ECS Transactions

Analysis of Microenvironment Data Using Low-Cost Portable Data Logger Based on a Microcontroller

To cite this article: Pradeep Bhadola *et al* 2022 *ECS Trans.* **107** 15099

ECS Transactions, 107 (1) 15099-15109 (2022)
10.1149/10701.15099ecst ©The Electrochemical Society

Analysis of Microenvironment Data using Low-Cost Portable Data Logger Based on a Microcontroller

P. Bhadola[a], B. Kunakhonnuruk[b], A. Kongbangkerd[b], and Y. M. Gupta[b*]

[a]Centre for Theoretical Physics & Natural Philosophy "Nakhonsawan Studiorum for Advanced Studies", Mahidol University, Nakhonsawan Campus, Phayuha Khiri, Nakhonsawan, 60130, Thailand.
[b]Department of Biology, Faculty of Science, Naresuan University, Phitsanulok, 65000, Thailand.

Understanding the ecological and species diversity of natural places also requires the data of natural environmental factors but due to environmental and geographical conditions, monitoring the micro-environment can be difficult. In this context, we propose, a portable and cost-effective weather station based on the micro-controller Raspberry Pi Pico mounted with a digital temperature and humidity DHT11 sensor and a portable battery for monitoring and studying the effect of micro-climates on the forest, plant nursery, and farmland. The developed prototype is tested by collecting the temperature and humidity data in the control and random environment. A seasonal decomposition using moving averages on time series is done determining the trend, seasonal, and noise components. We perform the multi-fractal detrended fluctuation analysis on the collected data and estimated the Hurst exponent to check for the trends and patterns and their variation for different environments.

Introduction

Understanding the ecological and species diversity of natural places also requires the data of natural environmental factors. Due to environmental and geographical conditions, monitoring the micro-environment can be difficult. It is especially tough when there is no electricity or internet. There are various instruments available to collect temperature and humidity data, but they are costly. However, cheap data logging devices are available but they are disposable, making them ineffective for long-term logging. As per our survey, most plant nurseries, national parks, farmlands are not equipped with data logging devices to monitor environmental conditions. While large weather stations can be found in a number of locations, they cannot be considered optional for studying micro-environments.

Recent research emphasized the importance of micro-climate within the forest (1). In their study, the author found that the micro-climate data inside the forest is very different than the outside the forest. It has been established that temperature can be an important parameter to detect forest fire and sensors can be employed for the early detection of forest fires (2). Researchers and environmentalists emphasized more intensive research on micro-climates in order to protect forests for long-term use, maintain their biodiversity, and ecosystem services for future generations.

Temperature and humidity data from the respective environment are critical, especially in this era of global warming. Climate change has an indirect and direct impact on forests because it affects a wide range of tree species with varying ecological requirements, as well as all organisms of the ecosystem (3). Temperature and humidity also have a considerable impact on the physiological and ecological features of plants as one of the key factors regulating plant productivity and distribution (4). As a result, their monitoring is essential for expanding our knowledge of plant growth and diversity in the natural environment. Despite the widespread usage of temperature sensors in everyday life, the application of monitoring the micro-climate remains limited. Several studies have discussed climate monitoring systems and the most commonly used are Arduino-based systems. However, these systems are expensive with the cost starting from US$240 (5). Therefore, one of the factors hindering the monitoring of the micro-climate data is the cost of the expensive instruments, which is less suited for small-scale nurseries, greenhouses, plant tissue culture laboratories, forests, and national parks. Therefore, a cost-effective, portable, and low-maintenance monitoring system is required.

As a result, we propose, a portable and cost-effective weather station based on a micro-controller for monitoring and studying the micro-climates especially temperature and humidity in the forest, plant nursery, and farmland. Temperature and humidity data have been collected using the developed device. The trends and patterns in the data were extracted along with the relationship between the variables.

The proposed device is based on the micro-controller Raspberry Pi Pico, which was introduced in January 2021 with a retail price of $4. The power consumption of Raspberry Pi Pico is low, making it perfect for use with a battery and mounting in a distant region for data logging. We have connected the Raspberry Pi Pico with a DHT11 sensor, which is a basic digital temperature and humidity sensor with a modest price tag. It measures the ambient air with a capacitive humidity sensor and a thermistor. Knowing the temperature and humidity pattern in the micro-environment allows us to adjust the conditions and take steps toward improved plant growth. There are several reasons which prompted us to develop a portable weather station that can collect environmental factors like temperature and humidity from a small environment. The first major reason is affordability as the cost is a major factor for small-scale nurseries. The second reason is customization, as the weather in a natural environment, farmland, or control nursery can be unpredictable. We can attach multiple sensors to the micro-controller that satisfy the needs of the user.

The research is aimed at developing the required hardware and then using it to monitor and study the variation of temperature and humidity in the controlled and wild environments in Thailand. Our aim is to study the fluctuations in the micro-climate data in different regions, and the relationship among the variables. We first perform the decomposition of the time series data using the moving averages. The seasonal decomposition, gives the three components namely trends, seasonality as well as random noise in the time series. At last, we perform the multi-fractal detrended fluctuation analysis (MF-DFA) on the collected data to check for the multi-fractal properties in the temperature and humidity and their variation for different environments. The estimated Hurst exponent shows the differences in the sample data collected for different environments.

Methodology

Research methodology consists of the following two phases

1. **Phase 1- Designing the portable weather station and prototype development:** The schematic of the portable weather station was made and is shown in Figure 1. A prototype was made using the micro-controller Raspberry Pi Pico introduced recently in January 2021. The choice of the above micro-controller was mainly based on the cost-effectiveness as well as the low power consumption. Raspberry Pi Pico was introduced with a retail price of $4, making it an ideal controller for developing a cost-effective weather station. The low battery consumption makes it ideal to mount it with a portable battery connected with a solar panel for portable use in distant regions such as farms and forests with no electricity. In the prototype, we mount the micro-controller with the DHT11 sensor, which is a humidity and temperature sensor. The device is configured with the micro-python code. Any compatible sensor can be easily connected with the micro-controller. In the future, we will include other sensors for monitoring other weather variables such as rainfall, wind speed, and direction, pressure, etc.

2. **Phase 2- Collecting data, analyzing data, and developing a graphical interface for visualization and monitoring the weather data.** In this phase, we test the prototype under controlled conditions and collect the sample data. During this phase, we used various research methodologies for the analysis and making sense of the collected data. Firstly, a simple descriptive statistical analysis on the data was done. Then we check for the patterns and trends in the variables (temperature and humidity). We perform the multi-fractal detrended fluctuation analysis (MFDFA) to check for the statistical self-affinity and investigate the long-term correlations within the weather variables. The details of the procedure and algorithms used for analysis are discussed in the "Results and Analysis" section. We will also devise a graphical interface to visualize the collected data.

Components and Setup

The components required to create the prototype are a micro-controller Raspberry Pi Pico, a DHT11 sensor, a power bank (or a battery). We have also tested other modules and sensors such as pressure sensor, raindrop module for detecting the rainfall with the micro-controller Raspberry pi pico, but was not included in the prototype.

Raspberry Pi Pico. It is a low cost (retail price of $4), high-performance, low-power sleep, and dormant modes micro-controller with flexible digital interfaces. Raspberry Pi Pico is based on a single RP2040 micro-controller chip released on 21 January 2021. It has 256 Kb of RAM and 2 MB of flash memory. Micro-python is used to program the micro-controller. It has an inbuilt temperature sensor with options to connect multiple programmable input/output (PIO) state machines for custom peripheral support. The small size, low power consumption, and the ability to hold multiple peripheral PIO make the Raspberry Pi Pico the best choice for the portable weather station, that can be customized based on the customer needs.

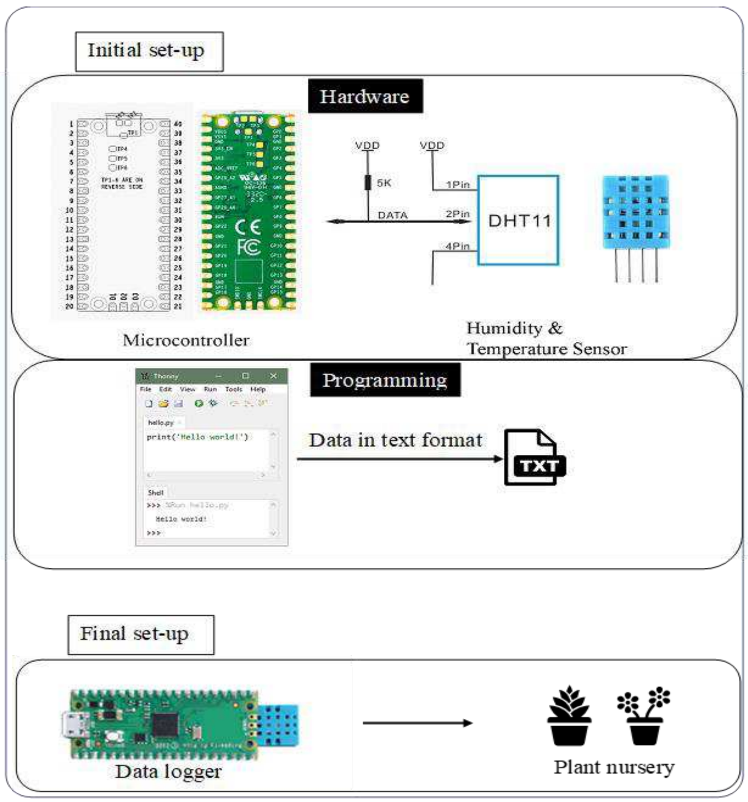

Figure 1. Schematic of portable weather station using Raspberry Pi Pico.

DHT11 Sensor. The digital temperature and humidity sensor DHT11 is the most commonly used temperature and humidity sensor with a small size of 2.0 cm X 2.0 cm. The sensor is connected with an 8-bit micro-controller. There are 3 pins available in the module namely VCC (Voltage Common Collector), data, and ground. The module works with a voltage of 5V DC. When the device is active, a start signal is sent through the data line of DHT11, in response to this start signal, a reply signal is returned back through the same data line. The received reply signal is a 40-bit data consisting of humidity and temperature information. The 40-bit data consists of 8-bit humidity integer, 8-bit humidity decimal, 8-bit temperature integer, 8-bit temperature decimal, and 8-bit checksum. This data is returned to the host. The sensor module work in the humidity range of 20% to 90% of Relative humidity (RH) and temperature range of 0 to 60 degree Celsius.

Power Bank or portable battery. Any power bank or a portable battery with a micro-USB output can be used.

The prototype was made with the above-mentioned components. The micro-controller Raspberry Pi Pico is mounted with a DHT11 sensor. The programming of Raspberry Pi Pico and interfacing of DHT11 with Raspberry Pi Pico is done using the micro-python. The temperature and humidity data are dumped into a data file in micro-controller flash memory. The micro-controller is powered with the micro-USB connected to the power bank and is ready to use for monitoring the micro-climate. The detailed schematic of the prototype as a portable weather station for monitoring the temperature and humidity is shown in Figure 1.

Results and Analysis

After checking the consistency of the sensors, we test the prototype within two environmental conditions a controlled environment and a random environment (Table I). For the control environment, we choose the Plant Tissue Culture Laboratory, Department of Biology, Faculty of Science, Naresuan University. For the random environment, we put the sensors outside the lab, in the hallway of the building.

TABLE **I** . Statistics of the sample data collected for the controlled environment

	Control		**Random**	
	Humidity	**Temperature**	**Humidity**	**Temperature**
Data Points	6470	6470	1841	1841
Mean	36.10	23.44	67.35	27.57
Std. Dev	5.49	0.49	5.07	0.58
Max	52.0	24.0	78.0	28.0
Min	26.0	23.0	57.0	26.0

For the control environment (Plant Tissue Culture Laboratory), we collect data continuously from 5th November 2021, 13:42:00 to 12th November 2021, 07:27:00 (UCT time +7 hours) for a period of 7 days. The data is logged with a frequency of 90 seconds with a total of 6470 valid data points. The fresh plant tissue culture medium-containing bottles were placed in the laboratory on November 8th, 2021, and sensor data were continuously recorded. Due to the fresh tissue plant culture, we observe a fluctuation in the relative humidity values within a range of 10% relative humidity. However, due to the controlled air-conditioning, the temperature value only fluctuated by one degree. The descriptive statistics of the collected data for the controlled environment are shown in Table 1 and the plot is shown in Figure 2.

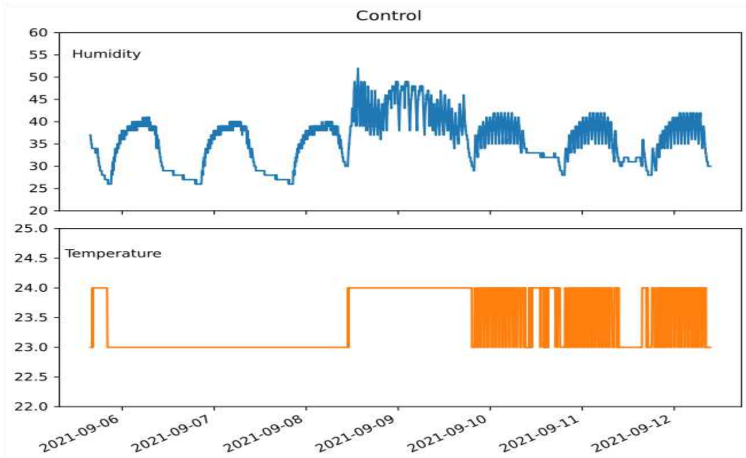

Figure 2. Plot of the humidity and temperature data as collected by the prototype for the control environment.

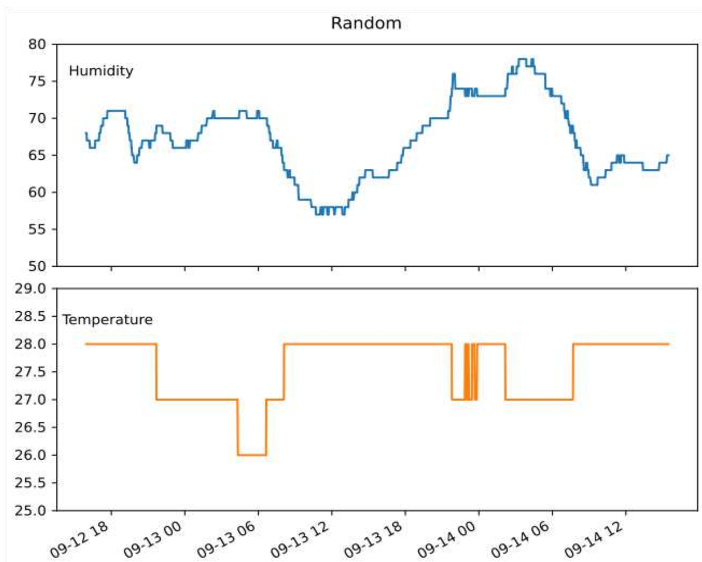

Figure 3. Plot of the humidity and temperature data as collected by the prototype for the random environment.

After finishing the readings for the seven days for the controlled environment, the prototype is placed outside the lab, from 12th November 2021, 15:56:00 to 14th November 2021, 15:29:00 (UCT time +7 hours) for a period of 2 days. A total of 1841 valid data points were collected and analyzed. The fluctuation as well as the value of relative humidity is higher than that of the control environment. The temperature is also on the higher side but the fluctuation is very little. The descriptive statistics of the collected data for the random environment are shown in Table 1 and the plot for the data is shown in Figure 3.

Time series decomposition

Time series decomposition involves separating the series into its components which include a trend, seasonality, and the noise component (6,7). The trend component signifies the overall increase and decrease in the mean values over a period, the seasonal component represents the recurring or repeating cycles in the data and the noise component is the remaining random residual in the data. In the present case, we consider the following decomposition model for a time series X(t) :

$$X(t) = \text{Trend} + \text{Seasonal Components} + \text{Noise} \qquad [1]$$

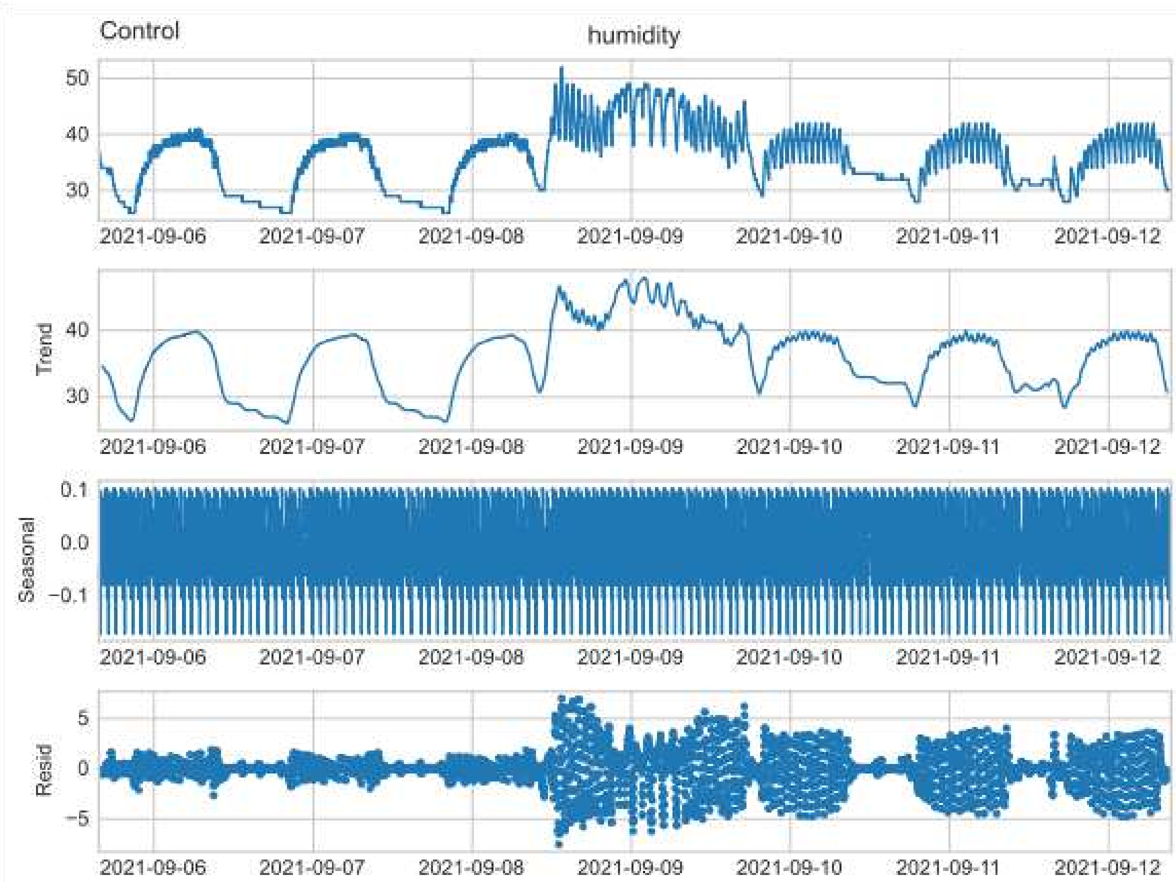

Figure 4. Decomposition of the humidity time series collected from the control environment into trend, seasonality and noise.

In our case, X(t) can be the humidity or the temperature values. For the sample data collected we try to find any trends and seasonality in the data series for the control and random environment. There are four basic steps for the decomposition of the series into its components. The first step is a smoothing procedure usually done by taking the moving averages. The second step is to de-trend the series by subtracting the trend estimated in the first step. In the third step, the seasonal component is estimated from the detrended series. The final step is to estimate the noise in the data which is simply subtracting the trend and the seasonal component from the original series.

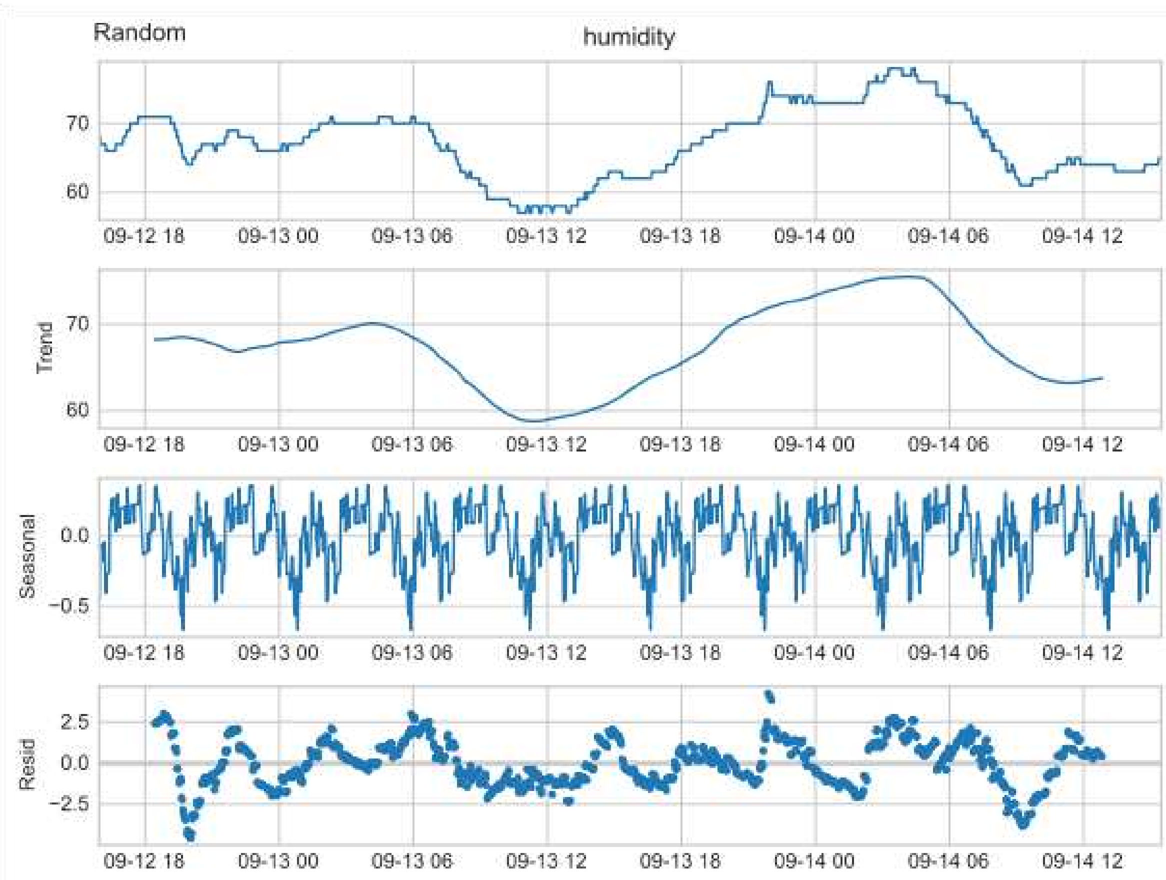

Figure 5. Decomposition of the humidity time series collected from the random environment into trend, seasonality and noise.

Since there are negligible fluctuations in the temperature values, and the values are nearly constant, it is hard to determine the trend and seasonality in the temperature values. Therefore, we use only the humidity to decompose into the trends, seasonality, and noise. Numerically, we use Python’s statsmodels library for the decomposition of humidity data. The method performs the seasonal decomposition using the moving averages. We use a total of 200 data points for the calculation of moving averages. This range is not fixed, one can choose any time frame to calculate the moving averages. In our analysis, we find the results are quite robust in the range of 100-250 data points. We perform the seasonal decomposition of the humidity data for the control as well as for the random environment. The results are shown in Figure 4 for the control environment and Figure 5 for the random environment. The results show that there is a definite trend and periodicity in the control environment for the humidity. The trends get disturbed when the fresh tissue culture medium was introduced into the lab. The random environment does not show such a trend.

Multifractality and Hurst Exponent

Next, we study the multifractal properties of the humidity based on Multifractal Detrended Fluctuation Analysis (MFDFA) (8,9,10). MFDFA has now become a standard methodology in many disciplines involving time-series data (11,12). MFDFA was first introduced by Kantelhardt et al (13), which was the generalization of detrended fluctuation analysis (DFA). For detailed method and the procedure of MFDFA see (13).

MFDFA results in the estimation of the generalized Hurst exponent of a time series. The Hurst exponent is one of the fastest ways to find the long-term memory of a time series. It also measures the amount by which a given time series deviates from a random walk. The detailed steps and algorithm involved in the estimation of the Hurst exponent are given in Kantelhardt, et al (13). In brief, to calculate the Hurst exponent (H), we first need to calculate the standard deviation of the differences between the series and its lagged versions. For a possible range of lag, estimate the Hurst exponent as a slope of the log-log plot of the number of lags versus the mentioned standard deviations. Based on the value of H we can classify the series as

1. For **H < 0.5**, the time series is a mean-reverting (anti-persistent) series. A mean-reverting series has a greater chance of a high value following a low value. Mean reversion is the highest when the value of H approach 0.

2. For **H = 0.5**, the time series resembles a geometric random walk.

3. For **H > 0.5**, the time series is a trending (persistent) series. It signifies a high probability that a high value will be followed by a much higher value.

We estimate the Hurst exponent for the control and the random environment, for different values of lag ranging from 5 to 500. The estimated Hurst exponent for control and random environment is shown in Figure 6. We find that the behavior of the humidity for sample data collected for the control environment and random environment is very different. For the small value of lag (<20), the humidity in the control environment is persistent with a trend. But if we increase the lag, the mean reversion is getting stronger and gets saturated with a value of Hurst exponent as 0.36. The behavior of the random environment is different from the control environment. The random environment behaves like a random walk for small values of lag and with the increase in lag shows persistent behaviors.

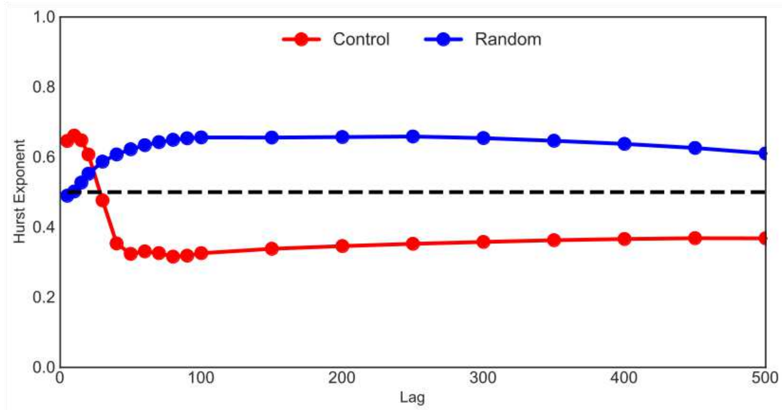

Figure 6. Hurst exponent with lag for humidity values for the control and random environment.

Conclusions

In conclusion, a prototype of a portable weather station based on Raspberry Pi Pico and DHT11 sensor is made. The device is tested in two environments once inside the tissue culture lab in the controlled environment and the other outside the lab. An analysis methodology is created based on the time series decomposition and Multifractal Detrended Fluctuation Analysis (MFDFA) to study the seasonality and trends in the collected data.

In our future work, we will try to incorporate other sensors to monitor other weather parameters such as air pressure, rainfall, wind speed, etc. We will connect our device to a cloud platform, to enable users to check weather parameters in real time. Although we have built a graphical interface based on python to visualize the collected data. The interface has limited functionality, we will try to improve the interface with advanced features showing trends and integrating it with the machine learning algorithms for localized micro-weather predictions. We are working to develop a machine learning algorithm based on the Long short-term memory (LSTM), which is an artificial recurrent neural network (RNN) architecture to predict and forecast the future values of the local weather variables to prepare for better management and monitoring of farms and forests.

Acknowledgments

The authors hereby acknowledge the Department of Biology, Faculty of Science, Naresuan University, Thailand for awarding a research grant [R2564C033], and also for their laboratory facilities. PB wants to thank Mahidol University for research support "MRC-MGR 04/2565”.

References

1. P. De Frenne, J. Lenoir, M. Luoto, B. R. Scheffers, F. Zellweger, J. Aalto, M. B. Ashcroft, D. M. Christiansen, G. Decocq, K. De Pauw, and S. Govaert, *Global Change Biology*, **27**(11), 2279 (2021). doi: 10.1111/gcb.15569.
2. E. A. Kadir, S. L. Rosa, and R. A. Ramadhan, *AIP Conference Proceedings*, **2217(1)**, 020003 (2020). doi: 10.1063/5.0000493.
3. B. L. Jakhar, N. Singh, P. V. Tapre, Y. Ravindrababu, and S. Venilla, *Journal of Agriculture and Ecology*, **4**, 37 (2017). doi: 10.53911/JAE.2017.4205.
4. Q. Song, C. Sun, Y. Deng, H. Bai, Y. Zhang, H. Yu, J. Zhang, L. Sha, W. Zhou, and Y. Liu, *Atmosphere*, **11**(8), 798 (2020). doi: 10.3390/atmos11080798.
5. D. A. McGranahan, *Rangeland Ecology & Management*, **76**, 43 (2021). doi: 10.1016/j.rama.2021.01.008.
6. R. B. Cleveland, W. S. Cleveland, J. E. McRae, and I. Terpenning, *J. Off. Stat*, **6(1)**, 3 (1990).
7. E. B. Dagum, *Statistica,* **70**(4), 433 (2010). doi.org/10.6092/issn.1973-2201/3597
8. Y. Wang, L. Liu, and R. Gu , *International Review of Financial Analysis,* **18**, 271 (2009). doi: 10.1016/j.irfa.2009.09.005.
9. K. Matia, Y. Ashkenazy, and H. E. Stanley, *Europhysics Letters*, **61**, p. 422 (2003).
10. L. Zunino, B. M. Tabak, A. Figliola, D. G. Perez, M. Garavaglia, and O. A. Rosso, *Physica A*, **387**, 6558 (2008). doi: 10.1016/j.physa.2008.08.028.
11. L. Zunino, A. Figliola, B. M. Tabak, D. G. Perez, M. Garavaglia, and O. A. Rosso, *Chaos, Solutions and Fractals*, **41**, 2331 (2009). doi: 10.1016/j.chaos.2008.09.013
12. P. Oswiecimka, J. Kwapien, and S. Drozdz, *Physical Review E,* **74**, 1 (2006). doi: 10.1103/PhysRevE.74.016103.
13. J. W. Kantelhardt, S. A. Zschiegner, E. Koscielny-Bunde, S. Havlin, A. Bunde, and H. E. Stanley, *Physica A*, **316**(1-4), 87 (2000). doi: 10.1016/S0378-4371(02)01383-3.