of the valve, respectively. When IN1/IN2 is high/low, the valve will open. When IN1/IN2 is low/high, the valve will close. When IN1/IN2 is the same or no input, the valve will not respond.

(A) 

(B)

Figure 6. Connection of valves with the data logger. (A) schematic illustration. (B) connection with the datalogger

2.5 IoT system and data collection

An Internet of things (IoT) system was established to connect the sensors, valves, and data loggers in the field. A LoRaWAN gateway (Sentrius™ RG191, Laird) was placed in an office which was 150 m away from the field. Figure 7 illustrates the procedure of the IoT system development. The gateway and data loggers were configurated in a free IoT server named The Things Network. Then an IoT platform AllThingsTalk (AllThingsTalk NV, Mechelen, Belgium) was used to store and display the sensor data and control the valves.

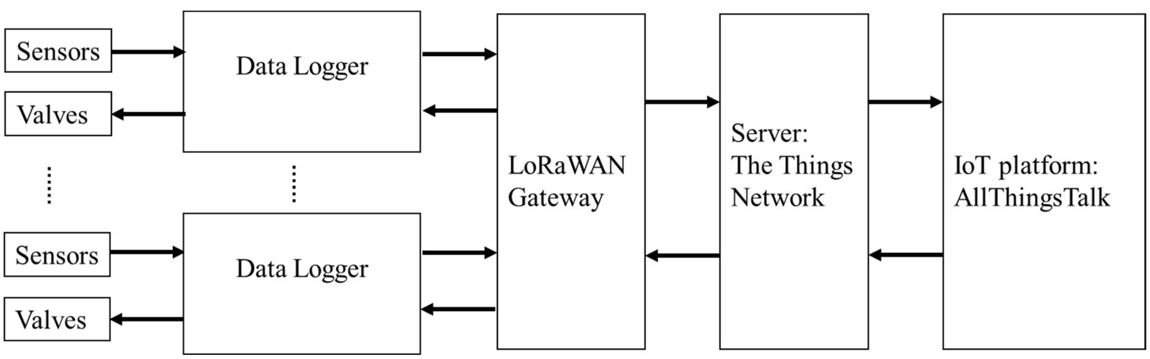


Figure 7. Structure of the experimental IoT system.

The first step was to configure the gateway and the data logger. The LoRaWAN gateway was first connected to a computer with Wi-Fi for matching the parameters, including using "The Things Network" as server and "915MHz" as band frequency. In the server interface, a gateway was created with the recorded gateway ID. Then an "Application" was built in the gateway to represent the proposed tomato field irrigation system. An Application Extended Unique Identifier (EUI) of the application was generated automatically by the server. Six devices were created under the "Application" to connect the six data loggers, respectively. They shared the same Application EUI while had unique App Keys. Algorithms were developed for these data loggers with different functions, including soil MP recording, valve control, and water pressure recording. The Application EUI and App Key were used for the data loggers to be connected to the gateway for uploading data (sensor data) and downloading data (control signal). Once the data loggers were powered, they were connected to the server after a few seconds.

The next step was to transmit the data to the AllThingsTalk IoT platform and process the data. In the web-based interface, integration "AllThingsTalk" was added to the created application. Then the IoT platform was linked to the server The Things Network. Sensor data was uploaded and stored in the IoT platform for monitoring and irrigation control. In the platform, six "devices" were added corresponding to the six data loggers. Then the "assets" were created in the "devices" to represent the corresponding sensors or valves in each data logger. The data communication frequency was applied with a pre-set time interval, which was 1 minute. The sensor data (uplink) and valve control (downlink) were communicated as binary payload. Each value, such as the battery voltage, sensor reading, and valve status was parsed from a byte between 0 and 255. These were converted to actual values by editing the payload format in the "devices" interface. The valves can be separately controlled to turn on or off through the IoT platform.

For DL 1, the battery voltage, valve status, and valve control switch were shown in the AllThingsTalk display. And for DL 2~6, the real-time sensor readings and battery voltages were displayed. The historic data of sensors and batteries were stored and can be exported in a comma-separated values (CSV) file. The status of all assets of six devices could be displayed to a pinboard (Figure 8). The status of the solenoid valves was shown by a circle indicator with black color for close and green color for open. The valves could be controlled by inputting a number between 0 and 15 in the textbox. The soil MP sensor readings were compared with the pre-set threshold, and a notification (Figure 9) can be sent by email or mobile application when the threshold is reached. However, full automation was not applied for the irrigation, instead a manual control through the IoT platform was used to start and end irrigations. The major reason was that there was signal loss occasionally on the farm which may lead to delayed response of valves with automatic setting.

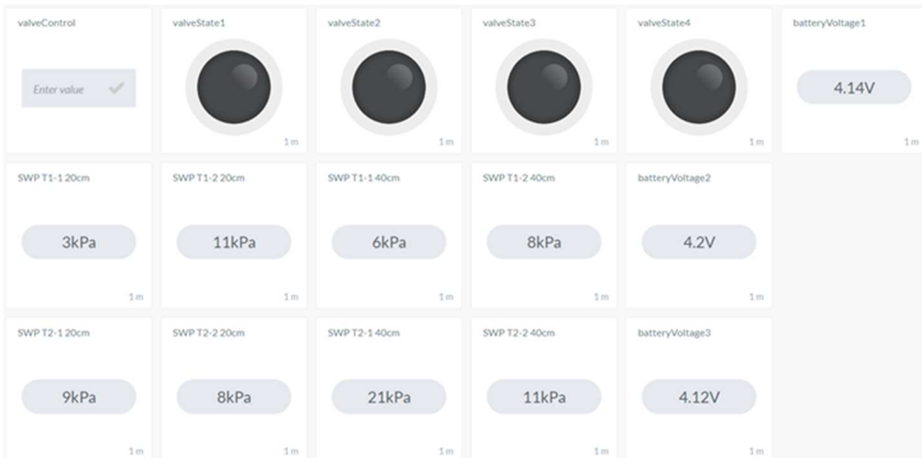


Figure 8. Sensor data display and irrigation valve control on the IoT platform.

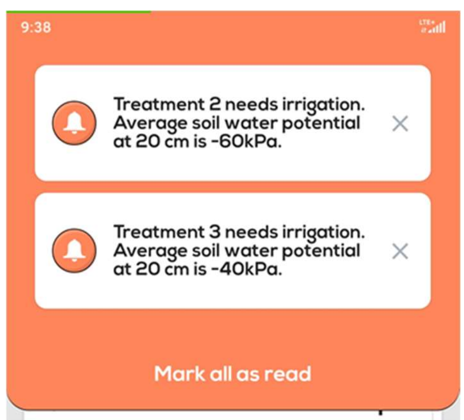


Figure 9. The notification of the IoT platform on its mobile application.

2.6 Harvest, yield components, and Irrigation water use efficiency

2.6.1 Yield

At harvest, ten continuous representative tomato plants were selected from the middle row of each experimental unit. Tomatoes ranging from mature green to ripe red in color were harvested on 8/7, 8/19, 9/1, 9/11, and 9/23/2020 in correspondence of 78, 90, 103, 113, and 125 days after transplanting (DAT), respectively. The experiment ended with the last harvest on 125 DAT. Harvested tomatoes were sorted into marketable and unmarketable fruit, and marketable fruit were graded into several size categories: extra-large ($d > 6.99$ cm), large ($6.35 \text{ cm} < d \leq 6.99$ cm), medium ($5.72 \text{ cm} < d \leq 6.35$ cm), and small ($5.40 \text{ cm} < d \leq 5.72$ cm), according to the U.S. Standards for Grades of Fresh Tomatoes (USDA, 1997).

Fruit number and fresh weight were recorded for each category.

2.6.2 Irrigation water use efficiency

Water usage was recorded after the last harvest by reading the flow meter. Water usage was measured by treatment and assumed to be the same for the four replications. Irrigation water use efficiency (iWUE) was calculated dividing the marketable fruit fresh weight by the total water usage.

2.7 Statistic analysis

The data of the of the IoT system between 6/25/2020 (35 DAT) and 9/23/2020 (125 DAT) was downloaded from the IoT platform AllThingsTalk. Data loss rate was calculated by the numbers of signals received divided by the expected numbers of signals received. Each data logger's and the average data loss rate was calculated. Each data logger's battery voltage, the soil MP sensor readings, weather data including solar radiation, rainfall, and air temperature during the experiment were processed using Microsoft Excel and presented in figures.

Analysis of variance (ANOVA) was applied to fruit fresh weight and iWUE for four different treatments and four different blocks. These statistical analyses were performed using PROC GLM procedure in SAS 9.4 (SAS Institute Inc., Cary, NC, USA., 2016). All means were compared by the least significant difference (LSD) test at $P \leq 0.05$.

3. Results and Discussion

3.1 Feasibility of the IoT system

3.1.1 Data loss in communication

The system generally worked well during 35 - 125 DAT. There were a few occasions of data loss in the IoT system. Six data loggers had similar data loss rate and the average data loss rate was 5.51 % (Figure 10). The gateway was placed inside a building about 150 m away from the field, which may have led to some signal loss. This can be improved if the gateway is installed outside with less occlusion. Meanwhile, the disconnection of any component such as the gateway, the server The Things Network, and the IoT platform AllThingsTalk can contribute to the signal loss. However, since data were uploaded at high frequency every minute, and there was no long period of data loss, the sensing system was not affected significantly. A few continuing data loss for more than 10 minutes was observed. If the irrigation was applied during these periods, it is possible that the valves would not respond on time.

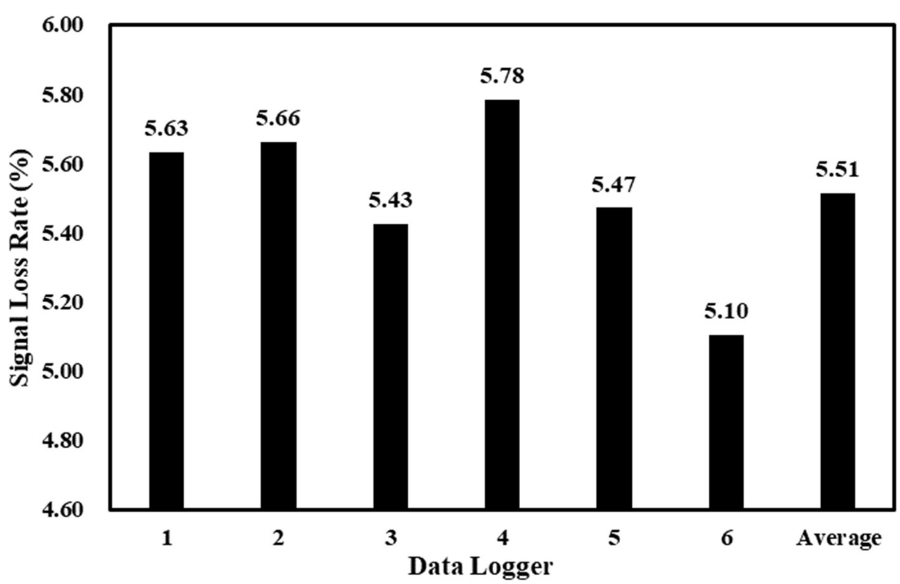


Figure 10. Signal loss rate of six data loggers during the experiment.

3.1.2 Battery

The batteries in the six data loggers were charged by solar panels and maintained sufficient power throughout the three-month experiment period. Figure 11 shows the voltage of these batteries over time. On 103 and 114 DAT there was voltage drop for all data loggers due to the continuing cloudy and rainy weather. A disconnection of the solar panel wires occurred for the data logger 3 between 60 and 70 DAT, resulting in an obvious voltage drop compared with other time period. Overall, the battery voltages during the experiment were always higher than 4 V, which showed that the 5000 mAh LiPo battery with solar panel could support a data logger continuously in the open field.

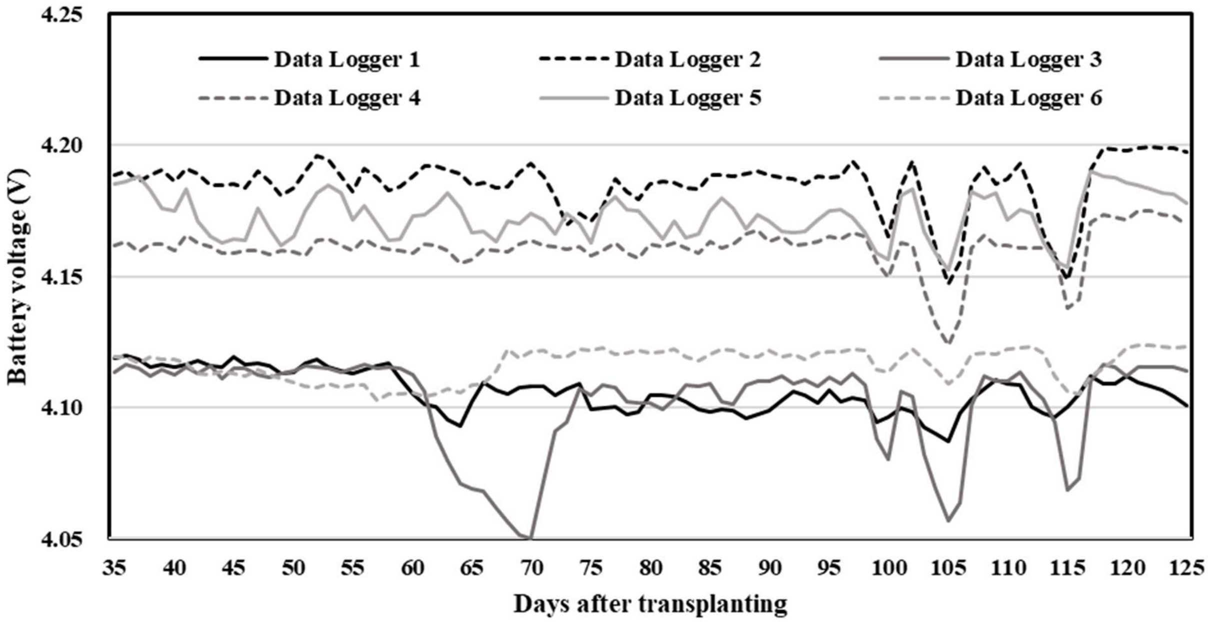


Figure 11. Battery voltage of six data loggers during the experiment

3.1.3 Valve control

During the experiment, the irrigation was applied successfully by controlling the status of the solenoid valves with the implemented IoT system. When the soil moisture threshold was reached, the platform sent a notification through the mobile application and an email to the end-user. Then the operator turned the corresponding valves on, and the irrigation started. When the valves were opened, the status of the valves were showing “Green” in the IoT interface, and the pressure of the water line was indicated with a positive reading. When the valves were closed after certain hours of irrigation, the valve status was showing “Black”, and the reading of the pressure sensors returned to zero. It was also observed that, the valve status changed to “Green” while the pressure sensor reading did not change accordingly. In this situation, the valve did not actually open with pressure water going through. In other words, the pin in the solenoid did not respond even if the signal was received by the controller. By sending the signal several times, the valves did finally open or close. This can be attributed to the clog in the solenoids or small voltage for powering the valves (4 V). In the future, a higher voltage (9 V) can be used to improve the response of the valve. Meanwhile, remote control with manual operation was used in the experiment, for a fully automatic irrigation system, the start and end of an irrigation will be programed into the controller according to the soil moisture thresholds.

3.2 Soil moisture monitoring

Figures 12-15 shows the daily average soil MP sensor readings, rainfall, and irrigation of four treatments between 35 and 125 DAT. Generally, the sensor readings presented the changes of the soil moisture level in the test field. When irrigation or rainfall happened, the sensor readings were increasing. The soil at 40 cm were generally dryer than the soil at 20 cm. It indicated that the irrigation did not drain the soil at 40 cm depth completely. Sometimes the sensors at 40 cm had no response after the irrigation, suggesting the irrigation volume was not enough and the water could not reach the depth of 40 cm.

For treatment ET (Figure 12), most sensor readings were higher than -100 kPa. The sensor reading did not respond consistently because the irrigation was based on ET_c, and the sensor readings were not considered. The readings of MP 1-1 were usually lower than MP 1-2 (treatment 1-ET, the second sensor installation place), which might be caused by uneven soil texture and hydraulic properties. The place where MP 1-2 was installed tended to get wetter than MP 1-1.

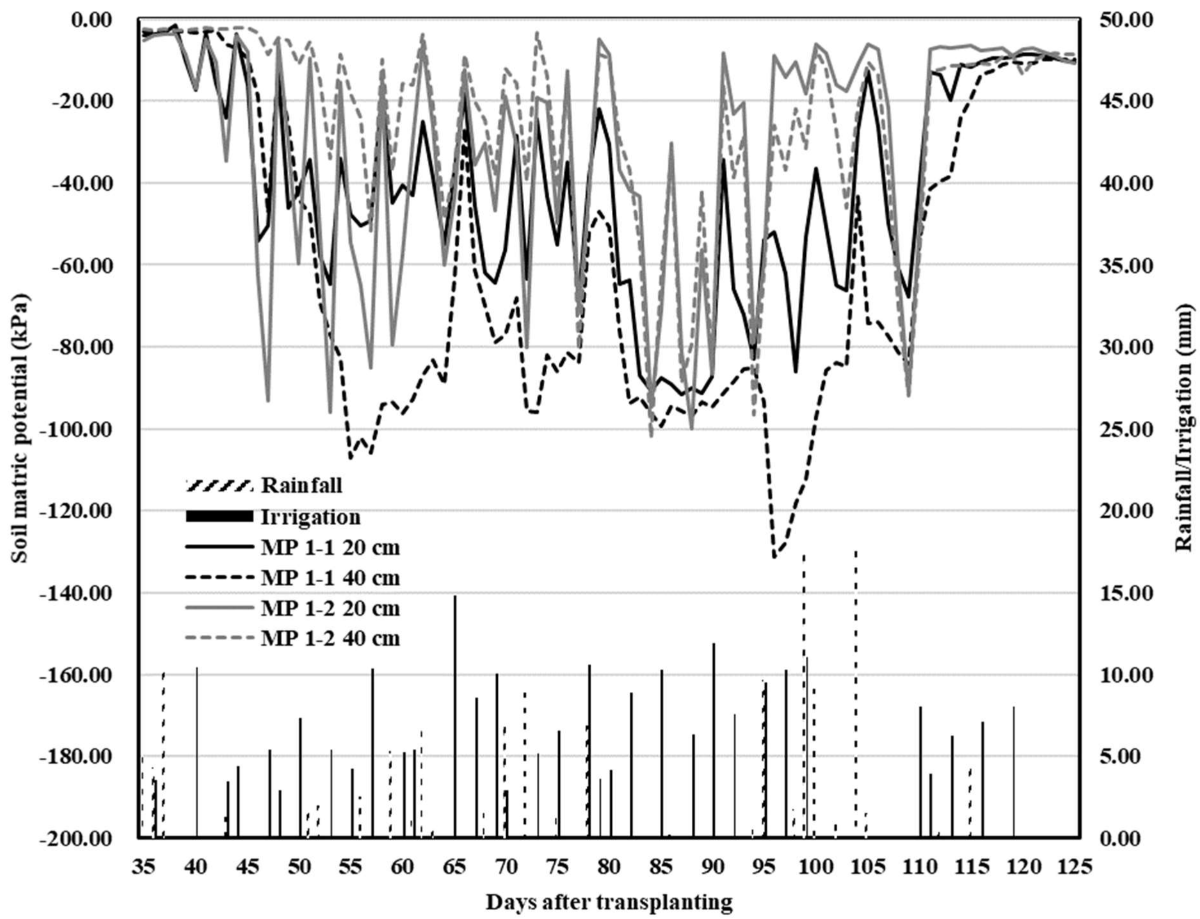


Figure 12. Daily average soil MP sensor readings, rainfall, and irrigation of treatment ET during the experiment

For the treatment MP60 (Figure 13), the sensor readings were all above -140 kPa throughout the experiment. When the average sensor reading at 20 cm reached -60 kPa, the irrigation was applied. Thus, the daily average readings of sensors at 20 cm were usually above -60 kPa during the experiment. However, between 35 and 55 DAT, MP 2-1 20 cm continuously got dryer, which was abnormal since there was irrigation. A new sensor was installed to replace that one at a near position, and the readings of the new sensors were consistent with the other sensors. Before the replacement, the irrigation was based on MP 2-2 20 cm only. There were two possible reasons for this abnormality. One possible explanation is that the position where the sensor was installed might have a dryer condition. A second explanation could be that the sensor was not in close contact with the soil. The volume of each irrigation was adjusted according to the sensor response during the experiment. The sensor readings of MP 2-2 40 cm kept low between 65 and 72 DAT but returned to higher level after irrigation on 72 DAT. This indicated that the irrigation volume was not enough during this period. Thus, the water could not reach the 40 cm depth. After 85 DAT, the irrigation depth was increased to over 10 mm each time. At this point, the response of the four sensors became more consistent.

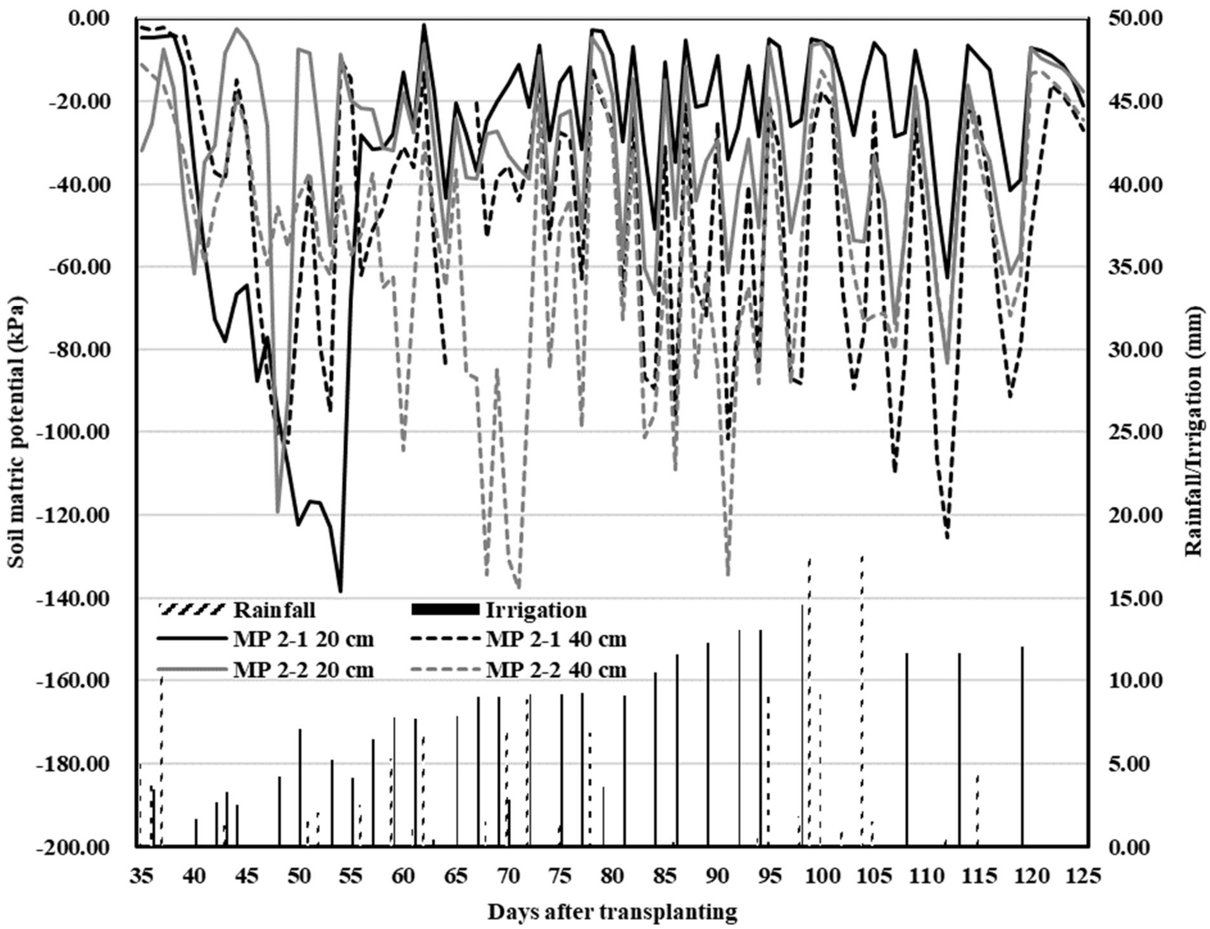


Figure 13. Daily average soil MP sensor readings, rainfall, and irrigation of treatment MP60 during the experiment.

For the treatment MP40 (Figure 14), all the sensor readings were above -120 kPa during the experiment. When the average sensor reading at 20 cm reached -40 kPa, the irrigation was applied. Thus, the daily average sensor readings at 20 cm were usually above -40 kPa. The sensor response kept consistent between 35 and 125 DAT, and all the sensors showed a high reading compared with other treatments. However, the total irrigation volume was much less than other treatments. In the field, treatment MP40 was dry during the experiment and tomato plants were more stressed because of lack of water. This outcome indicated that the sensor readings did not show the real condition of treatment MP40. A possible reason could be variations of soil texture within the experimental field. The sensors of each treatment were installed at only two positions, and the two positions were not far from each other because the wire of the sensors was only 5 m long and they needed to connect to the same data logger. Meanwhile, the position where the sensors were installed was wetter than the average condition of treatment MP40. Thus, the sensors readings of treatment MP40 showed wetter readings than the actual soil moisture level, making the irrigation not adequate.

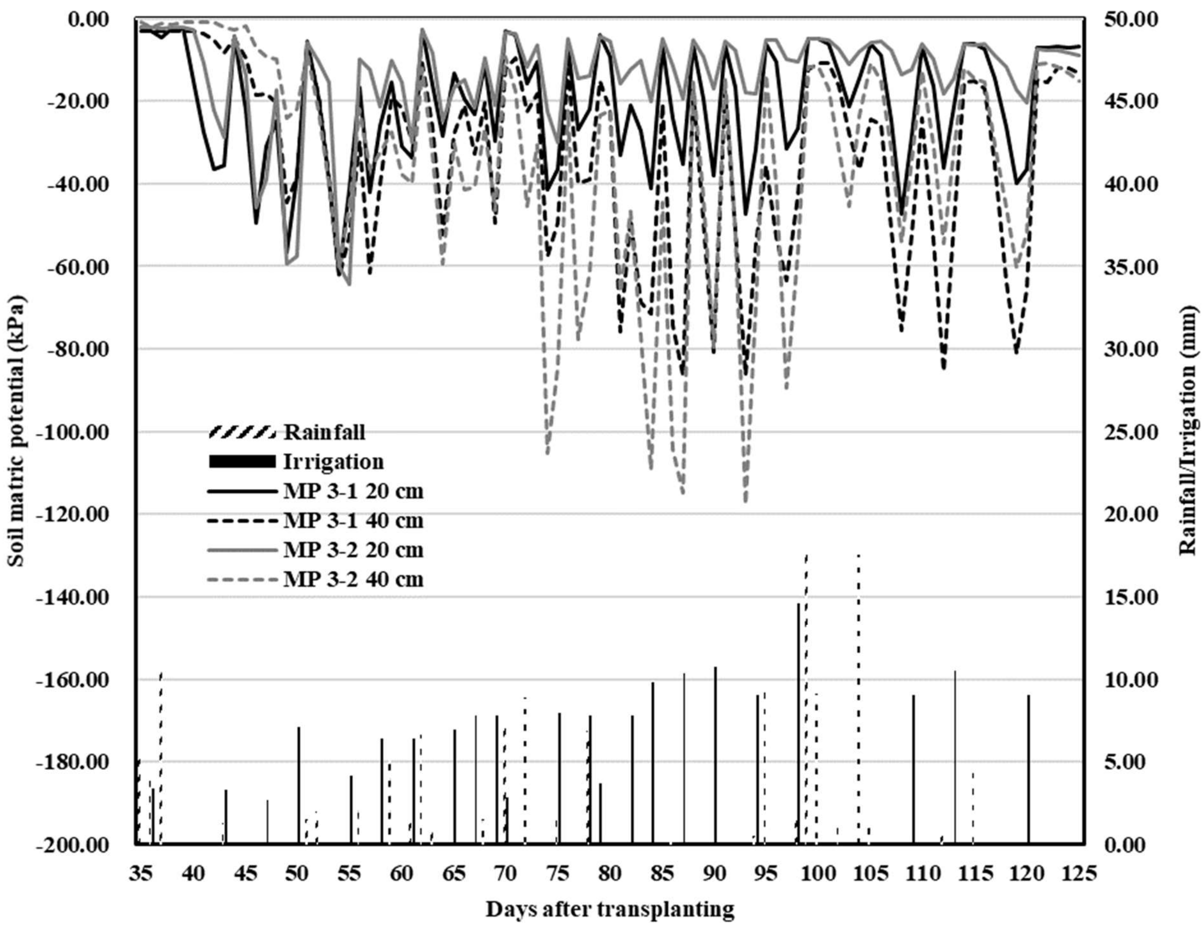


Figure 14. Daily average soil MP sensor readings, rainfall, and irrigation of treatment MP40 during the experiment.

For treatment GesCoN (Figure 15), most sensor readings were above -140 kPa. Two sensors at MP 4-2 continuously dropped between 70 and 80 DAT and between 100 and 110 DAT. The drip tapes of the area where the sensors were installed was found disconnected during that period, and the area did not get any irrigation. However, this issue affected only one of the guard rows from which tomatoes were not harvested. Therefore, the issue did not affect the results. However, the issue could be detected by monitoring the sensors, which suggests that integrating the use of soil moisture sensors with GesCoN could provide some benefits.

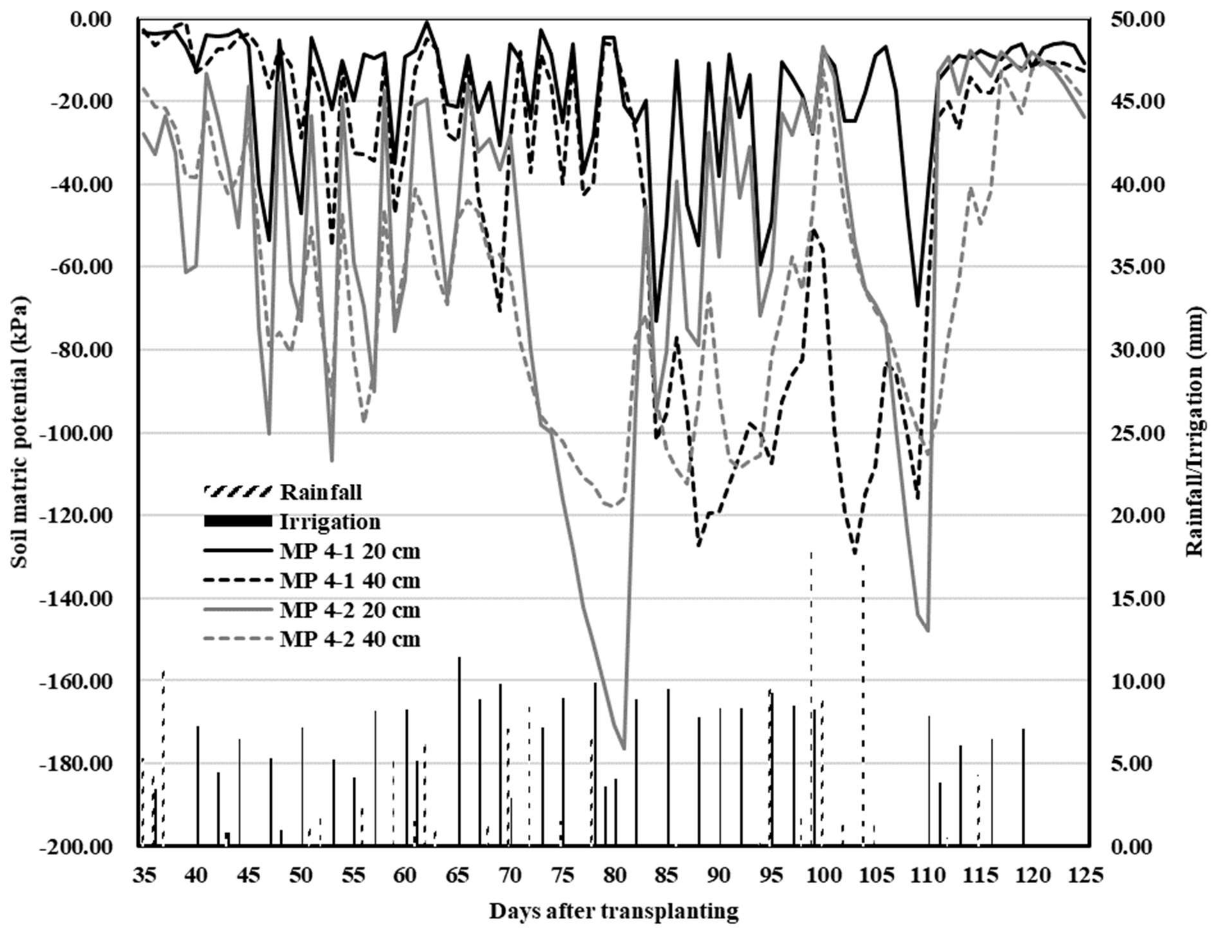


Figure 15. Daily average soil MP sensor readings, rainfall, and irrigation of treatment GesCoN during the experiment.

Figure 16 shows the sensor readings around an irrigation event of treatment MP60 at 77 DAT. The irrigation was based on the average of two sensor readings at 20 cm. When the average readings reached -60 kPa at 18:50, the notification was sent, and the valve was opened remotely. The increased water pressure readings showed that the water was on. The sensor readings increased in 30 minutes and stopped increasing in about 2 hours. Sensors at 40 cm and at the first installation position responded first. Commonly, water reached 20 cm first, then 40 cm. But the sensors were not close to the drip tapes, and the irrigation water spread in both vertical and horizontal direction to reach the sensors. For this reason, sometimes the irrigation water reached the 40 cm sensors first. At 22:20, the irrigation ended, and the water pressure readings went back to 0. Before the irrigation, the sensors readings at 20 cm were near -60 kPa, and the sensor readings at 40 cm were at -100 and -140 kPa. During the irrigation, all the sensor readings increased to above -20 kPa, and sensors at 40 cm were still dryer than sensors at 20 cm. After the irrigation, the readings of MP 2-1 40 cm decreased a little, and then became higher. The possible reason is the water flowed through the area and that the soil was not evenly moist just after irrigation. Sensors at 40 cm would become dryer faster than sensors at 20 cm.

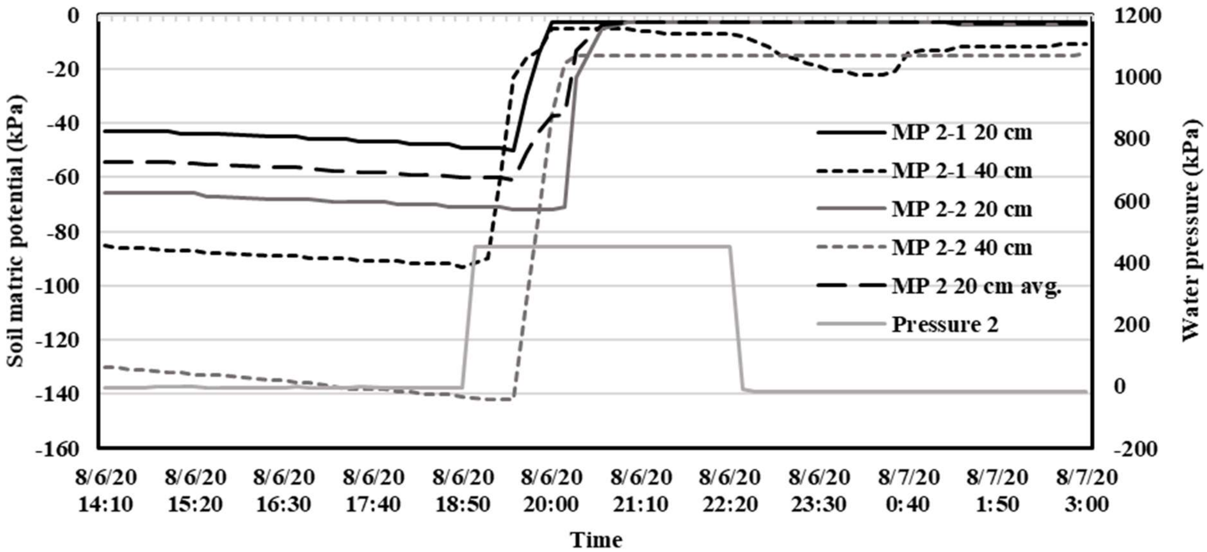


Figure 16. Soil MP sensors and pressure sensor readings of treatment MP60 during an irrigation event on 77 DAT.

3.3 Fruit yield components

Tomato fruit yield components were recorded at each harvest for all four treatments. Table 2 shows the cumulative fruit fresh yield determined cumulating the yield after each harvest. MP60 was not significantly different from ET and GesCoN for most yield components. However, MP60 had more large fruit fresh weight than ET until the last harvest, more unmarketable weight than GesCoN until the 3rd, 4th, and 5th harvest, and more marketable and total weight than ET until the 4th harvest. Comparing MP40 with ET, MP40 had lower extra-large fruit fresh weight than ET until the 3rd harvest, lower marketable yield than ET until the 2nd, 3rd, and 4th harvest, and lower total yield than ET until the 3rd and 4th harvest but more total yield in the 1st harvest since there was a high proportion of unmarketable fruit. MP60 and GesCoN had a total marketable yield 15.2% and 22.1% higher than ET, respectively. MP40 had a marketable yield 12.5% lower than ET. MP60 was not significantly different from ET and GesCoN. However, MP40 had significantly lower marketable yield than MP60 and GesCoN but was not significantly different from ET. MP60 and MP40 are sensor-based irrigation using different soil moisture levels of thresholds. MP40 was expected to be wetter than MP60, thus, it was expected to suffer less water stress and potentially have more yield. However, as mentioned in the soil moisture monitoring section, MP40 used less water than other treatments, presumably because of improper sensor positioning or positioning of the sensors in an area that was not representative of the entire field, which led to lower yield. Nevertheless, the results of MP60 shows the sensor-based irrigation scheduling with the IoT system is effective and suitable for precision irrigation management at field scale.

Table 2. Irrigation strategies effects on fresh-market tomato cumulative yield and yield components until each harvest.

Harvest Day	Treatment	Fruit Fresh Weight (Mg ha^{-1})					
		XL	L	M	Cull	TMY	TY
78	ET	3.68	0.70	0.23	2.03 b	4.62	6.65 b
	MP60	4.13	0.71	0.09	1.43 b	4.92	6.34 b
	MP40	4.21	0.74	0.26	3.48 a	5.21	8.69 a
	GesCoN	4.70	0.78	0.15	1.48 b	5.62	7.09 b
	P-value	*0.69*	*0.92*	*0.30*	*0.001*	*0.68*	*0.03*
until 90	ET	15.92 a	0.85	0.29	9.03 ab	17.06 a	26.09
	MP60	17.35 a	1.03	0.09	6.32 b	18.47 a	24.79
	MP40	12.70 b	1.01	0.42	11.71 a	14.13 b	25.84
	GesCoN	16.92 a	0.94	0.15	7.73 b	18.01 a	25.74

	P-value	*0.03*	*0.71*	*0.08*	*0.03*	*0.03*	*0.90*
until 103	ET	34.00 b	1.53	0.40	21.32 a	35.93 b	57.25 a
	MP60	37.42 ab	2.36	0.32	18.58 a	40.11 ab	58.68 a
	MP40	24.45 c	1.44	0.42	21.72 a	26.31 c	48.03 b
	GesCoN	40.35 a	2.44	0.34	14.82 b	43.13 a	57.94 a
	P-value	*0.002*	*0.11*	*0.89*	*0.003*	*0.001*	*0.01*
until 113	ET	40.37 b	1.98	0.64	24.39 ab	43.00 b	67.38 b
	MP60	47.21 ab	3.55	0.45	22.20 b	51.22 a	73.42 a
	MP40	29.66 c	2.07	0.47	25.61 a	32.21 c	57.82 c
	GesCoN	50.19 a	3.18	0.58	18.31 c	53.95 a	72.26 a
	P-value	*0.0008*	*0.16*	*0.87*	*0.001*	*0.0004*	*0.0005*
until 125	ET	46.35 bc	4.52 b	3.34	25.73 ab	54.21 bc	79.95 ab
	MP60	52.71 ab	6.46 a	3.26	23.66 b	62.43 ab	86.09 a
	MP40	38.16 c	5.43 ab	3.75	27.49 a	47.34 c	74.83 b
	GesCoN	56.72 a	5.95 a	3.52	20.00 c	66.19 a	86.20 a
	P-value	*0.01*	*0.04*	*0.66*	*0.002*	*0.01*	*0.06*

XL = Extra-Large, L = Large, M = Medium, Cull = Unmarketable, TM= Total marketable, T = Total
Treatments are grouped by LSD t-test if they are significantly different.

3.4 Irrigation water use efficiency (iWUE)

Table 3 shows the total water usage per area and iWUE of four treatments. Treatment MP40 used much less irrigation water compared with other treatments, leading to the low yield. ET, MP60, and GesCoN had similar irrigation volume. MP60, MP40, and GesCoN had 19.2%, 25.7%, and 27.7% higher iWUE than ET. MP60 was not different from the other treatments. However, MP40 and GesCoN had significantly higher iWUE than ET. Considering the lack of yield in MP40, its high iWUE is not an advantage.

Table 3. Total irrigation water usage per area and irrigation water use efficiency (iWUE).

Treatment	Volume (m^3 ha^{-1})	iWUE (kg m^{-3})
ET	2440	22.22 b
MP60	2357	26.49 ab
MP40	1695	27.94 a
GesCoN	2339	28.38 a

4. Conclusion

An IoT-based precision irrigation system with LoRaWAN technology was developed and evaluated in the study. In general, the system worked well for the irrigation application in an open tomato field. The batteries for the data loggers were charged sufficiently by the attached solar panels. A series of data were recorded and displayed for the soil matric potential sensors and pressure sensors. Irrigation was applied successfully by controlling the solenoid valves based on the soil moisture level. Even though no significant negative effect was observed in the sensor data monitoring and valve control, the IoT system had a data loss rate of 5.5% in average, which may be attributed to the indoor gateway placement and disconnection of each component in the network. High frequency of data communication (every minute) mitigates this problem. Meanwhile, it was observed a couple of times that the valves did not respond with the first sent signal, which may be caused by the low voltage power used for the valves. The fruit yield and irrigation water use efficiency were analyzed and compared for all four treatments. MP40 used much less irrigation volume than other treatments because of improper installation position. Other three treatments used similar irrigation volumes. MP40 has less yield. For the other three treatments, considering the yield and iWUE, GesCoN was the best, followed by MP60 and ET. However, there was no significant difference between MP60 and other two treatments. According to the results of MP60, the developed IoT-based system using LoRaWAN technology can be potentially used for precision and automatic irrigation application for practical vegetable production.

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