Forecasting microclimates with a low-cost LoRa enabled weather station network

1st Adam Sidnell
Computer Science MSc
University of Bristol
Bristol, United Kingdom
adam.sidnell@gmail.com

2nd Ruzanna Chitchyan
Professor in Computer Science
University of Bristol
Bristol, United Kingdom
r.chitchyan@bristol.ac.uk

***Abstract*—General weather forecasts are often too broad to accurately capture the small climatic variation that exists on farms. This can lead to sub-optimal decisions on tasks such as crop spraying, frost prevention or irrigation. While commercial weather stations exist, there is often a trade-off between their cost and transmission range. Additionally, these hardware products do not attempt to use their data to offer farmers improved forecasting on their fields. This paper presents the prototype design and evaluation for Agriscanner: An end-to-end, low-cost IoT weather station network that incorporates machine learning (LightGBM) to predict future weather within a field. Data is streamed to a web application for live visualisation. Evaluation shows the hardware system achieves a 1,200m range between nodes for a total range of 2,400m in non-ideal conditions. This was achieved at a cost of £520 for the complete system which includes two sensor nodes, a repeater and a WiFi gateway while outperforming commercial alternatives in range and cost. The machine learning model showed mixed results, outperforming general forecasts for certain climate factors (wind-speed) but highlighting the need for a larger, more diverse training dataset.**

***Index Terms*—machine learning, smart farming, forecast, microclimate, IoT, LoRa, LightGBM**

I. Introduction

Accurate weather data is critical for decision making in agriculture. Farmers rely on forecasts for various daily farming functions with significant financial and environmental costs attached. For example, it is required by law that pesticide spraying must be done in low wind speed to prevent spray drift which can damage nearby ecosystems [1]. Similarly, spring frosts pose a significant risk to crop yields; a single frost night can reduce crop yields by as much as 24% [2], highlighting the need for an accurate prediction allowing farmers to take appropriate counter measures (in the case of frosts this could be installing high power fans over the field).

However, general weather forecasts, as provided by the MetOffice in the UK, are based on macro-scale models which are not designed to capture local climate variations, known as microclimates. Farmers rank the accuracy and reliability of weather forecasts as one of the largest limiting factors when making decisions in growing season [3].

To address this issue, this paper presents a complete end-to-end system called Agriscanner. While commercial IoT weather stations exist, simply viewing current and historical data is insufficient for effective planning. The primary contribution of this work is a deployable system that applies an open-source machine learning procedure using locally collected sensor data to forecast the microclimate.

This approach is distinct from related work in three key areas. First, unlike studies relying on public datasets or existing sensor networks, we designed and built the entire low-cost hardware network required to collect data from remote fields. Second, while other systems focus on complex deep learning models, we demonstrate the application of an efficient, tree-based machine learning model (LightGBM) as a more accessible alternative. Third, this model is applied in a challenging open air environment, as opposed to more controlled contexts such as greenhouses.

A. LoRa

To ensure the hardware system was appropriate for the off-grid context of most agricultural applications, the communication technology chosen for the devices was highly important.

LoRa (Long Range) is a radio modulation technique invented in 2014 that allows for the transmission of data over very long distances. The technology is notable for achieving this long-range transmission (over 4000 times greater than WiFi [4]) while using remarkably little power. This makes it the preferred technology for the remote, off-grid application in this project.

The most important principle that separates LoRa from traditional radio modulation is its ability to demodulate incoming signals more efficiently. This allows the receiver to distinguish signals that are below the noise floor - that is, even when background noise is ”louder” than the LoRa signal, the data can still be processed.

This efficiency gives LoRa a far greater effective range despite their low power output. Relatedly, it also reduces the power budget for both the transmitter (sending weaker signals) and the receiver (easier demodulation), which is ideal for battery-powered devices. For a technical understanding of the technical aspects of LoRa refer to [5].

The main disadvantage of LoRa is a comparatively low data throughput - around 5 kbps in the configuration used here.

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However, since the data packets in this project were very small this was not a major issue.

II. Related Work

A. LoRa based IoT in agriculture

IoT devices have seen widespread adoption in agriculture, with digital solutions offering the potential to improve yields even in remote areas. LoRa is an especially relevant technology in this context as the range of these devices enables data to be transmitted over long distances and the low power allows for the use of gridless power solutions - such as solar-battery as used here.

There are relatively few papers examining the effectiveness of LoRa in agriculture but some notable examples include [6] where LoRa was used in an edge computing exercise. In this study the authors used CNN machine learning to create a compressed image that holds thousands of simulated climate readings. This image can then be sent over LoRa to a receiver node which can infer the readings of each node from this single image. While only one sensor node was created for the exercise they also tested the range of this device at a distance of 200m. This system would be useful in particularly large networks of LoRa devices where the low data transfer speed of LoRa would start to be a limiting factor.

The authors in [7] implement a LoRa based weather station prototype in India. The authors create a node that measures temperature, humidity and soil moisture in an experimental setting with no field deployment. Readings are then sent via LoRa to a receiver and can be read manually from the device's screen or viewed on an IBM dashboard.

B. Weather forecasting microclimates with machine learning

General weather models operate at magnitudes between 1 and 10 km and microclimate predictions require models that operate at scales of roughly 100m or less. Using existing general forecast models for micro-scale predictions is computationally expensive [8], and these models have lower accuracy rates than predictions using machine learning due to the inherent complexity and non-linear nature of microclimates. Therefore a number of studies have focused on building bespoke models to predict very local forecasts using machine learning processes.

A 2021 study by Kumar et al [9] developed an ML framework called DeepMC as a part of a Microsoft Research initiative. Their model is able to predict a variety of climatic variables such as soil moisture, wind speed and temperature using inputs from weather station forecasts and IoT sensors. They were able to get up to 90% accuracy with a 12-120 hour forecast range.

Zanchi et al [10] used physical modelling of local terrain combined with deep learning (DL) to forecast the microclimate in the foothills of Lombardy. The objective was to predict the local conditions at the meter-scale as opposed to the 10km+ scale of regional and global weather forecasts. The initial model combined data about the morphology of the local terrain and weather forecast data to provide the input data for two feed-forward neural networks. These neural networks were trained to predict the local weather variables using data from 25 sensors deployed in the region being studied. The study demonstrated that local predictions were more accurate when using forecast data from local weather stations as opposed to global climate datasets, but accuracy good in both.

Blunn et al [8] ran a study focussed on predicting temperatures in urban environments during heatwaves, using data from eight heatwaves in London, UK. They used data from the UKV - a high-resolution weather forecasting model - and from citizen weather stations (CWS). The authors used a similar model training design to that in this study. A number of ML models were trained on UKV variables (i.e. a general forecast) and CWS variables (local sensor data) to bias correct the UKV readings and create a forecast prediction model that could predict the CWS readings accurately (mean average error: 0.12°C) compared with the general weather readings from UKV (mean average error: 0.64°C). The main points of difference to this paper are the use of only temperature versus a wider range of variables in this study, along with the use of custom weather stations here compared to public weather data.

A recent paper from Abdelmadjid et al 2025 [11] used online datasets from Kaggle (a public repository of various datasets) to develop an ML tool to predict changes in temperature and humidity within greenhouses in response to changes to external weather conditions. They used these data to test three ML models and three DL models and selected the LightGBM ML model and the LSTM DL model as the best performing models for prediction. The overall system design consisted of four LSTM models feeding into the LightGBM model. This design resulted in 98.45% accuracy for temperature predictions and 99.61% accuracy for humidity predictions. Due to these results LightGBM was also chosen for this experiment.

III. Methodology

A. IoT hardware

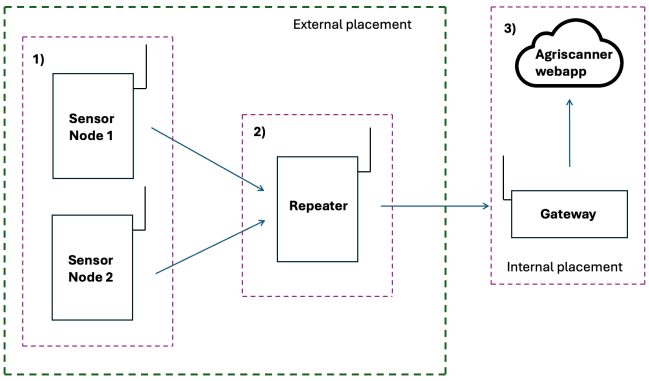

Fig. 1. Network diagram of the system

The design of the hardware consisted of two sensor nodes, a repeater and a gateway. The purpose for each is outlined below:

1) Sensor node: Collects temperature, humidity, wind speed and soil moisture data every 6 seconds. These readings are then averaged and sent as a single packet each minute to the repeater. Figure 2
2) Repeater: Receives LoRa signals from the sensor nodes and then immediately re-transmits these to boost range.
3) Gateway: A hub that receives LoRa signals and then transmits weather data using WIFI.

Fig. 2. Sensor node

All components were commercially available, and assembling the final hardware required only basic tools. Each device used an RP2040 based microcontroller (iLabs Challenger LoRa) microcontroller, which provided the necessary computing power and included built-in LoRa capability for wireless communication. The gateway node was additionally equipped with a Raspberry Pi to enable WIFI connectivity and remote access via VNC Viewer.

1) Weatherproofing: All sensitive electronics were housed in an IP65-rated waterproof junction box. Most external components were water resistant by design with the exception of the soil moisture sensor: In this case the electronics were coated in non-conductive nail varnish and sealed with heat-shrink. All cable entry points to the main box were sealed with silicone to prevent water ingress.

B. Deployment

The nodes were completed by mid-august and were installed in a private garden for a test deployment collecting local readings from two different locations in the garden. This helped facilitate easy repairs and updates to the devices.

The system ran continuously in this location from the 15th of August, 2025, which provided the data used for the machine learning model's training and evaluation later that month.

C. Webapp design

Weather data was sent from the gateway to a purpose built webapp called Agriscanner. This webapp allowed for the displaying of current, historic and future (predicted) weather.

The dashboard (Figure 3) displayed live weather data from the nodes with a 1 minute update frequency. Clicking on a particular data point allows the user to see a graph of past and future weather data in a way that is familiar to any user of standard forecasting apps (Figure 4).

Fig. 3. Webapp main dashboard

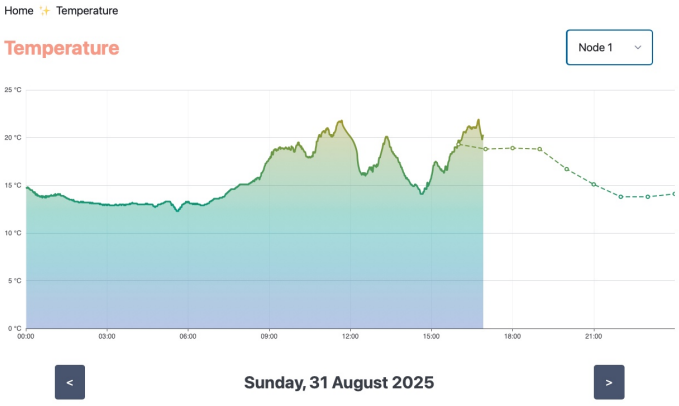

Fig. 4. Webapp temperature page showing current and predicted weather

D. Training and deployment of Machine learning algorithm

To forecast microclimate date up to 48 hours in advance, we trained 10 separate machine learning models using the LightGBM algorithm. One model was created for each of the

five sensor variables (temperature, humidity, wind speed, gust speed and soil moisture) for each of the two nodes. LightGBM was selected for its high performance on tabular climate data as the authors in [11] show. An additional benefit of this set up is that LightGBM is compatible with the m2cgen library which allows the conversion of the final models to individual JavaScript files.

The model was trained using both historical sensor readings collected in the field and general forecast data taken from OpenWeather's API. The final models were then able to take future general weather forecast data as input and bias correct with the aim of improving accuracy.

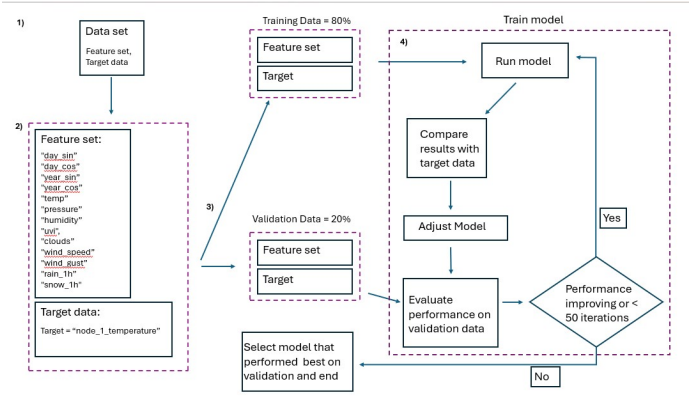

Fig. 5. Infographic showing training steps for training with LightGBM

The following steps were followed to train each of the ten models, also shown visually in Figure 5

1) **Dataset prepared:** A single cleaned dataset was created by matching timestamps between the api weather data and the sensor node data. As API readings are taken every 10 minutes and node readings every 1 minute, this meant that 9/10 node readings were discarded. The final dataset was roughly 1,400 rows. The data used for training spanned the period 15 - 27 August.
2) **Feature set and target data defined:** The feature set from the weather API and targets from the node data were defined, and unnecessary columns discarded. The database timestamp field was transformed into sine and cosine representations of day and year. This is necessary when training on a time-series data set as the algorithm must be able to understand the cyclical nature of time. For example, using raw timestamps would incorrectly suggest to the algorithm that the times of 23:00 on day 1 and 00:00 on day 2 are not closely related.
3) **Dataset split into training data (80%) and validation data (20%):** The data are split by time so the training data consists of the first 80% of the rows and the validation data the last 20%. These data are then supplied to the model.
4) **Iterative training:** For each iteration, the model looks at the inputs (training features) and the correct answers (training target) of the training rows, and determines where it is getting incorrect outputs. It builds a small decision tree that specifically aims to correct those mistakes on the training rows and adds that tree into itself so its predictions change a little. It then applies the updated model to the validation inputs (validation features) and compares those predictions to the validation answers (validation target) —to see how well the model would do on new "unseen" data. The validation data are never used to build the tree; they are only used to check the accuracy of the model. If the validation check shows no improvement after a number of iterations, the training stops and the model keeps the version that performed best on validation. The process will perform a minimum of 50 iterations. I set the maximum number of iterations to 250 to prevent the models getting too large, as each iteration increases the model size substantially (The humidity model is over 40,000 lines long in JavaScript format for example).

Once the ten models had been trained, they were uploaded to the web server. An automated function in the webapp provides the models with datapoints from the OpenWeather forecast data for the next 48 hours, and updates this data every ten minutes to adjust the predictions as the forecast changes. The outputs from the models are recorded as hourly predictions for each datapoint in a JSON file, which is requested by the frontend software and used to display a line graph of predicted values for the next 48 hours.

IV. Results

The system was evaluated in two key areas. First, we evaluated the performance of the machine learning forecasting. Then we evaluated the custom hardware by qualitatively analysing its benefits compared with commercial alternatives.

A. Machine learning performance

The accuracy of the machine learning prediction was evaluated over a period of 48 hours from 12am on 2025/08/30 to 12am on 2025/09/01. This was the period following the training of the model so was not included in the training data.

The performance of the model was compared to two alternatives:

1) **Raw general forecast from OpenWeather:** This was the input to the machine learning model and would give an indication of whether the accuracy could be improved.
2) **Alternative mean average adjustment:** This simple alternative model applied a constant mean average adjustment to the above raw forecast. This would help identify if a simpler model than the LightGBM process could be used instead.

	Average MAE (%)					Average RMSE (%)				
	temperature	humidity	wind speed	gust speed	soil moisture	temperature	humidity	wind speed	gust speed	soil moisture
General forecast	3.4%	5.5%	333.6%	381.9%	N/A	9.8%	14.7%	348.8%	398.6%	N/A
ML prediction	2.9%	14.9%	43.6%	37.6%	162.0%	13%	18%	58%	47%	162%
Alternative prediction	1.3%	11.1%	232.4%	264.0%	N/A	9.2%	17.5%	253.7%	287.6%	N/A

Fig. 6. Heatmap results showing MAE and RMSE averaged over both nodes

Figure 6 shows the machine learning model performance had mixed results.

1) Wind and gust speed: One relative success of the model was in the prediction of wind speed. The general forecast and alternative model were completely unusable in this regard with MAE of around 200 to 400%. This overestimate is likely due to the macro-scale forecast using wind speed data from much higher positions (often 10m) where wind speeds are much higher. Even the adjusted model does not correct this enough to come close to the true figure with an MAE of 232%. The machine learning model

B. Range and cost

V. Conclusion

A. Example figure and table

TABLE I
TABLE TYPE STYLES

Table Head	**Table Column Head**		
	Table column subhead	***Subhead***	***Subhead***
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[a]Sample of a Table footnote.

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