A smart-and-connected low-cost sensor system for measuring air and soil properties in the Central U.S.: first results

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***Abstract*—This article describes the design and development of a smart-and-connected low-cost Iowan-designed canopy (I-Canopy) sensor system that is enabled by the Internet of Things (IoT) devices capabilities, empowered by solar-based rechargeable batteries, and developed for community science applications. The I-Canopy sensor, is designed for real-time monitoring of near-surface air properties (temperature, relative humidity, pressure) and soil properties (temperature and moisture) for a wide range of weather and canopy conditions. The sensor is well suited for rural areas where the real-time data of air and soil is lacking in part due to the lack of broadband internet connection, and in part due to the limited (if any) ground-based weather stations in the current federal and state observation network. The canopy sensor has been tested in rural communities in western Nebraska to provide information for farmer's decision-making of irrigation and agricultural water use in the crop growing season. The sensor is capable to transmit data through both WiFi and LoRaWAN in real-time to a cloud data server and the local data server. Presented here are the first results of the sensor design and sensor data evaluation in various out-door environments, which illustrates the high-level readiness of the sensor for large-scale deployment for either routine or scientific applications for rural areas.**

***Index Terms*—IoT, sensor network, Citizen Science, Earth and atmospheric science**

I. Introduction

Land-air interaction is important for climate change and prediction in the central U.S. However, the assessment of climate change and prediction in central U.S. is hindered by the limited number of weather stations in its large rural and peri-rural areas. For example, the two-week outlook for regional weather conditions and the seasonal outlook for rainfall amount and temperature are routinely provided by federal agencies such as NOAA and USDA, but the trustworthiness of these outlooks is unknown in local and regional communities that don't have surface observations. Furthermore, as the demand for weather intelligence at high spatial resolution in real time increases, weather stations in the central U.S., which rely on their respective mesonets to observe mesoscale meteorological phenomena, may not be able to meet the demand for describing local weather and climate variations. For example, in the states of Kansas, Arkansas, Nebraska, and Iowa (KANI), while the weather and climate data at various lengths and time frequencies are available across the KANI states from the Community Collaborative Rain, Hail and Snow (CoCoRaHS) networks and the Global Historical Climate Network (GHCH), the National Weather Service (NWS), the Federal Aviation Administration (FAA), the Automated Weather Data network (AWDN), and the mesonet for each state, only 172 weather stations provide weather information to the public in real time (less than one hour) and this number is only around 50 % of the states' 375 counties. Furthermore, the number of stations providing soil moisture information in real time is far smaller than the number providing real-time weather information (Fig. 1).

While CoCoRaHS observations are not available in real time and have no measurements for soil moisture, its large number of participants show the citizen's enthusiasm to engage in the weather observations. Therefore, development of a smart and low-cost sensor system for the citizens to measure weather and soil properties and enable the seamless collection and display of these data in real time is highly needed to enrich existing observation network for soil and atmosphere. This system fits well with the general public's interest in weather and climate change and their need of weather and soil information for planning of agricultural activities in crop growing season and other outdoor activities (such as transportation). It also fits the research needs to better understand the air-land interaction and regional climate change assessment in the central U.S.

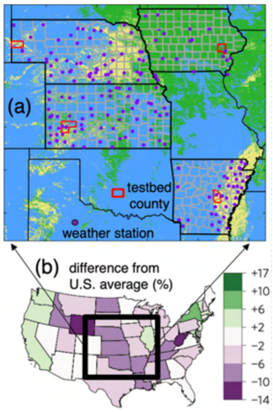

Fig. 1. 1.(a) The KANI states. County boundaries gray, except for those hosting farmland testbeds for intensive sensor network deployment and for summer intensive field campaign, which are ted. Areas of irrigated croplands are shown in yellow; other cropland are green and remaining are blue. (b) Map depicting the relative difference from the national average for each state for percentage of adults who believe in global warming; [1]

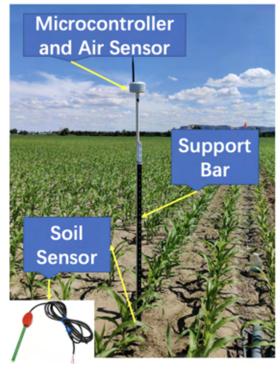

Fig. 2. Setup of the I-Canopy sensor system in a crop field in western Nebraska. Major components are denoted in the figure, including parts for measuring air and soil properties and the support bar.

In addition, Howe et al. [1] showed that the percentage of adults in the KANI states who believe that global warming is happening is among the lowest in the nation. By having observations of weather data in citizens' backyards, farmlands, and local communities and through citizen science activities (such as a summer camp), the network of distributed low-cost sensors will increase the awareness of climate change and improve climate literacy among KANI citizens.

Here, we present a canopy sensor system designed by The university of Iowa for measuring near surface soil and weather properties that is low cost (<\$200) and integrates with the Internet of Things (IoT) seamless for data collection. Existing IoT- enabled sensors also include PurpleAir that measures the mass concentration of air particulate matter (including smoke particles) [2] [3] and other sensors for measuring atmospheric parameters in marine environments, indoor air quality, ambient air quality , and water quality [4] [5] [6] [7] [8]. However, our I-Canopy sensor system is uniquely designed to use solar energy to empower the system for measuring both air and soil parameters simultaneously and has been tested in both irrigated and rain-fed fields in the great plains of central U.S.

II. Sensor Design Concept

There are a few very important environmental factors for crop growth and yield: air temperature, air relative humidity, air pressure, soil temperature, and soil moisture. In addition, in the great plains of U.S. where precipitation amount is low, these parameters are also key variables needed by farmers to make decisions about irrigation scheduling and amount. Measuring these parameters, however, are challenging, because we could not go to the farmland to manually check the sensor one by one to record the data. Therefore, the aim is to design a system capable to operate seamlessly to measure these variables and send the data to the fingertips of farmers, all in real-time. This requires the following consideration in our design: (a) weatherproof; (b) small, and compact layout so that sensor has low cost and can work all times in operation; (c) the stable and renewal power source for the sensor; (d) data transmission at low cost and with low bandwidth; and (e) a data server with on-demand web service to provide a friendly interface for users to inquiry and visualize the data.

A. Hardware Implementation

To fulfill the requirement of small and compact design, our design used the ESP32 as the micro-controller, BME280 as the air sensor, RMF95 as the LoRaWAN transceiver, VH400 as the soil moisture sensor, and DS18B20 as the soil temperature sensor (Fig. 3). To fulfill the demand for a stable and renewable power source, all devices on the PCB board are powered by 3 AA NiMH rechargeable batteries that are in turned trickle charged by the Seeed 0.5 W solar panel connecting to the PCB. For the purpose of weatherproof, we used the Stevenson screen case designed and made in house through 3D printing technology. Additionally, the combination of ESP32 and RMF95 provides a reliable solution for data transmission. Below we provide the descriptions of each key components of the I-Canopy sensor system.

The heart of I-Canopy, micro-controller ESP32, is selected here for a few reasons. First, it works with the widely-used Arduino IDE platform in concert to reduce the work for the development of hardware and firmware, enabling the easier update of sensor development for our project. Second, ESP32 has 38 of pin-out, which gives us enough port to connect the sensor and transceiver. Last, this micro-controller has a build-in Wi-Fi connection capability already.

The RMF 95 is used for the LoRaWAN transceiver. The reason we need the LoRaWan technology given that we already have a Wi-Fi connection provided by the ESP32 is that farmland in the rural communities often have difficulties to have the full coverage of Wi-Fi signal. In addition, the subscription of WiFi via phone or wireless community providers can be costly. In contrast, LoRWAN stations are more economic, and each of them could provide wireless signal in a radius of a 15 km, and in cases battery is needed to power the station, it has a great battery life as well [6].

The air sensor module, BME280, is selected because it measures air temperature, air pressure, and air relative humidity together, with a very good accuracy and a good service provider of Bosch. Another temperature sensor is DS18B20, which is selected to measure the soil temperature due to the fact that it is waterproof [9].

Soil sensor is often more expensive than air sensor. To select soil moisture sensors that are low cost and have good accuracy, we did many experiments and tried different type of sensors including KeeYees, SHT20, and SHT30 from Makerfab, Campbell Scientific CS616, watermark model 200ss, and VH400 from Vegetroni. The Hydra Probe II Soil Moisture Sensors are used as the reference for evaluating these sensors. We found that watermark model 200ss has a good accuracy, but the power consumption and complex design of the circuit make the design difficult to have it integrated with IoT. We found that the VH400 is a good candidate and can be integrated with the BME280. It has low power consumption, and low-cost. But, we also found that its calibration curve suggested by its manufacture seems to not work well with dry or completely saturated soil. Therefore, we have modified the calibration curve for the typical soil types in the central U.S. The VH400 uses superior transmission line techniques (a.k.a, time domain reflectometry or TDR) to measure the water moisture in any soil regardless of soil salinity [10] and is manufactured for IoT applications. We found that with the new calibration curve, the measured soil moisture has a relative error of 5%.

Next NiMH battery and solar panel are chosen here because they have relatively simple charging circuit, enabling us to make the smallest PCB board possible to save cost for the 3D printed case. Also, we have designed a voltage reading system to provide information to help us check the sensor working status. If the sensor working status is not correct, we will notify the user to take care of this problem and get ready to provide help for the user.

In addition to the sensors and our PCB design, we also have a well-designed case for the air sensor. The case would provide a few functions to this project. First, the case makes our sensors and PCB board weatherproof. secondly, the case will provide a good place to hold the solar panel. Third, the case could help us to attach the sensor to a location easily. Lastly, the case provided enough air pass through so the reading of the air sensor is always correct.

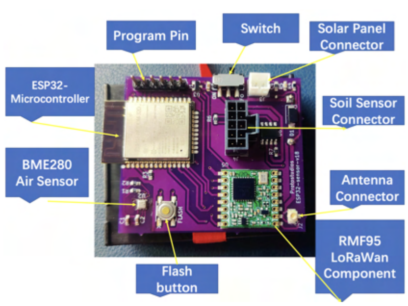

Fig. 3. The PCB design of our sensor

B. Firmware

The design for the firmware has the goal to ensure that the sensor works stable and the is user friendly. To achieve the stability, the library from Adafruit is used. Similarly, we use the LMIC library from IBM for LoRaWAN to improve the stability. For the same reason, we also used the official library of DS18B20. But VH400 doesn't come with a library and we wrote it by ourselves. Tests showed that VH400 with our own library can work with high stability and efficiency.

Wi-Fi Manager library is used here to improve the I-Canopy's user interface. Instead of putting in the Wi-Fi name and password into the firmware, we have an wireless access point to allow the user to input the Wi-Fi name and password and other information. By using this method, the user could use our sensor directly without know anything about our firmware and it also improve the stability and privacy of the firmware.

C. Software

To have a user-friendly sensor, we not only have the the sensor transmit the data, but also have the set of software to help the user to read, analyze, and visualize the data, in near real time. Two methods are provided here for this purpose. First, users are welcome to use our LoRaWAN function and pair the I-Canopy with their own LoRaWan gateway. In our experiment, we use a Laird gateway here. The data is sending to the gateway, then the gateway connect the internet and send the data to The Things Network. Using The Things Network as an agent, we send the data to Amazon AWS S3 to store the data, after which the data can be transmitted to other data servers (including users' own server). Second, Wi-Fi, if available, can be used by the users as well, and the data will be transmitted via MQTT to the Amazon AWS S3. Regardless, after the data arrive the AWS S3, we can forward the data to AWS IoT and pull the data to our local data server that will be subsequently analyzed and displayed on the website (here, https://esmc.uiowa.edu). In addition to the web page, we also developed an IOS version app software to make it easy for user to check the status of their farmland's environment. Details can be found in the paper by Wang [11].

III. Field Deployment and Validation

A. Air Data Accuracy Assessment Via Citizen Science Project

We have the I-Canopy sensor system installed and run in many places in Iowa and Nebraska. We first compared the I-Canopy data measured in the Iowa City with the atmospheric data measured by NOAA National Weather Service (NWS) stations. Our initial assessment show that the measured air pressure and relative humidity have a relative error of 0.1% and 1% (compared to professional measurements) respectively, and the measured temperature uncertainty of 1-2 °F. As an example of our initial test, Figs 4-5 show the comparison of measured temperature, relative humidity, and pressure, respectively. The 2-m air temperatures measured by a citizen in his backyard agree well with the 2-m air temperature measured by NWS station 10 miles from that citizen's house: the linear correlation coefficient is 0.89 and there is 1.1 °F systematic difference. To explain if the difference is due to the distance, we also compared the sensor-measured temperature with the one predicted by WRF-Chem (that is driven by NCEP's analysis data and is run in near-operational mode here in University of Iowa, https://esmc.uiowa.edu). At least for this case studied, it appears that WRF predicted temperature have slightly better agreement with what was measured by the citizen: linear correlation coefficient of 0.96 and the mean difference is only 3 °F. Note, the WRF data is at every 6 hours, while the sensor data is at each hour (although not every hour due to the interruption of wireless in the citizen's house). The measurements of RH have an uncertainty of 3%. The accuracy of pressure overall is excellent (Fig. 5), although there might be systematic difference in the comparison in part because the elevations are different between the location where I-Canopy sensor is set up and the NWS's weather station. We found that the data loss rate is about less than 1% due to the instability of wireless.

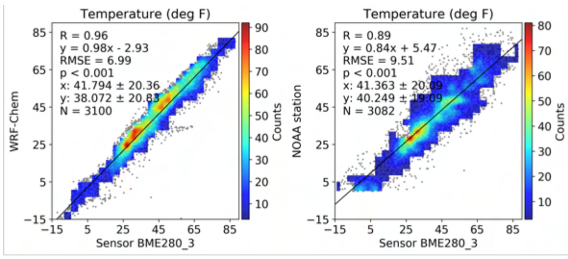

Fig. 4. Comparison of IoT sensor-measured hourly temperature in a citizen's backyard in Iowa City, IA, with (a) model predictions and (b) measurements by a NOAA weather station 10 miles west of the citizen's house. Period: Jan-May, 2021.

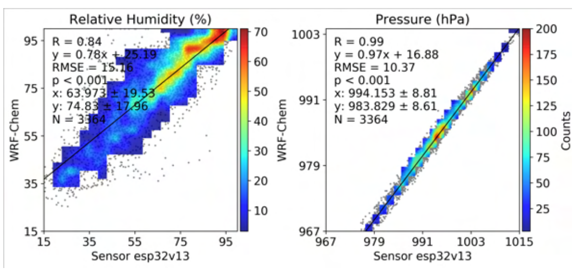

Fig. 5. The relative humidity and air pressure comparison for our sensor and WRF-Chem

B. Data Accuracy Assessment Via Crop Field Project

Another experiment was performed in the western Nebraska via a USDA-funded smart-and-connected community project. In the experiment, the I-Canopy was set up side-by-side with off-the-shelf weather sensors such as the Western Sugar sensor, Radio Bridge sensor, Dragion sensor, and a professional-grade 2000 dollars reference weather sensor by Vaisala. The result is showed in (Fig. 6), some of the low-cost sensors have problems with their relative humidity while for air temperature most of the devices are very accurate. For example, Dragino sensor's relative humidity reading is always around 40%. Nerveless, our I-Canopy sensor's measurements always have great correlation with the reference sensor.

IV. Conclusion

The canopy-air sensor with soil reading ability provide the farmer ability to monitoring the near surface air properties and soil properties at real time, which will provide important information for farmer decision-making of irrigation and agriculture water use for their farmland. The NiMH batteries

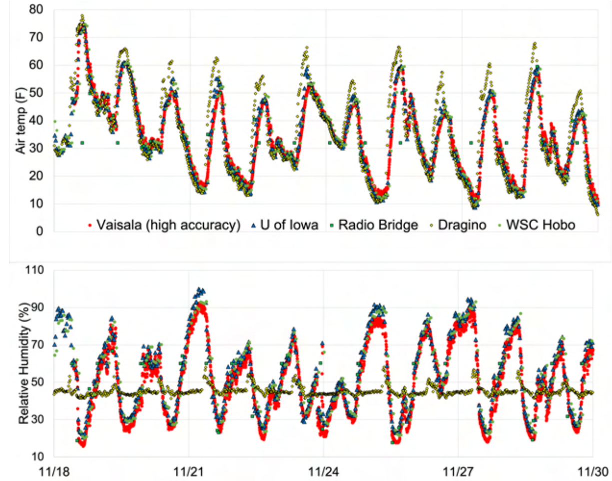

Fig. 6. Compared with other cheaper sensor, our sensor have a great accuracy of Temperature and relative humidity

and solar panel provide the sensor power to running all the time. The LoRaWan provide the sensor with long range communication ability. Together with all of the air and soil sensors, the whole package provide a immense result as our first test shown.

Acknowledgment

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