Development and Validation of Low-Cost IoT Environmental Sensors: A Case Study in Wuhan, China

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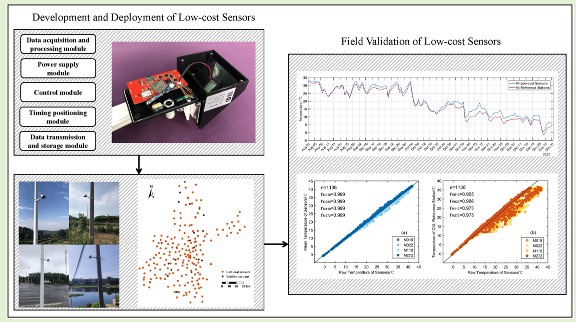
***Abstract*—Meteorological observations are the basis of the development of atmospheric science and meteorological research. Due to the complexity of the different scales and regional environments of cities, researchers have deployed intensive and sustainable low-cost environmental sensors throughout a large area. In this study, we developed a low-cost sensor integration device and data monitoring Internet of Things (IoT) platform that can automatically collect data on meteorological factors and transmit nearly real-time data. We deployed 252 units in Wuhan, some of which were compared with standard meteorological stations in the field. The correlation coefficient for the comparison of multiple devices with reference stations was greater than 0.9. The relative deviation and mean absolute error (MAE) were small. This study demonstrates the feasibility of this low-cost integrated sensor and its great potential in regional meteorological observations.**



***Index Terms*—Field validation, Internet of Things (IoT), low-cost sensors, meteorological observations, sensor deployment.**

I. Introduction

CURRENTLY, meteorological observations play an important role in many aspects, such as weather forecasting [1], [2], environmental protection [3], [4], traffic safety [5], space exploration [6], [7], disaster warnings [8], [9], agricultural production [10], [11], and human health [12], [13], [14]. As of April 2020, China had constructed 2423 national-level observation stations and more than 60 000 regional observation stations in an area of 9.6 million square kilometers. However, with the continuous acceleration of global urbanization [15] and the construction of smart cities [16], the types of urban surfaces are gradually becoming more complex and diverse, and the demand for urban environment perception management and application has increased. On the urban scale, the distribution of observation stations is still uneven and there is an obvious lack of local observations. This is mainly because the construction of a complete set of automatic weather monitoring stations is limited by many factors, such as the power supply, terrain, surrounding scenes, and costs [2].

Low-cost sensors often consist of a single sensor element manufactured by the original manufacturer and the related systems, including data acquisition, conversion, processing, and transmission, as well as the power supply system and housing design [17]. Low-cost sensors are usually deployed in the entire research area, such as in residential, commercial, and school zones, to form a dense observation network that covers a small area [18].

As a system that can quickly exchange a large amount of information, the Internet of Things (IoT) is widely used in cloud computing, big data, artificial intelligence, and other fields, and it plays an important role in the construction of smart cities and environmental monitoring [16], [19], [20]. In recent years, low-cost sensors have become massive data producers in the IoT era [21]. Moreover, densely distributed, static, or mobile wireless sensor networks (WSNs) can be deployed on fine spatial and temporal scales to intelligently

Manuscript received 14 November 2022; accepted 3 December 2022. Date of publication 12 December 2022; date of current version 31 January 2023. This work was supported in part by the National Key Research and Development Program of China under Grant 2019YFB2102900 and in part by the Open Fund of Hubei Luojia Laboratory under Grant 22010004. The associate editor coordinating the review of this article and approving it for publication was Dr. Thilo Sauter. *(Corresponding author: Chao Zeng.)*

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Digital Object Identifier 10.1109/JSEN.2022.3227308

collect and inspect remote monitoring data [22], [23], [24]. Compared with traditional meteorological observation networks, low-cost sensor networks can effectively narrow the large gap between meteorological and air monitoring caused by a lack of observation data, especially in many areas within developing countries [25].

Many low-cost monitoring sensors and systems for meteorological parameters, such as temperature, have been proposed and applied as supplements and replacements for expensive traditional monitoring methods [26], [27], [28], [29], [30], [31]. However, they still have many limitations. Because these low-cost, nonprofessional meteorological data sources are often weather stations installed or maintained by amateurs, there is a lack of unified collection, processing, and professional control of equipment and data, resulting in less truly available data [27]. In addition, the evaluation of low-cost temperature monitoring equipment and systems is usually carried out in a single indoor environment, which is greatly affected by factors, such as human interference and the power supply, and has fewer applicable scenarios. There is also a lack of tests in harsh environments in the field, especially long-term field comparison with the reference stations operated by the meteorological department [26], [29], [30], [31]. In field observations, it is also common that the study area is small, the low-cost weather stations are placed far apart, and the total number of low-cost sensors is low [28].

Therefore, in this study, we developed a low-cost IoT environmental sensor that realizes the sensing and wireless transmission of air temperature, humidity, and air pressure. A total of 252 devices were deployed in Wuhan City, and verification experiments and comparison with reference stations were carried out. Our low-cost sensors can be quickly installed in a variety of scenarios without an external power supply and professional maintenance. The reference station equipment and construction cost used for comparison were about U.S. $8240, while the cost of producing and deploying one of our sensors was about U.S. $120, which is a huge cost reduction. The goal of this research was to realize the development and deployment of low-cost meteorological sensors, build a WSN, and evaluate its availability through field verification experiments to achieve both stable and reliable performance and low cost. Ideally, this research may contribute to the spatially refined analysis of weather changes, effectively complementing the reference station network to a certain extent, and it will likely be of great benefit to extreme temperature and local microclimate analysis. In conclusion, this is a unique attempt to integrate the development, deployment, and validation of low-cost meteorological monitoring sensors and systems.

II. Materials and Methods

A. Study Area

Wuhan, the capital of Hubei Province (30°35′ N, 114°17′ E), is a typical megacity in central China (see Fig. 1). Rivers and lakes are widely distributed in Wuhan, accounting for about 26% of the total area; as a result, it is often called the City of a Hundred Lakes [32]. Wuhan has a northern subtropical monsoon humid climate, with abundant rainfall, relatively high temperatures, a cold winter, a hot summer, and four distinct seasons. The annual average temperature is 15.8 °C–17.5 °C, and the annual average precipitation is about 1200–1300 mm [33].

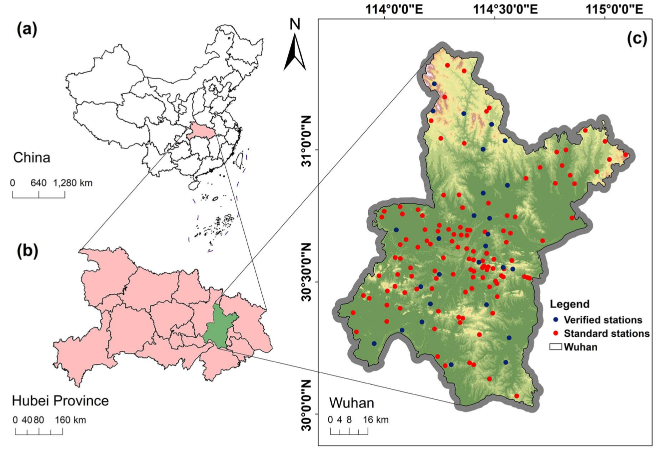

Fig. 1. (a) Hubei Province, China. (b) Regional division of Hubei Province. (c) Standard meteorological stations in the Wuhan area.

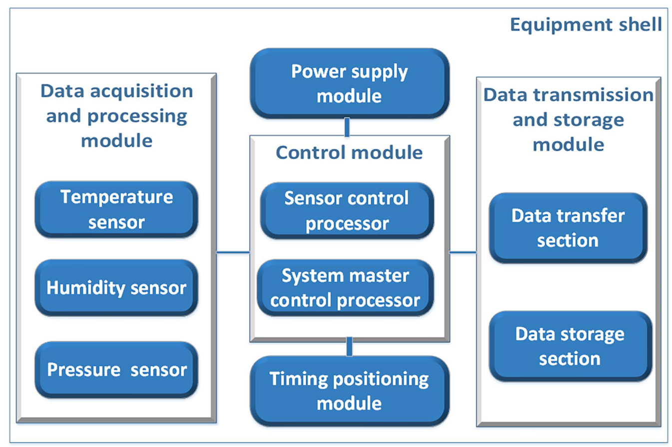

Fig. 2. Internal architecture and system modules of the low-cost integrated meteorological sensor.

B. Reference Stations

By the end of 2021, there were 149 standard weather stations in Wuhan (red dots in Fig. 1). These stations can provide accurate measurements, including temperature, humidity, and wind speed and direction. A total of 27 standard sites were selected as reference stations for the validation experiment (blue dots in Fig. 1) in this study.

C. Low-Cost Integrated Meteorological Sensors

1) Models and Specifications: In this research, a low-cost integrated meteorological sensor with innovative and practical features was developed. Fig. 2 describes its internal system, including the data acquisition and processing module, data transmission and storage module, timing positioning module, control module, power supply module, and shell module.

The low-cost meteorological equipment integrates the Si705x temperature sensor, the SHT35 humidity sensor, and the BMP280 pressure sensor, which are small in size and

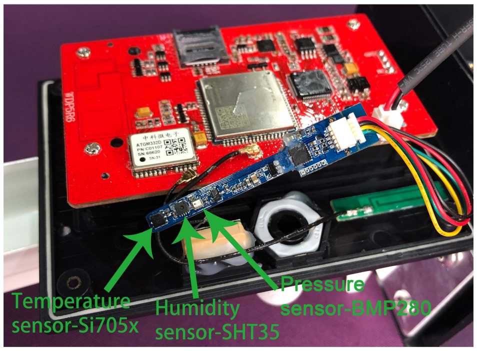

Fig. 3. Integrated circuit board.

TABLE I
DETAILS OF LOW-COST SENSORS

Type	Manufacturers	Model	Precision	Unit Price
Temperature sensor	Silicon Labs (USA)	Si705x	±0.1°C	$72
Humidity sensor	Sensirion (Switzerland)	SHT35	±1.5% RH	$14
Pressure sensor	Bosch (Germany)	BMP 280	±0.12 hPa	$3

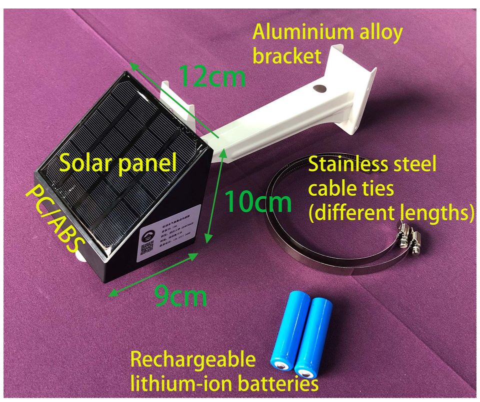

Fig. 4. Low-cost integrated sensor.

flexible in terms of scalability. The combination of internal multifunction modules can not only realize multielement observations but can also greatly reduce the cost and energy consumption. The integrated circuit board is shown in Fig. 3, and Table I presents the details of the low-cost weather sensors.

2) System Design: The low-cost integrated meteorological sensor is lightweight and small, which allows for easy installation. The length, width, and height of the main body are 12, 9, and 10 cm (see Fig. 4). The shell is constructed of acrylonitrile butadiene styrene (ABS) and polycarbonate (PC), which has the advantages of high-temperature resistance, oxidation resistance, and small deformation, providing a safe and stable working environment for the integrated system. In addition, the wind-resistant and stable stainless-steel bracket can be adjusted to achieve multiple angles.

The equipment control unit is connected to the power supply, data acquisition/processing, timing/positioning, and

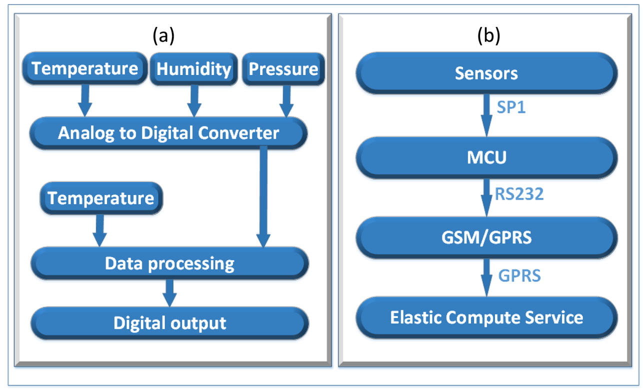

Fig. 5. (a) Data collection process. (b) Data transfer process.

data transmission/storage modules by the control plate. The temperature sensor, humidity sensor, and pressure sensor collect real-time meteorological parameter data and convert these data through analog-to-digital conversion (ADC). Then, the data and sensor calibration parameters are transmitted to the sensor control processor and output to the external processor [see Fig. 5(a)]. The calibration parameters are factory default settings. Finally, the observations with positioning and timing information are converted into wireless public network information and sent to the cloud server [see Fig. 5(b)].

The power supply module is an AXP173 produced by X-Powers Technology (Shenzhen, China). It is a highly integrated power management unit, which can meet the needs for accurate power control. Each device contains two rechargeable lithium-ion batteries, which can be replaced safely and easily. The batteries can be recharged by a 2-W 6-V solar panel on the shell of the device. Compared with the power supply of a traditional meteorological monitoring station, the power supply mode using solar charging and battery recycling greatly reduces the manufacturing cost and the postmaintenance workload.

3) Sensor Deployment: In this study, three deployment schemes were carried out in Wuhan, and a total of 252 devices were deployed.

First, to validate the sensor performance in a local area, a dense deployment was carried out at Wuhan University. The campus has lush vegetation, intricate man-made features, and natural surfaces. It is an excellent location for testing the power and endurance of the low-cost integrated sensors. There is also a standard weather station in this area (red dot in Fig. 6), which was used as a reference. Then, 19 low-cost integrated sensors were deployed evenly (yellow dots in Fig. 6) with a sampling frequency of once every half hour.

Second, to better evaluate the sensor accuracy, a total of 39 integrated sensors were deployed at the same locations as standard meteorological stations [see Fig. 7(a)]. Moreover, four reference stations were selected and multiple sensors were deployed in these locations for comparison, which allowed us to better evaluate the differences and stability between individual devices. The reference station monitors conditions, such as precipitation, wind speed, wind direction, temperature, air pressure, and humidity. The overall volume of its equipment is

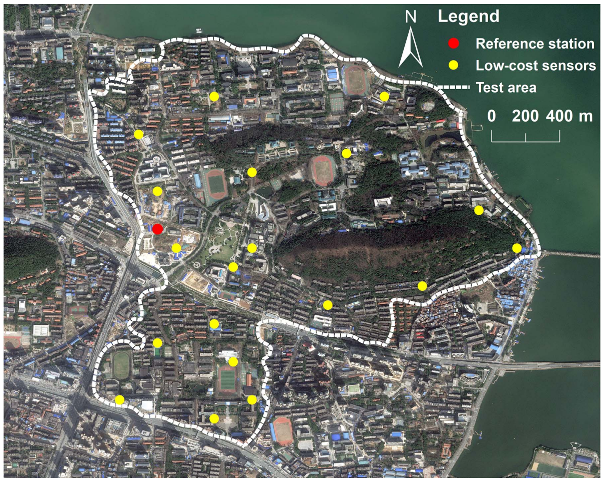

Fig. 6. Deployment of the low-cost integrated sensors at Wuhan University. (The map was obtained from Global Mapper.)

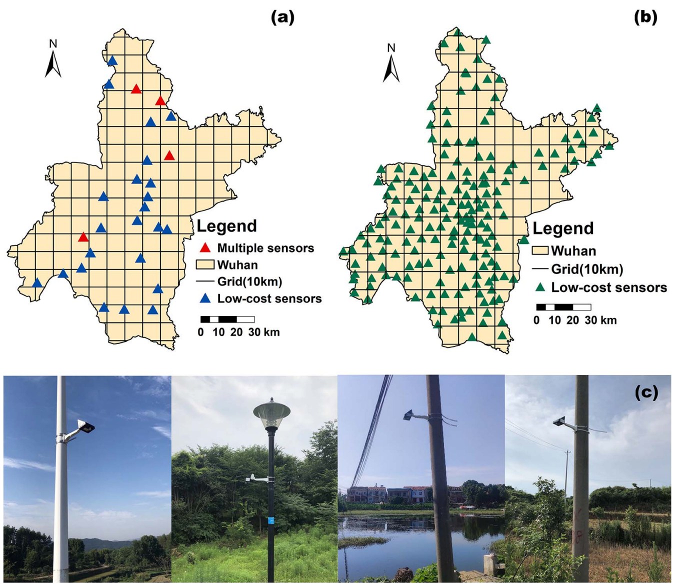

Fig. 7. Schematic showing the deployment locations. (a) Low-cost sensors at reference stations, (b) low-cost sensors independently distributed in Wuhan, and (c) field photographs.

large and fixed. In contrast, our sensors are very small and easy to install and remove. They monitor the temperature, humidity, and air pressure. Considering the different land surface types, we selected reference stations uniformly and randomly within Wuhan City, and the low-cost sensors deployed were also randomly selected.

The third deployment was a large-scale and uniform deployment throughout Wuhan [see Fig. 7(b)]. The layout was planned based on the different land cover types, vegetation, and terrain differences, and the monitoring was mainly carried out in locations lacking standard meteorological stations to obtain complementary datasets. The deployment scenarios took into account the strength of the heterogeneity and whether the spatial structure was regular, including bare wasteland, woodland, lawns, farmland, lakeshore, and artificial surfaces. The field photographs in Fig. 7 show the rich and diverse surface types of the sites.

4) Monitoring Platform: A monitoring platform was also developed for this WSN. The platform consists of five parts: the system homepage, site map, data chart, equipment management, and operation monitoring. The users can specify the basic information about the device, including the last data transmission time, server IP, port, data sampling interval, detailed location information for the sensors, and photographs of the deployment environment. The monitoring platform has a power alarm setting, which can send early warning information to users promptly when the power of the sensor is too low. Moreover, this system is both secure and open, and it fully considers the need for exchange with external information systems to ensure that it cannot only perform the basic functions but also connect with other platforms.

5) Data Collection and Preprocessing: Each low-cost integrated sensor can be bound to multiple server IPs. The highest priority is the main IP, and the data are only sent to the main IP. If the main IP fails, the system automatically switches to the backup IP. If all of the servers fail, the data can be temporarily stored in the device.

The original data for the standard meteorological stations used in the experiment were confidential data obtained from the Hubei Provincial Meteorological Bureau. The sampling frequency of the low-cost integrated sensors was 30 min and that of the reference site equipment was 60 min. Due to the slight delay in the data transmission process, multiple pieces of repeated sampling data may be returned, and such repeated data are filtered and deleted. In extreme cases, the equipment may have data missing due to power loss, failure, and irresistible external factors.

6) Evaluation Metrics: The correlation coefficients, relative deviation, and mean absolute error (MAE) were used to evaluate the consistency, stability, and accuracy of the low-cost meteorological integrated sensors. Equation (1) was used to calculate the correlation coefficient

$$r = \frac{\sum_{i=1}^{n}\left(\overline{X}_i - \overline{X}\right)\times\left(\overline{Y}_i - \overline{Y}\right)}{\sqrt{\sum_{i=1}^{n}\left(\overline{X}_i - \overline{X}\right)^2 \times \sum_{i=1}^{n}\left(\overline{Y}_i - \overline{Y}\right)^2}} \tag{1}$$

where r is the correlation coefficient, $\overline{Y_i}$ is the average value of the measured data for each sensor to be tested, $\overline{Y}$ is the average value of the measured data for the n groups of sensors to be tested, $\overline{X_i}$ is the average value of the data for each reference device, and $\overline{X}$ is the average value of the measured data for the n groups of reference devices. The closer the correlation coefficient is to 1, the better the consistency of the equipment is. The relative deviation was calculated using the following equation:

$$d = \frac{\left(\overline{X}_j - \overline{Y}\right)}{\overline{Y}} \tag{2}$$

where d is the relative deviation, $\overline{X}_j$ is the total average value of the measured data for each device at the same location, and $\overline{Y}$ is the total average value of the measured data for all of the equipment at the same location. The closer the relative deviation is to 0, the better the consistency of the equipment

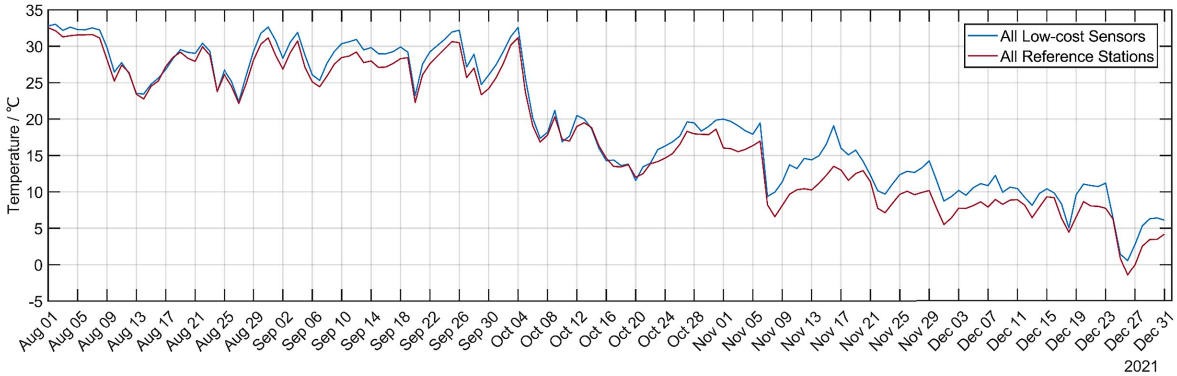

Fig. 8. Comparison of the average daily temperatures of all of the low-cost integrated sensors with the reference stations on the urban scale in Wuhan.

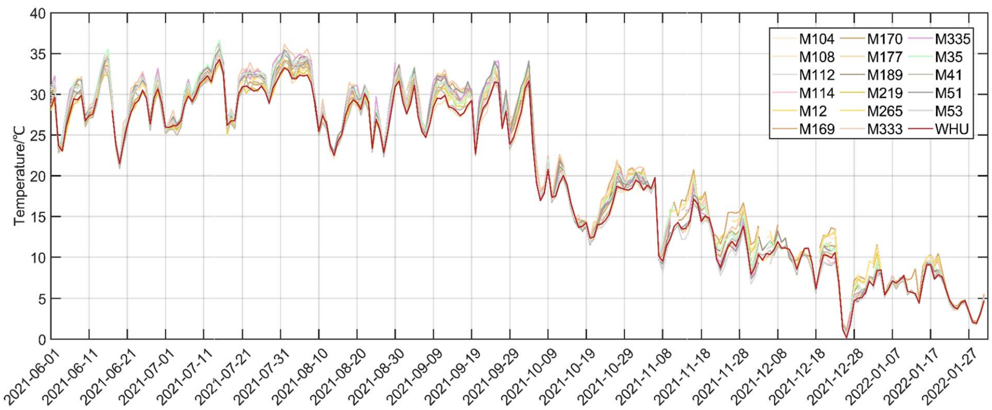

Fig. 9. Comparison of the daily average temperatures of 17 low-cost integrated sensors deployed at Wuhan University with the WHU reference station.

is. The MAE was calculated using the following equation:

$$\mathrm{MAE} = \frac{1}{m}\sum_{i=1}^{m}|y_i - x_i| \tag{3}$$

where MAE is the mean absolute error, y_i is the measured air temperature data at the reference station, i.e., the true value, and x_i is the air temperature data measured by the low-cost sensor at the corresponding time.

III. Results

A. Urban Scale Evaluation

To validate the performance of the integrated sensors on the urban scale, the measured daily average temperatures were compared with the average values of all of the reference stations. The experimental period was from August 1 to December 31, 2021. Due to the different deployment times of each device, 79 of the low-cost integrated sensors distributed throughout Wuhan were selected. In meteorology studies, the temperatures at 02:00, 08:00, 14:00, and 20:00 in a day are usually used to calculate the average temperature of the day. Fig. 8 shows the daily average temperatures measured by the low-cost integrated sensors and reference stations on the urban scale in Wuhan. The changes in the daily mean values had similar trends, but the daily mean values of the low-cost sensors were mostly higher than the values of reference stations. Especially in November and December, the error increased significantly, which may have been related to seasonal effects, such as temperature anomalies.

B. Neighborhood Scale Evaluation

Based on the dense low-cost integrated sensors deployed at Wuhan University, a comparative experiment was carried out to assess the performance of the sensors in a local area. In the experiment, raw data were obtained from the reference station (WHU) and the 17 low-cost integrated sensors (M104, M108, M112, M114, M012, M169, M170, M177, M189, M219, M265, M333, M335, M035, M041, M051, and M053) deployed in this area. The experimental period was from June 1, 2021, to January 31, 2022.

It can be seen from Fig. 9 that the operation of the 17 sensors tended to be very close, which reflects the consistency and stability of the equipment. In addition, compared with the reference station, the change trends of the sensors were similar. The daily average temperatures of the low-cost integrated sensors were generally slightly higher than the measurements of the reference station, but the overall difference was not large.

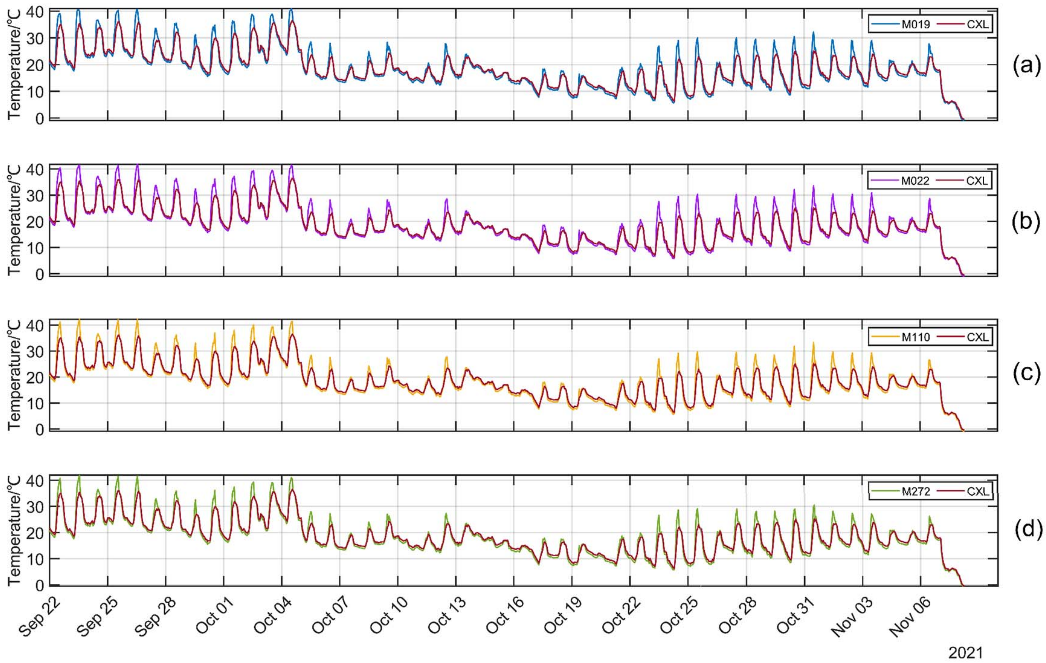

Fig. 10. Comparison of the raw hourly data from four low-cost integrated sensors with the CXL reference station. (a) Comparison of M019 and CXL. (b) Comparison of M022 and CXL. (c) Comparison of M110 and CXL. (d) Comparison of M272 and CXL.

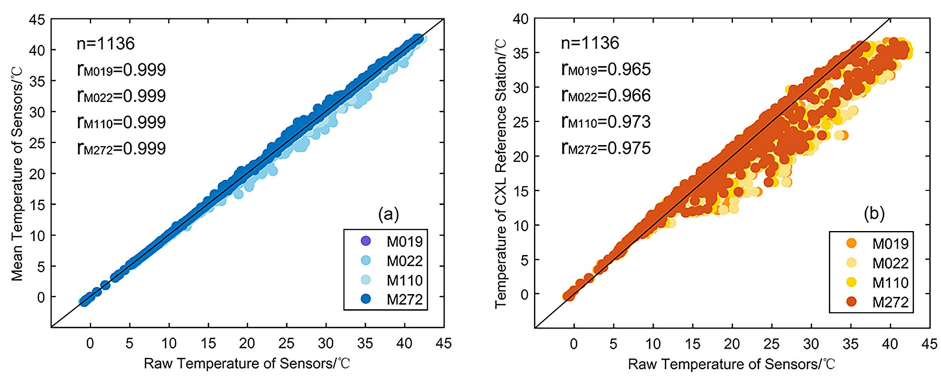

Fig. 11. (a) Correlation between hourly data from sensors located at CXL and the average of the four devices. (b) Correlation between sensor data and CXL reference device data.

C. Station Scale Evaluation

To further explore the performance of the integrated sensors on a fine scale, four integrated sensors (M019, M022, M110, and M272) were deployed at reference station CXL. The experimental period was from September 22 to November 8, 2021. A total of 1136 hourly measurements from each device were received and are presented in Fig. 10. Through comparison of the hourly data, it was found that the changes in the four low-cost integrated sensors were very similar, reflecting the consistency and stability of the sensors. Moreover, compared with the reference station data, they exhibited the same overall trend. However, the temperatures measured between 11:00 and 15:00 on each day were mostly overestimated. This is because the reference instrument was installed on a thermometer screen, while the low-cost integrated sensor was exposed to direct sunlight at noon [34]. Nevertheless, at other times of day, the hourly data of the low-cost integrated sensors and the reference instrument were very close, and the overall trend was also very consistent, which confirms the feasibility of the equipment and system.

To validate the station scale performance, the measurements of station CXL and the corresponding sensors from September 22 to November 8, 2021, were compared. Fig. 11(a) shows the correlation between the measured raw hourly data of each device and the average value of the four devices. In addition, their correlation coefficients were all >0.999, indicating that the equipment was relatively consistent during the long-term field operation. Fig. 11(b) shows the correlation between the data measured by each device and the reference station. The correlation coefficient r is greater than 0.96, which reflects the stability of the low-cost integrated meteorological sensors and the accuracy of the original data.

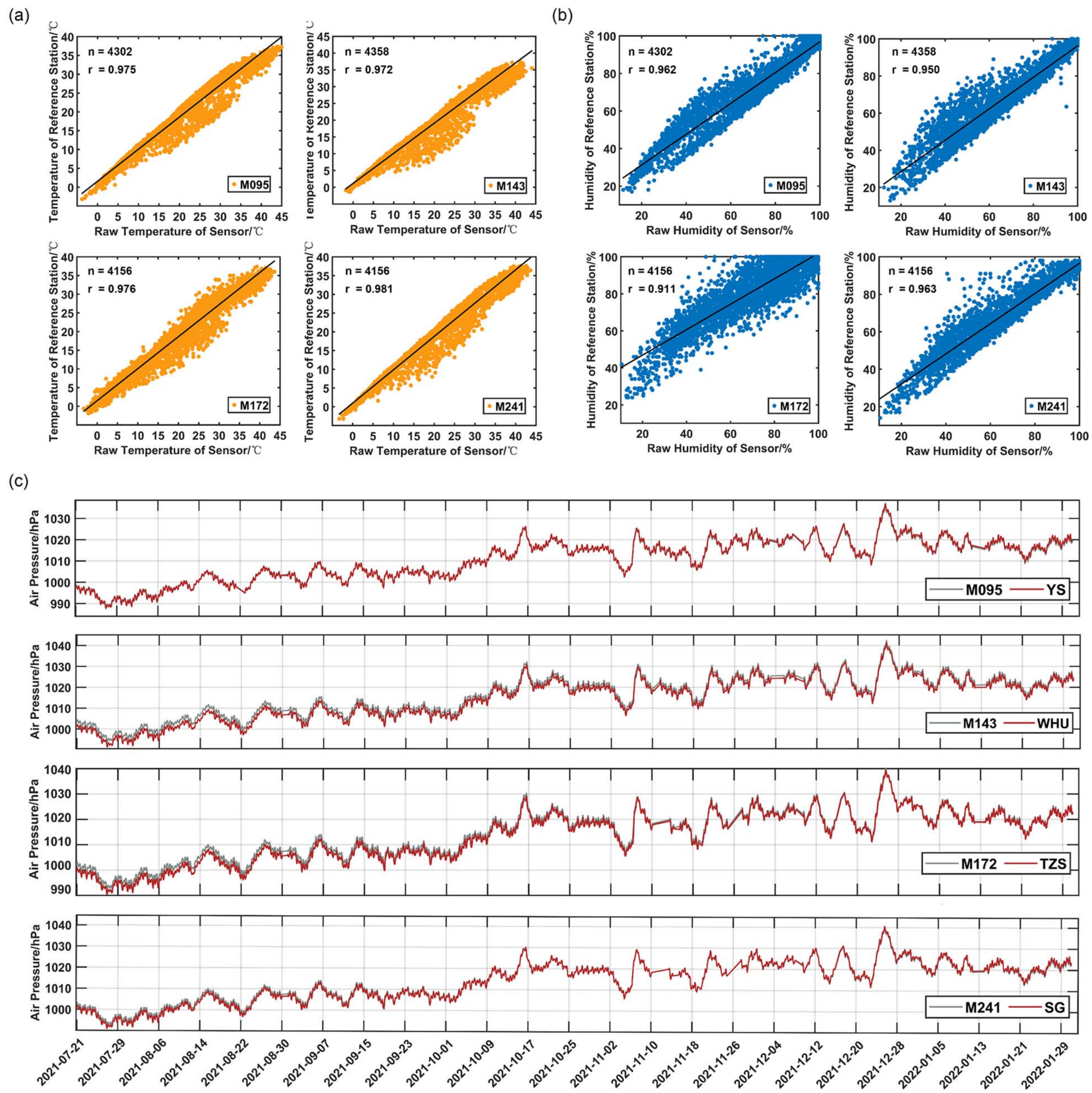

Fig. 12. (a) Correlation between the hourly air temperature data of the four sensors and the corresponding weather station data. (b) Correlation between the hourly humidity data of the four sensors and the corresponding weather station data. (c) Comparison of raw hourly pressure data from four sensors with corresponding reference stations.

In addition to reference station CXL, we deployed four low-cost integrated sensors each at the other three reference stations (XJS, SXY, and LZJ). Among them, low-cost integrated sensors M005, M162, M185, and M221 were deployed at reference station XJS; M045, M097, M267, and M304 were deployed at reference station SXY; and M021, M158, M326, and M334 were deployed at reference station LZJ. The multiple devices deployed at the four different reference stations performed in a consistent trend over the 11 consecutive days of testing. The detailed evaluation information is presented in Table II. The correlation coefficient between the daily average temperature of each device and all the devices is represented by r, and the relative deviation between the 11-day total average of each device and the 11-day total average of all the devices is represented by d. The correlation coefficients are all close to 1. Among the 16 devices, the relative deviations of 14 devices were within $\pm 3\%$, indicating that the consistency and stability of the low-cost devices are good, and the differences between the individual devices were small. In addition, sensor M221 deployed at reference station XJS was faulty, and its data were quite different from the data collected by the other three devices. Table II also shows the MAE of the air temperature between the low-cost sensor and the reference station. The first group represents four low-cost

TABLE II
CORRELATION COEFFICIENT AND RELATIVE DEVIATION OF EACH LOW-COST SENSOR AND THE DAILY MEAN TEMPERATURE OF ALL OF THE LOW-COST SENSORS AND MAE COMPARED TO THE REFERENCE STATION

Sensor number	r	d (%)	MAE
M 005	0.997	-2.70	2.20
M 162	0.997	-3.04	6.03
M 185	0.999	-3.47	5.98
M 221	0.984	9.21	7.07
M 045	0.999	0.62	1.65
M 097	0.999	-0.54	1.41
M 267	0.999	0.36	1.73
M 304	0.999	-0.44	1.70
M 019	0.998	0.08	1.26
M 022	0.994	2.47	1.63
M 110	0.999	-0.78	0.98
M 272	0.997	-1.77	0.81
M 021	0.999	-0.29	1.87
M 158	0.999	0.85	2.01
M 326	0.999	-0.50	1.71
M 334	0.999	-0.06	2.07

TABLE III
DAILY AVERAGE TEMPERATURES AND ABSOLUTE DEVIATION OF ALL OF THE LOW-COST INTEGRATED SENSORS AND STANDARD REFERENCE METEOROLOGICAL STATIONS DURING THE EXPERIMENT

Reference station	Average of all sensors (℃)	Reference data (℃)	Absolute deviation (℃)
XJS	26.83	25.24	1.59
SXY	23.83	23.13	0.71
CXL	25.41	25.05	0.36
LZJ	23.61	22.45	1.16

TABLE IV
MAE OF HOURLY HUMIDITY AND PRESSURE DATA FROM FOUR LOW-COST SENSORS AND THE REFERENCE STATION AT SXY

Sensor number	MAE of hourly humidity	MAE of hourly pressure
M045	4.33	1.68
M097	3.75	1.42
M267	5.47	1.97
M304	5.46	1.54

sensors simultaneously deployed at the XJS reference station, and their overall MAE is on the high side, with that of M221 being the most pronounced. The remaining three groups contained multiple low-cost sensors that performed well, and overall, each group operated in the same environment with little variation between individual sensors.

The change trends of the daily average values of the low-cost integrated sensors and the reference stations are approximately the same. The average value of the four devices at each reference site and the average values of the corresponding reference stations are presented in Table III. The absolute deviation of the average value of the integrated sensors and the reference station was small, which reflects the good accuracy of the low-cost integrated sensors developed in this study. Due to instrument failures, only the SXY station has humidity and pressure measurements among the four reference stations. In this case, a validation experiment is carried out on the sensors deployed at the SXY station. Table IV presents the MAE of hourly raw humidity and barometric pressure data from the four low-cost sensors and the SXY station over 11 consecutive days. The results show that the humidity and air pressure data collected by the low-cost integrated sensor have high accuracy, and the MAE is smaller than that of the standard weather station. In the same location with basically the same field conditions, multiple sensors perform stably and have good consistency.

To further verify the accuracy of the sensors across the city, we also deployed one sensor each at 23 other standard weather stations for comparison. Considering the amount of data, 4 of these 23 stations were selected to compare hourly temperature, humidity, and air pressure data with standard weather stations, from July 21, 2021, to January 31, 2022 (see Fig. 12). The results show that all the data collected by the low-cost sensors are well correlated with standard weather stations, with r greater than 0.9. It is confirmed that the temperature, humidity, and pressure sensors in the sensor network have good performance in long-term field operation, and the overall performance is also stable.

IV. CONCLUSION

In this study, we developed, deployed, and validated a low-cost meteorological comprehensive sensor network based on different urban scales and scenarios, with continuous multiday observations, and validated against reference stations. From the test results, our low-cost sensors and the entire system have good accuracy and stability and are highly adaptable in different scenarios. They can acquire high-precision and high-resolution temperature, humidity, and pressure data at a low cost to reflect the characteristics of local weather changes.

Overall, we not only integrated three different low-cost sensors but also achieved large-scale deployment of multiple devices and unified data management, which is an innovative attempt. As a supplement to the traditional weather station network, it is conducive to a more comprehensive and efficient detailed analysis of weather change warning events. Low-cost sensors are generally considered less representative than the traditional standard weather stations, but this study is very exploratory and a unique attempt to combine the development, deployment, and validation of low-cost weather monitoring sensors and systems. Long-term field verification results prove that low-cost sensors can also operate stably and have high accuracy. In addition to significant cost savings, the sensor offers the advantages of a small footprint and easy installation. It has strong adaptability to complex environments and can be deployed in various areas. It is suitable for efficiently obtaining spatially distributed meteorological data and has the potential to be widely used, such as providing a richer scientific basis for environmental management and planning.

However, there are still some shortcomings in the implementation work, such as the short duration of some measurements. As the sensor operating time increases, longer term field measurements can be obtained for further analysis. Due to the limited climatic conditions in Wuhan, field testing of the sensors lacked validation for more extreme weather conditions. During the experiment, uncontrollable situations such as failure and shutdown of the standard weather station occurred, and some verification data were limited, which needs to be strengthened in the future.

Based on this research, it is planned to connect the traditional meteorological monitoring network and satellite remote sensing data in the future to generate a high-resolution monitoring network. Furthermore, based on the synergistic control of ozone and $PM_{2.5}$, we have completed the preliminary development of the second-generation low-cost air quality sensor that can measure wind speed, wind direction, ozone, $PM_{2.5}$, and PM_{10}. The implementation of the second-generation sensor will be improved in combination with the shortcomings of this research, and it is expected to form a more complete and lower cost environmental monitoring IoT.

Acknowledgment

The authors would like to thank Tian Xie from Wuhan University, Wuhan, China, for his assistance in field work. They would also like to thank Koi Lin from Wuhan University for his suggestions on the writing of this article.

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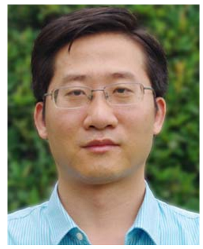

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