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Understanding the Effect of Agricultural Practices on Valley Fever through a Novel Statistical Model Using Dust Emissions

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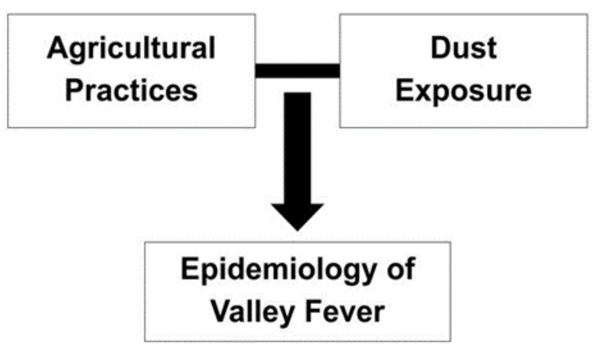
ABSTRACT

Valley Fever (VF), or coccidioidomycosis, is a disease significantly influenced by dust exposure. Current statistical models fail to depict the nature of VF's prevalence over time accurately. Looking to understand potential intervention plans, we determined that agricultural practices (APs) are already used in agriculture to lower dust emissions. Therefore, to investigate the impact of APs on VF epidemiology, dust emission measurements were plugged into the SIR (Susceptible, Infected, and Recovered), a standard epidemiological model to predict change in infected individuals in a population. The analysis demonstrated a clear link between dust exposure and VF incidence, with mulch emerging as the most effective AP at reducing VF cases compared to salt brine and organic material cover. Following this initial testing, soil samples were collected and tested from different locations around the Phoenix Metropolitan area, implementing another variable into this model. This additional testing revealed that the effectiveness of APs in reducing VF cases could vary depending on the soil's location. The computational model, which showed promising results in demonstrating the relationship between dust exposure and VF incidence, holds potential for broader application. It could be utilized by various stakeholders across the southwestern United States to develop interventions to mitigate the impact of VF. Modifications are proposed to ensure the accuracy of the epidemiological model. These include testing a more comprehensive range of APs, integrating machine learning (if granted access to substantial data), and acquiring advanced hardware. Such enhancements refine the model's predictive capabilities and broaden its applicability in VF mitigation efforts.



Flow Chart 1. Diagram displaying the theoretical link between agricultural practices, dust exposure, and the epidemiology of valley fever.

Introduction

Background Information

Valley fever (VF or coccidioidomycosis) is a disease caused by inhaling *Coccidioides* spores, mainly found in the soil of the Southwestern United States. Although the disease has a more extensive geographical range, it is found primarily in this region (Valley Fever: Timely Diagnosis, 2017). Various factors, including environmental hazards, ethnicity, pregnancy, a weakened immune system, diabetes, or age, can stimulate VF. Furthermore, VF has numerous symptoms, depending on the severity of the disease; the most common form of VF, acute coccidioidomycosis, results in a fever, cough, and shortness of breath, along with a slew of other symptoms (Valley fever, 2023). VF can also be the gateway to other diseases, such as community-acquired pneumonia (CAP), a deadly infection. In the past few decades (1998-2019), VF cases have steadily increased, ranging from 2,271 to 20,003 cases in the US alone. Moreover, there have been, on average, 200 deaths per year from this disease in this timeframe (Valley Fever (Coccidioidomycosis) Statistics, 2022). The Arizona Department of Health and Safety corroborates this statistic, as 75.4 million dollars were charged to Arizonans with a primary diagnosis of VF in 2020, highlighting the economic impact that this disease can have as well (Valley Fever 2020 Annual Report, 2020). Although many factors could contribute to contracting VF, one of the most significant is exposure to environmental factors such as dust (Comrie, 2021). This is especially seen with people such as “construction, road and agricultural workers, [and] ranchers” (Valley fever, 2023).

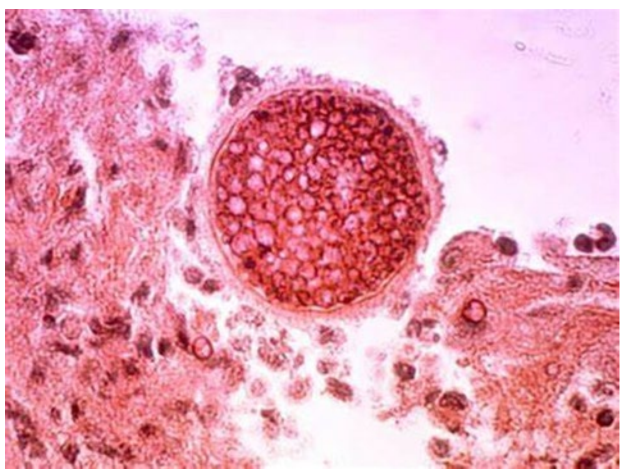


Figure 1. Picture of Coccidioides spores (llibutti, 2016)

Finding a way to limit the exposure of these dust particulates to this demographic in agricultural environments can be vital to determining the cases of VF: “Epidemiological studies suggest … more frequent soil-borne dust exposures … as possible causes for increased coccidioidomycosis rates” (Ramadan, 2022). So, understanding which agricultural practices (APs) in which locations would be most beneficial to limiting dust exposure, using a computer model, would be essential in preventing the spread of VF. This would also provide valuable data to government officials about suitable VF prevention plans. Studies have been conducted linking these two factors, but they have not been able to pinpoint precisely which APs would work the best (Johnson, 2014; Comrie, 2021). This discovery would be crucial in implementing safer and healthier agricultural practices. In conclusion, due to the significant need for information on which APs would be best in limiting VF cases, creating a computer model that would not only be able to test each AP accurately but also forecast the

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predicted change in VF cases for each AP will aid in the fight against VF as a valuable indicator of the best solutions to dust exposure.

Defining the Compartmental Epidemiological Model

A compartmental epidemiological model is a very common statistical modeling technique for infectious diseases. The specific compartmental model used is the SIR model, with the variables S, I, and R interacting with one another through the differential equations shown below (Bazant, 2021).

Equation 1. Rate of Change of Susceptible Population

$$\frac{dS}{dt} = -\beta \frac{SI}{N}$$

Equation 2. Rate of Change of Infected Population

$$\frac{dI}{dt} = \beta \frac{SI}{N} - \gamma I$$

Equation 3. Rate of Change of Recovered Population

$$\frac{dR}{dt} = \gamma I$$

These three equations define the base of the epidemiological model used: the change in the rates of the susceptible, infected, and recovered populations, respectively. The following chart indicates the variables included in this equation and their purpose.

Table 1. Functionality of Variables Used in Compartmental Epidemiological Model

Variable	Functionality
$S(t)$	Susceptible population over time
$I(t)$	Infected population over time
$R(t)$	Recovered population over time
β	Dust transmission rate
γ	Recovery rate
N	Size of population

Although these variables all play an essential role in defining this epidemiological model, the additional variable of location (L) is also critical in how this compartmental model works.

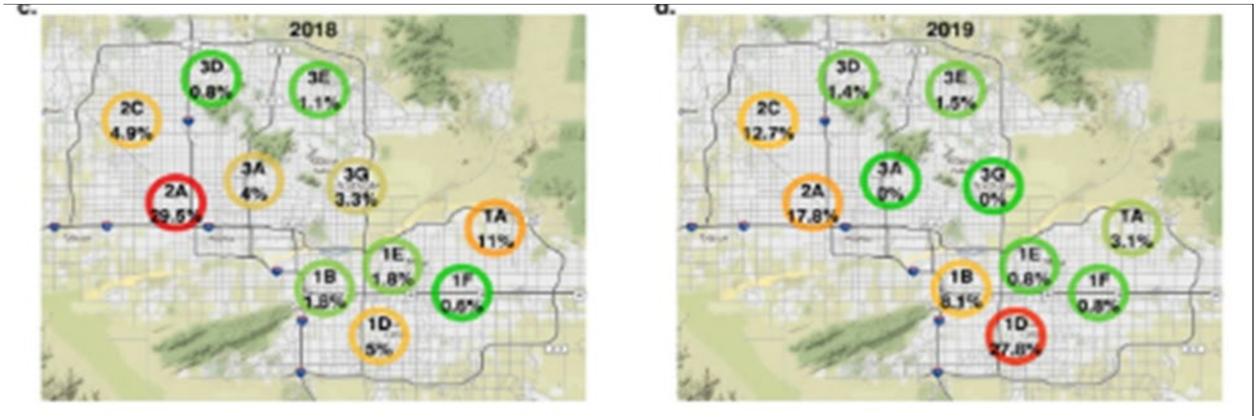

Figure 2. Prevalence of *Coccidioides* in Ambient Air across the Greater Phoenix Metropolitan Area during 2018-2019 (Porter et al., 2024)

L affects β in two ways: firstly, L redefines the initial value of β using the transmission rates shown in Figure 2, and secondly, alters the dust emission rates (E) for each AP as different soils change E's value.

A more robust compartmental epidemiological model can be created through the additional variables of L and E.

Research Question

What is the effect of different agricultural practices on the epidemiology of Valley Fever?

Methods

Initial Methods

The prototype for the initial stage of testing consisted of a fan, "Miracle-Gro Cactus, Palm & Citrus Soil," a Make Code Microbit microcontroller, an Octopus Dust Sensor, jumper wires, a plastic protective covering, and micro-USB cords. Along with this, four identical rectangular boxes were utilized to hold soil for testing the following four APs: control (only soil), organic material cover (OM: a mixture of plants, branches, etc.), mulch, and salt brine. These three APs, excluding the control, are all recommended by the Arizona Department of Agriculture to prevent dust exposure (*Guide to Agricultural PM10 Best Management Practices "Agriculture Improving Air Quality" Crop Operations Maricopa County or Potential Moderate Nonattainment Areas Governor's Agricultural Best Management Practices Committee*, 2015).

The dust sensor was placed in the plastic protective covering to protect the hardware from dust, as shown in Figure 3, and oriented on the short side of the rectangular box. The fan was placed on the other end to ensure a constant air stream. Without the fan, in the early stages of testing, there was not enough dust flowing in the dust sensor, so the fan was used to stimulate this process.

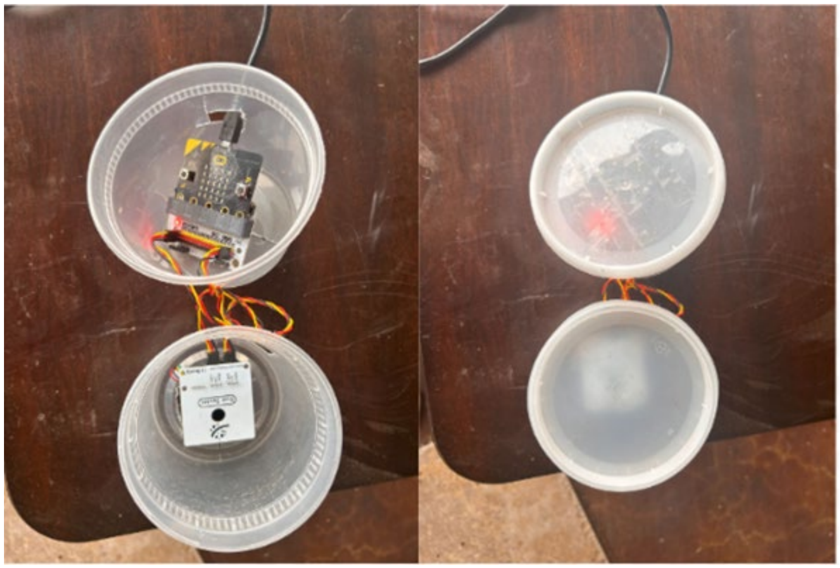

Figure 3. Coding Hardware and Plastic Protective Covering (Photographed by S. Kale)

The dust sensor detected dust particles over a thirty-second interval, providing a value for dust emitted by the soil for each AP. This interval was used to acquire a substantial amount of data, as the sensor detected dust (in $\mu g/m^3$) approximately every 0.2 seconds and the detected values varied considerably in intervals of less than 30 seconds. After all the values were detected over three trials for each AP, an average was taken for each of these trails to gauge the amount of dust emitted.

Table 2. Dust Sensor Values ($\mu g/m^3$) of APs over Three Trials and Average

APs	Trial 1	Trial 2	Trial 3	Average
Control	1.7197	0.1004	0.2636	0.6946
OM	0.1925	0.1381	0.0628	0.1311
Mulch	0.0460	0.1088	0.0753	0.0767
Salt brine	1.674	0.1046	0.1506	0.1409

These values were then input into the statistical model coded in Python. This model created a graph of the epidemiology of Valley Fever using equations 1-3 in code form (Kale, 2024). The three data points tested for each AP were the maximum number of cases in the 150-day time frame simulated, the day this peak was reached, and the percent efficiency of each AP compared to the control. These three data points were collected to understand the disease curve and what important information we can extract from the epidemiological simulation.

Adjusted Methods

In the future stages of experimentation, L was implemented into the compartmental model. The methods were slightly adjusted from the initial phase to accommodate this adjustment. Smaller, more compact boxes were used to collect soil samples from each location across the Phoenix Metropolitan area, as highlighted in Figure 2. Along with this, salt brine was no longer a viable AP to use, as the nature of some of the soils resulted in mud being created when salt brine was added, resulting in it being unusable in agriculture and, therefore, unusable in this experiment. If salt brine were kept as an AP, the resulting mud would likely result in values of 0 as the water would weigh down the dust.

Of the locations indicated in Figure 1, the following five locations were chosen because of proximity and variance in transmission rates: 2A, 3A, 3D, 3E, and 3G.

Table 3. Average Dust Sensor Values (μg/m^3) of APs over Three Trials for Locations 2A-3G

	Control	OM	Mulch
2A	4.7521	1.3201	3.1594
3A	7.9949	9.4967	7.3514
3D	19.7424	1.6016	2.8520
3E	15.7849	0.5537	2.4115
3G	3.4248	1.9133	1.9454

Additionally, an average was taken over the 2018 and 2019 timeframe to determine each location's most representative transmission rate. The statistical model used a nested dictionary to hold each location's dust values and, similarly to the initial testing stage, printed out five graphs for each location. The same data points were analyzed over a 225-day timeframe to determine when the disease curve reached 0 cases.

Results

Initial Results

After the initial methods were conducted, specific analyses based on Table 2's dust emission data could be concluded. The similarity of each dust value from trial to trial demonstrates the accuracy of my dust sensor readings, allowing me to be sure that my model will acquire accurate values. An exciting finding is shown by Trial 1 of the Control, where a significant outlier is seen. This outlier results from the random chance that large dust particles have of entering the dust sensor, causing a spike in the dust sensor's reading.

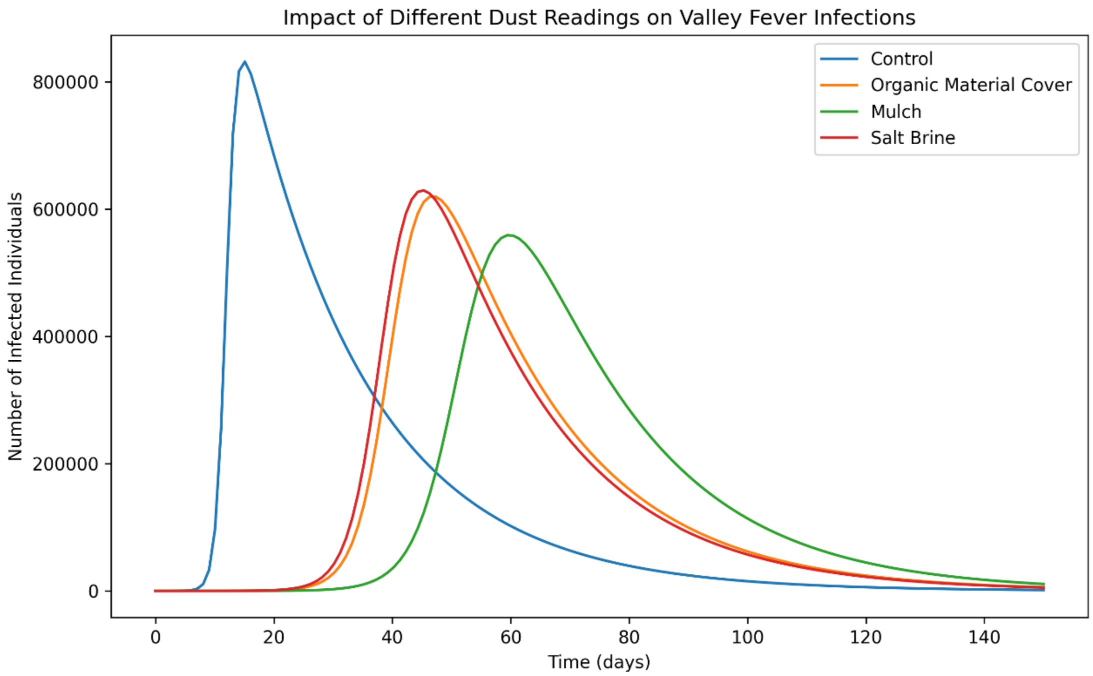

Figure 4. Epidemiological Curve of VF Based on Different APs (Kale, 2024)

Table 4. Maximum Number of Cases Caused by Implementing APs

APs	Day	Max Cases
Control	15	831,394
OM	47	619,518
Mulch	59	558,680
Salt Brine	45	629,201

The peak of each disease curve provides valuable insight into how the curve behaves. According to the data, the control results in significantly more cases than the three other agricultural practices, a phenomenon supported by the dust sensor values shown in Table 2. To display the efficacy of each AP, a percent decrease was calculated by subtracting the maximum number of cases caused by each AP from the maximum number of cases caused by the control and dividing that number by the cases caused by the control. Finally, the decimal value was multiplied by 100 for the percent decrease.

Table 5. Percent Decrease of Valley Fever (VF) Cases caused by Agricultural Practices (APs) tested Compared to Control

APs	Percent Decrease
OM	25.484
Mulch	32.802
Salt Brine	24.32

Mulch was the most successful at reducing VF cases, with a decrease of 32.802% compared to the Control. However, OM and salt brine were almost equally successful at reducing VF cases, so increased testing, with extra variables, needs to be done to understand which can best be utilized to prevent VF.

Results

With the implementation of the location variable, the dust readings collected and transmission rates from Table 3 and Figure 2, respectively, were inputted into the computational model.

Table 6. Maximum Cases of Agricultural Practices (AP) Tested over 225 Day frame for 5 Locations
Similarly to the initial results, a percent decrease was calculated similarly, but with respect to the location's control.

	Control		**Organic Material Cover**		**Mulch**	
	Day	Max Cases	Day	Max Cases	Day	Max Cases
2A	4	95,092,424	5	95,219,331	4	96,312,471
3A	29	77,177,084	27	78,666,307	30	76,307,707
3D	54	65,034,937	106	47,752,719	99	49,584,551
3E	45	68,948,888	92	51,621,836	81	54,883,678
3G	35	73,676,555	46	68,604,230	45	68,794,608

Table 7. Percent Decrease of Valley Fever (VF) Cases caused by Agricultural Practices (APs) tested Compared to Control

AP	**2A**	**3A**	**3D**	**3E**	**3G**	**Average**
OM	-0.1335	-1.9296	26.5737	25.1303	6.8846	11.3051
Mulch	-1.2830	1.1265	23.7571	20.3995	6.6262	10.1252

Overall, OM was a superior AP at decreasing Valley Fever cases, but by a very slim margin compared to mulch. This data contradicts the findings found in Figure 4 in the initial part of the experimentation.

Furthermore, a qualitative data table demonstrating the soil's qualities is shown below for more information pertaining to the soil composition for each location, which could be important for drawing a general conclusion on the effect of each AP.

Table 8. Color, Texture. Stone Content (Ranked 1-5) and Location Collected of Soil Samples

Location	Color	Texture	Stone Content	Location Collected
2A	Dark Brown	Loamy	5	Industrial area
3A	Brown	Loamy	4	Downton Phoenix
3D	Brown	Loamy	3	Next to Road
3E	Light Brown	Sandy	1	Backyard Soil
3G	Light Brown	Sandy	2	Neighborhood

Discussion

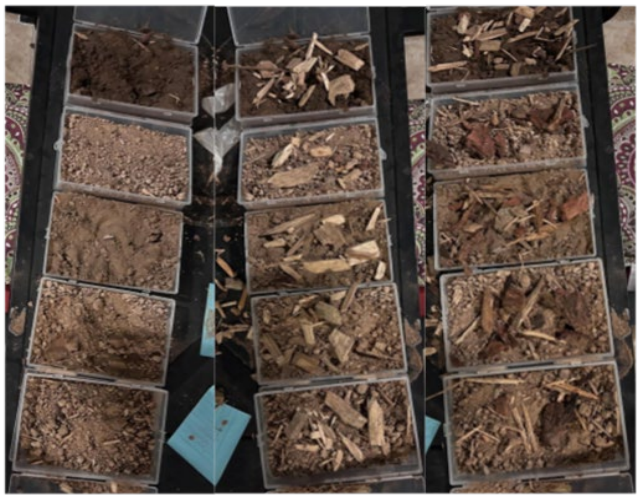

Figure 5. APs in Adjusted Methods (Control, Mulch, and OM) ((Photographed by S. Kale)

For locations 2A and 3A, the efficiency of both APs reducing VF cases was extremely low due to the similar epidemiological curves and nearly identical max case values. Based on 2A and 3A's locations, as shown in Table 8, which are industrial areas and downtown Phoenix, respectively, the darker color shows a high soot concentration in the soil. These areas with higher air pollution resulted in an overall higher transmission rate and maximum reached compared to the other locations, an evident conclusion displayed in Table 6.

For locations 3D, 3E, and 3G, OM is barely more efficient than mulch at reducing VF cases. The average percent decrease of OM for all 5 locations is 11.3%, while the average percent decrease for mulch is 10.1%. Each area had less air pollution compared to locations 2A and 3A. Therefore, it can be suggested that the best AP to be implemented varies on location.

Error Analysis

A few errors need to be considered in the experiment. One of these errors is the random chance of external dust flowing into the sensor. While necessary precautions were taken to prevent this, such as the plastic protective covering and tilting the apparatus downwards to collect data, this systematic error still stands as a potential factor to skew the data. This error could have been avoided if testing was completed in a closed environment.

Another systematic error that could have skewed the results is the difference in the amount of organic material cover and mulch placed on the soil. An even amount of each AP was attempted to be accurately added to the soil, but an error of unevenness could still skew the data. Along with this, the random error of lapses in the functionality of the dust sensor could play a huge role in skewing the data. One of the biggest obstacles at the start of the experiment was getting consistent functionality from the dust sensor, so this error could have been prevalent during testing. More accurate data could be collected with an improved dust sensor, influencing the computational model.

Furthermore, after testing all the other APs in the initial stages of experimentation, too much salt brine was poured into each soil sample, resulting in the soil turning into thick mud. This resulted in the recorded dust emissions for salt brine being 0 $\mu g/m^3$, removing salt brine from the data analysis. Compared to further experimentation, a much larger box was used in the initial stages, which could also skew the results.

Conclusion

In conclusion, the computational epidemiological model programmed effectively shows the efficiency of specific APs compared to others and indicates the number of cases of VF that implementing these APs would result in. This model aims to provide epidemiologists, government officials, and agricultural workers with valuable information on what APs should implement to prevent the spread of VF. The data shows that the model can link dust exposure and VF cases. Although the model contains a few drawbacks preventing it from being used in a real-world setting, it can still be utilized by various stakeholders across the southwestern United States to understand how to mitigate VF.

This statistical model concludes that the best AP to be implemented varies by location. Given dust readings for each area, the model could predict the efficiency of APs. Through further research, an increasingly robust model can be developed to identify the best AP to implement in areas across the southwestern United States. Thousands of lives can be saved using predictive modeling, highlighting its relevance in medicine.

For future experimentation, various modifications can be put in place to ensure the utmost accuracy of the epidemiological model. These differences include utilizing more advanced epidemiological models, testing more APs, accessing real-time VF data to implement machine learning, and acquiring more advanced hardware. Utilizing more advanced compartmental models containing more variables past location can be valuable in calculating further factors affecting VF cases, improving the precision of the model. Granted access to further VF data would provide the opportunity to optimize this model using AI, increasing its accuracy with Python libraries such as TensorFlow. A more accurate/industry-grade dust sensor would undoubtedly increase this experiment's value through improved data quality. All of these ideas are essential in building off the experimentation in this project and creating a helpful tool that can be implemented to save lives from VF.

Limitations

The research conducted through this study is as accurate as it can be, given the limitations of my experiment. A fundamental limitation of the experiment includes access to Sandy Loam/Casa Grande Soil. These soil types are Arizona's most found soils, thus being prime candidates for my experiment. However, after looking through various department stores and not finding either of these soils, we resorted to using “Miracle-Gro Cactus, Palm & Citrus Soil” in my experiment.

The delimitations of my experiment are the number of Coccidioides per dust particle and different soil types. We are intentionally not testing the number of Coccidioides per dust particle as it goes beyond the scope of my experiment. However, it is relevant to the data collected. Moreover, we are not testing different types of soil, as manipulating this variable is not the primary aim of my experiment, as the variable being manipulated is the APs. While collecting dust sensor readings, WE wore gloves and a mask to avoid inhaling large amounts of dust.

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