

A Novel Drone-based Application to Monitor and Determine Air and Soil **Temperature Distributions in Indoor Farming Environments** Arnab Sircar

ABSTRACT

Indoor farms require frequent monitoring of environmental parameters. This is done manually today and is infrequent and error-prone. Dronebased monitoring can be employed to substantially increase productivity. Various sensors can be mounted on drones, and their flight paths can be programmed to automate the process, allowing direct measurements of parameters. This idea was explored for a mushroom farm. Mushrooms require uniform temperature distributions of ambient air and soil. With drone-based monitoring, temperature measurements can be frequent rather than employing a single thermometer for each large room, giving poor estimates of the temperature distribution. A drone was flown, and air temperatures were collected at designated points. Computational kriging was used to impute missing values and obtain near-continuous distributions that showed a 0.41% error upon validation. Using the air temperatures, a convective-diffusive heat flow model provided soil temperature estimates at boundaries of soil beds. These were then used in a Laplace heat conduction equation to obtain soil temperature distributions. Upon validation, a 1.02% error was observed. Results show that dronebased monitoring can be deployed in indoor farms to increase efficiency and reduce operation costs.

RESEARCH OBJECTIVES

• Use drone-based data collection for air temperature distribution and utilize heat flow and heat transfer based models to estimate soil temperature distribution in a mushroom farm which is typically indoors. • Increase and improve the frequency of more fine-grained data collection for better control in maintaining uniform temperature distributions.

• Extensions: Currently in the project, the drone is to be flown manually, but it is envisioned that with an indoor path planned and programmed for the drone, automated flight can be achieved several times a day. The ultimate vision is to achieve such a capability.

• Purpose: Mushrooms are grown indoors, and it is important to maintain uniform air and soil temperatures for their healthy growth. Therefore, there is a need to monitor the temperatures for suitable control actions. Manual operations for monitoring are costly and error-prone; they have only sparse data collection and are infrequent. With a drone-based operation, frequent monitoring and estimation may be possible as more data is quickly collected with greater resolution.

• Question: Is it possible to develop a drone-based air temperature monitoring and physics-based modeling methodology to estimate soil temperatures in a mushroom farm that produce results within acceptable error limits (3% or less error)?

PRIOR STUDY

• Drones are increasingly used in agricultural applications. Using them for an indoor agriculture application and in greenhouses together with physicsbased modeling is new.

• Sensors with fast data acquisition will be required for such applications since the drone with the mounted sensor may only hover briefly to collect data.

• Physical models for heat flow and heat transfer are quite well-developed and have been used in many industrial applications.

• Every environment presents new factors that require careful modeling for accurate results

• Air temperatures can be collected directly, and the soil temperatures are estimated by heat flow equations involving convective and conductive heat transfer.

MATERIALS AND METHODS

Assumptions

• There is minimal turbulent air draft in the room where temperature measurements are taken.

• The drone with temperature sensor can be flown close to the rack and hover while acquiring data.

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Controlled Variables

• Drone hovers for 20 sec. for every reading.

• Temperature recording points are separated by exactly the same distance along y and z axes.

PROCEDURE

A thermal sensor with rapid response time and sufficient memory is mounted on a drone.

<u>2</u>. The drone is flown along the x, y, and z axis in sequence for each rack housing the "prisms." At each of the top four vertices of the prism, the drone hovers for 20 secs to record the air temperature.

3. A series of data along the three axes are uploaded to a laptop where this is logged.

<u>4</u>. Kriging models with the data are produced to show the near-continuous temperature distribution for all the "prismatic" sections.

PROCEDURE (cont.)

Specifically, ordinary Kriging was used, which involves the use of a linear combination of the measured values around the location of an unknown value to determine that unknown value. This estimator is in the following

$$Z^*(u) = \sum_{i=1}^n \lambda_i Z(u_i)$$

Where u is the position of the unknown value, u_i is the position of the nearest known values, and λ_i is the relative weight of u_i in the estimation of the value at *u*. Essentially, the weights of each nearest known value has to be found in order to determine the value at the unknown position. Thus, we consider $Z^*(u)$ and $Z(u_i)$ to be random variables and determine the estimation variance by utilizing the covariance function C. We can consider these to be random variables due to the stationarity principle, where we expect that our unknown value remains relatively constant for all samples. Thus:

$$\sigma^{2}(u) = \operatorname{Var} \left[Z(u) - Z^{*}(u) \right] = E\left[\left(Z(u) - \sum_{i=1}^{n} \lambda_{i} Z(u_{i}) \right)^{2} \right]$$
$$= E\left[\left(Z(u) \right)^{2} + \sum_{i=1}^{n} \sum_{j=1}^{n} \lambda_{i} \lambda_{j} Z(u_{i}) Z(u_{j}) - 2 \sum_{i=1}^{n} \lambda_{i} Z(u_{i}) Z(u) \right]$$
$$= C(0) + \sum_{j=1}^{n} \sum_{i=1}^{n} \lambda_{i} \lambda_{j} C(u_{i} - u_{j}) - 2 \sum_{i=1}^{n} \lambda_{i} C(u_{i} - u)$$

We consider the best linear estimator to be the one that minimizes the estimation variance with respect to the condition that all the weights add to 1. Thus, with Lagrange multiplier μ , we minimize:

$$\sigma^2(u) - 2\mu(\sum_{i=1}^n \lambda_i - 1)$$

Using the partial derivatives with respect to λ_i and μ , the estimation variance equation shown above, and the condition that the sum of the weights is 1, one can solve the system and determine the weights. Finally, evaluating the linear combination yields the unknown value at position *u*. 5. A steady-state convective-diffusion heat transfer model is used to estimate the soil temperature at the four corners of the bottom of the "prism" for soil surface temperatures.

The following one-dimensional convective-diffusion equation was used:

$$\frac{d}{dx}(u\Phi) - \frac{d}{dx}(\Gamma\frac{d\Phi}{dx}) - S = 0$$

Here, u represents the velocity of the transport fluid, Φ represents the scalar quantity that is transported by the fluid (Temperature in this case), Γ represents the diffusion coefficient, and S represents a volumetric heat term. In this case, there is no volumetric heat source, so the term effectively becomes 0. As it can be seen, there is no time-derivative in the model.

The following analytical solution was used to perform computations:

$$\frac{\varphi - \varphi_0}{\varphi_L - \varphi_0} = \frac{e^{\frac{\mu \Lambda}{\Gamma}} - 1}{e^{\frac{\mu L}{\Gamma}} - 1}$$

Here, *L* is the distance between the initial and final boundary conditions. To calculate *u*, the following equation was used:

$$v = c(\frac{P}{L})^{\frac{1}{3}}$$

v represents the velocity of the air, which is the heat transfer medium in this case. cis a constant, which for my purposes can be left equal to 1. *P* represents the power of the heat source. It was found that on average, rich soil emits about 15W of power per day, and the energy is dissipated through convective heat currents into the air.

<u>6</u>. A Laplace heat conduction model is used with temperatures from Step (5) as boundary conditions for soil temperature distribution. Heat maps of soil surface temperatures are generated for all the "prismatic" sections in all the racks.

The following elliptic partial differential equation was used:

$$\frac{\partial^2 \psi}{dx^2} + \frac{\partial^2 \psi}{dy^2} = 0$$

A python program was written to numerically solve the equation.

<u>7</u>. Validation steps are performed by comparing the estimated temperatures with actual measurement of temperatures (from random samples) to get % errors.



The research question was answered affirmatively; we can indeed use a dronebased temperature monitoring system to obtain estimated temperatures of air and soil in the mushroom farm to be within an error bound of 3%.

In this instance, the height of the "prism" is not too large, and so, there is a small change in air temperature at the top of the prism from the soil surface temperatures at the bottom. \succ Normally, the sizes of these prismatic sections could be much larger,

The edges of the "prism" provide boundary temperatures that is an averaged value of the end points. The 2-dimensional conductive heat flow in steadystate provides a good approximation for the soil surface temperature distribution. This is very informative for the mushroom farmer.

ANALYSIS OF RESULTS

•Since the air temperatures are *measured*, we see a diffused distribution at the top of the "prisms." After validation of the kriging model, the error was 0.41%.

•The soil surface temperatures are *estimated* using a heat flow model, and so, the distribution appears a little regular at the bottom of the "prisms." After validation, the error was 1.02%.

•These temperature distributions were produced in a matter of 4 hours, whereas if these were to be produced manually, it would take a whole day. •Similar temperature distributions were observed for other "prisms." This visual depiction would be very useful to the mushroom farmer.

Air temperature distribution heat map (for entire room at a given height)



Soil surface temperature distribution heat map (for one prism)

CONCLUSIONS

> We may further hypothesize that similar method may be employed more generally for other indoor farming environments.

- and we could expect a bigger difference between the soil surface temperature at the bottom and air temperature at the top.
- > The diffusivity used in the calculation was for normal dry air. It could be higher for moist air (which exists in normal operations), and hence, we can expect larger differences.
- > If the soil temperature distribution in deeper layers is required, heat flow by conduction can be employed using the thermal conductivity parameter along the z-axis.
- > Where the temperature in soil bed shows large variation, there can be targeted heat infusion by infusing exothermic heat sources.

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