AUTOMATED FARMLAND CONTAMINATION MONITORING USING INTERNET OF THINGS

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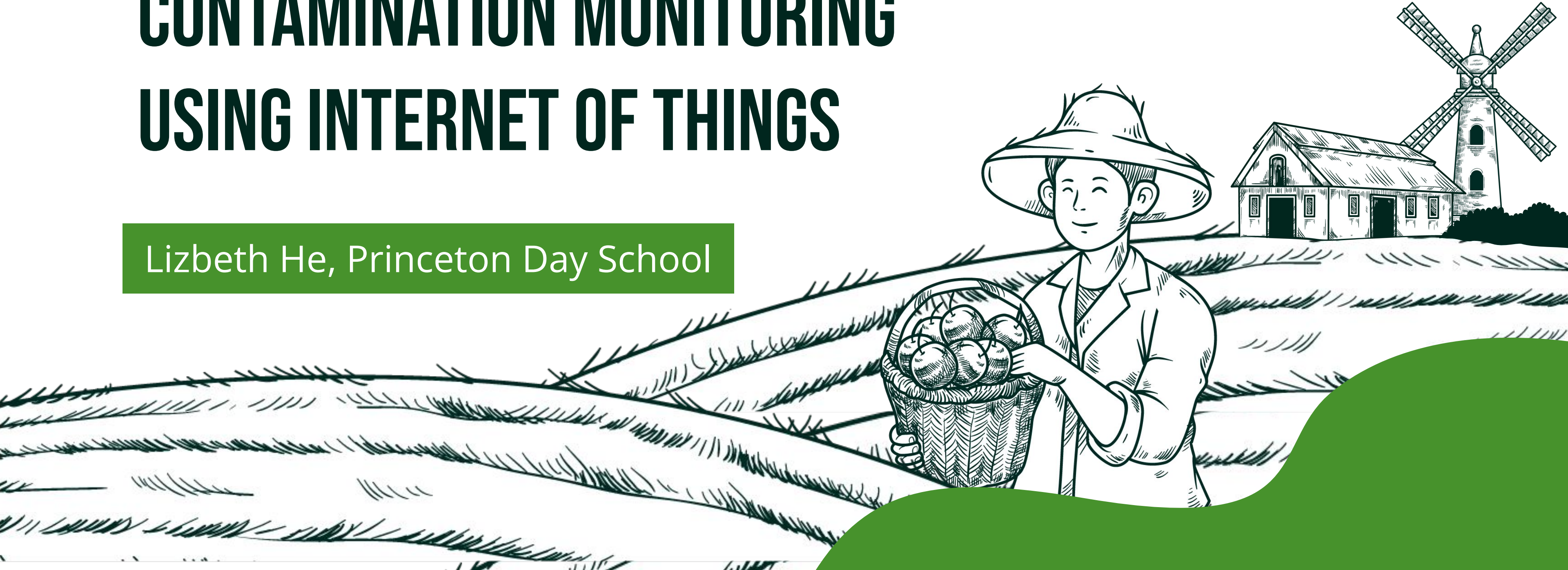


GOAL

In order to address the rising issue of farmland contamination, it is imperative to accurately monitor pollutant levels in the soil.

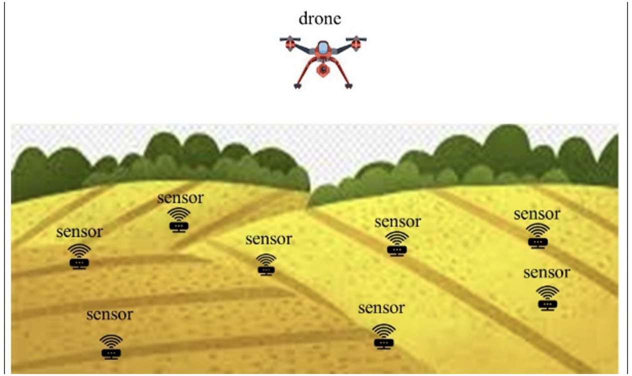
This research proposes using involving drones, sensor networks, and numerous other Internet of Things components that are wirelessly connected together in a network to make the entire process automated and more efficient.

MAJOR STEPS OF THE PROCESS

1. **Evaluate the area of farmland** that will be monitored using historical data or drone aerial mapping.
2. **Determine the ideal sensor arrangemen**t to maximize the land coverage while minimizing the number of sensors needed. If possible, try to reduce the overlap between every sensor’s detection area.
3. **Deploy the sensors** in the arrangement from (2) using drones. Keep in mind potential weather conditions, such as wind and precipitation, that could hinder this process.
4. Regularly **collect a sufficient number of readouts** using the sensors over a pre-scheduled duration.
5. Wirelessly **collect the sensors’ data** by flying out the **drone** again. Collection by drone allows for a quick turnaround time between the monitoring and analysis steps.
6. **Return the drones** to their charging station. There, **forward the drone and sensors’ collected data** through **IoT gateways.**
7. Eventually, **transmit the data** to be securely **stored in IoT servers and data storage**
8. Able to **remotely access the data** through an Internet connection. **Environmental scientists and agricultural professionals** can now conduct **analysis** and draw conclusions.

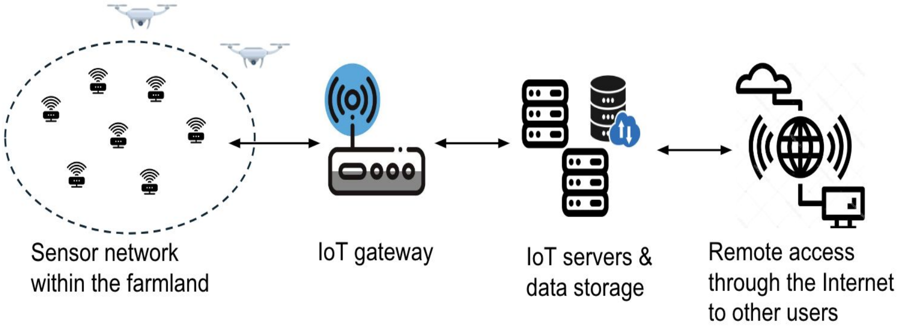
COMPONENTS

DRONE-AIDED SENSOR NETWORK



A **sensor network** is formed with **sensors wirelessly connected to drones**. Sensors detect environmental factors, while drones deploy them and collect their data.

INTERNET OF THINGS (IOT)



The sensor network is also connected to numerous other **IoT components,** such as **gateways, servers,** and finally, the **Internet.** This facilitate the efficient and reliable **transmission, storage, and access** to the collected data.

WHAT EXACTLY IS AN INTERNET OF THINGS (IOT)?

A network of physical devices embedded with sensors, software, processing ability, and network connectivity. Ultimately, this allows them to collect, store, and exchange data with other devices and systems over the Internet.

This proposed Internet of Things system includes physical devices such as:

- Environmental sensors
- Unmanned aerial vehicles or drones
- Gateways
- Transmitters
- Servers
- Data storage
- Computers (to remotely access the final stored data)

MATHEMATICAL MODEL PARAMETERS

Numerous factors are needed to realistically model this issue:

Parameter	Definition
P	Farmland perimeter
S_i	Detection area of Sensor i
A	Farmland area
R	Total number of readouts
K	Minimum number of readouts required for contamination analysis
T	Farmland monitoring time
M	Time for a sensor to produce a measurement
N	Minimum number of sensors needed to cover the land and produce no less than K readouts

MATHEMATICAL MODEL EQUATIONS

We can assume that the land area is a generic irregular polygon with a given perimeter P. The land size A is then represented within the bounds based on the isoperimetric inequality:

$$4\pi A \leq P^2 . \qquad (1)$$

This inequality implies that the land area A cannot exceed the maximum area of a circle with the same perimeter P, as the circle is the shape with the largest area within a given perimeter. The maximum value of A, denoted as A_{max}, is calculated as:

$$A_{\text{max}} = P^2/4\pi . \qquad (2)$$

To ensure effective coverage, the minimum required number of deployed sensors N is determined by the ratio of the land area A to the sensor detection area S_i:

$$\sum_{i=1}^{N} S_i \geq A \qquad (3)$$

The total amount of readouts R during the monitoring time is another key parameter. It is derived as:

$$R = \frac{NT}{M} \qquad (4)$$

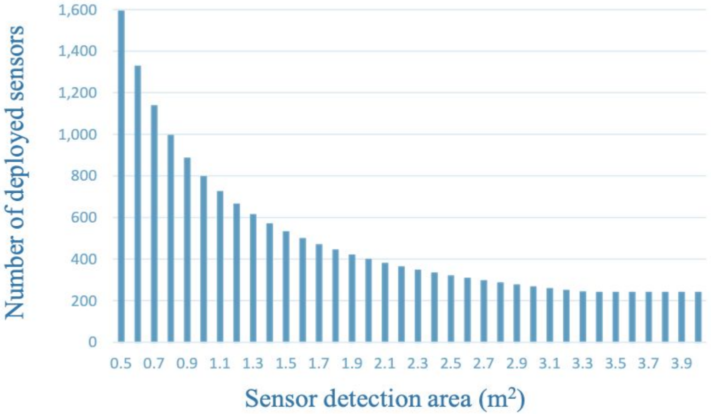
The model ensures that th[illegible]y meets or exceeds the minimum required readouts K:

$$K \leq R \qquad (5)$$

This inequality accounts for the time M it takes for each sensor to produce a measurement. The goal is to find a balance between data granularity and monitoring efficiency.

SIMULATION SET 1

FIG 1: EFFECT OF SENSOR DETECTION AREA ON TOTAL NUMBER OF DEPLOYED SENSORS



Assumptions:

- Land perimeter (*P*) : **100 meters**
- Minimum number of needed readouts (*K*) : **20,000 readouts**
- Total monitoring time (*T*) : **1 week** or **168 hours**
- Time needed for one sensor to produce a measurement (*M*) : **2 hours**

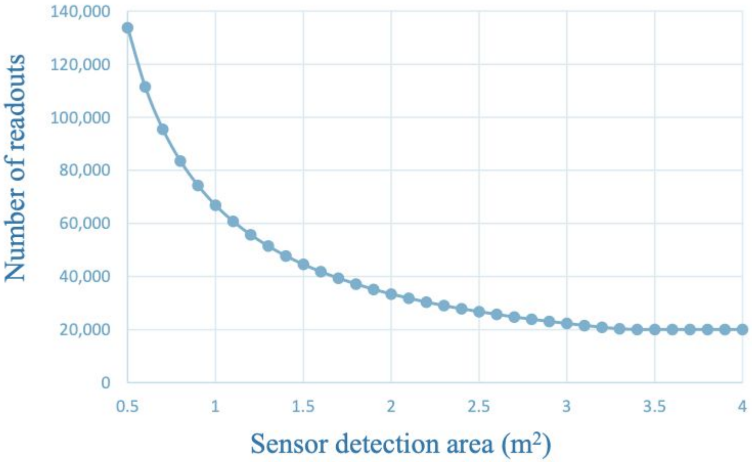
- Sensor detection area (S_i), the independent variable, ranged from **0.5 to 4.1m^2.**

The optimal sensor detection area was **3.4m^2**, which required **239 sensors.**

Beyond this threshold, increasing the sensor detection area still resulted in a required amount of 239 because of the time it takes a sensor to produce a readout.

SIMULATION SET 2

FIG 2: EFFECT OF SENSOR DETECTION AREA ON TOTAL NUMBER OF PRODUCED READOUTS



Assumptions:

- Same as previous simulation
- Sensor detection area (S_i), the independent variable, ranged from **0.5 to 4.1m^2.**

The optimal sensor detection area was **3.4m^2**, which required **239 sensors** and produced a total of **20,076 readouts.**

This fulfilled the minimum requirement of 20,000 readouts while also not being too wasteful of resources.

SIMULATION ANALYSIS

- Both of these graphs appear to be exponential, but are actually **a piecewise function** formed by **Equations (1) - (5)** listed previously

- *Increasing each sensor's detection area **DOES NOT always yield favorable** results (decreasing amount of sensors needed to be deployed and/or increasing total amount of readouts)

- Beyond certain **thresholds,** increasing the sensor detection area does not have an effect because:
    - Simulation Set 1: A minimum number of sensors is required to produce a **sufficient number** of readouts considering the time each sensor needs to produce a singular readout
    - Simulation Set 2: Having significantly more readouts than the **required amount** is unnecessary and **wasteful of resources**

- Given this situation's factors held constant, the threshold value for both sets of simulations was a sensor detection area of **3.4 m^2**

THANK YOU!

References

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