

# Multi-Drone Agricultural Monitoring System

## Theoretical Framework & Implementation Logic

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# 1 Introduction

This document outlines the theoretical foundations and decision-making logic behind the Multi-Drone Agricultural Monitoring System. The system deploys swarms of autonomous drones to monitor farmland, assess drought risks using meteorological data, and validate data integrity through multi-sensor fusion.

## 2 Theoretical Background

### 2.1 Drought Probability Model

The system estimates drought risk based on the methodology proposed in "*DroughtCast: A Machine Learning Forecast of the United States Drought Monitor*" (Brust et al., 2021).

Rather than relying on single inputs, the model aggregates multiple meteorological indices:

- **SPI (Standardized Precipitation Index)**: Measures rainfall deficit.
- **SMI (Soil Moisture Index)**: Assesses water availability in the root zone.
- **VCI (Vegetation Condition Index)**: Evaluates crop health via satellite imagery proxies.
- **TCI (Temperature Condition Index)**: Accounts for thermal stress.

The final probability  $P_{drought}$  is derived from a weighted non-linear combination of these features, normalized to a  $[0, 1]$  range using a logistic function:

$$P(y = 1|X) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \dots + \beta_n X_n)}} \quad (1)$$

### 2.2 Sensor Fusion (Inverse-Variance Weighting)

To mitigate sensor noise and errors, the system employs **\*\*Inverse-Variance Weighting\*\*** for merging probabilities from multiple drones. This method gives more weight to precise sensors (low variance) and less weight to noisy ones.

Given a set of measurements  $x_i$  with known variances  $\sigma_i^2$ , the fused estimate  $\hat{x}$  and its variance  $\hat{\sigma}^2$  are calculated as:

$$w_i = \frac{1}{\sigma_i^2} \quad (2)$$

$$\hat{x} = \frac{\sum_i w_i x_i}{\sum_i w_i} \quad (3)$$

$$\hat{\sigma}^2 = \frac{1}{\sum_i w_i} \quad (4)$$

This ensures that the final fused probability is statistically the most reliable estimate possible given the available data.

### 2.3 Fault Detection Logic

The system automatically detects malfunctioning sensors using statistical hypothesis testing. A sensor reading  $x_{sensor}$  is flagged as **\*\*faulty\*\*** if it deviates significantly from the expected model prediction  $x_{model}$  or the consensus of other drones.

The fault condition is triggered if:

$$|x_{sensor} - x_{model}| > (2 \cdot \sigma_{noise} + \delta_{threshold}) \quad (5)$$

Where:

- $\sigma_{noise}$  is the standard deviation of the sensor (noise floor).
- $\delta_{threshold}$  is a configurable safety margin (e.g., 15%).

If a fault is detected, the system automatically dispatches an **\*\*Auditor Drone\*\*** from the reserve pool to verify the reading.

## 3 Frequently Asked Questions (FAQ)

### 3.1 Probabilty & Data Merging

**Q: How do we merge probabilities from multiple drones?**

**A:** We use a technique called **Sensor Fusion** (specifically, Inverse-Variance Weighting). Imagine Drone A reports a drought risk of 60% with high confidence (low noise), and Drone B reports 40% with low confidence (high noise). Instead of just averaging them to 50%, the system "trusts" Drone A more. The mathematical formula (see Section 2.2) ensures that the final combined probability leans closer to the more accurate sensor.

**Q: What happens if the Model and the Sensor disagree?**

**A:** The system trusts the drone's physical sensor reading *unless* the deviation is statistically impossible (see Fault Detection).

- **Small Disagreement:** The system fuses the model prediction and sensor reading mathematically to find a middle ground.
- **Large Disagreement:** The system flags the sensor as potentially faulty and dispatches a second drone (Auditor) to double-check.

### 3.2 Drone Behavior & Allocation

**Q: How are drones assigned to areas?**

**A:** Assignment is based on **Risk Prioritization**. 1. **High Risk Areas (> 70%):** Get multiple drones (up to 3) to ensure frequent monitoring. 2. **Medium Risk Areas (40–70%):** Get at least 1 drone. 3. **Low Risk Areas:** Monitored if resources allow.

We also keep a **Reserve Pool** (approx. 10% of the fleet) idle at the base. These reserves are only launched if a sensor failure is detected and an Auditor is needed immediately.

**Q: Why do drones sometimes hover instead of moving?**

**A:** This is usually due to the **Geofencing Safety Protocol**. If a drone drifts near the boundary of its assigned circular area, it enters a "Hold" or "Correction" state. It stops exploring and applies a velocity vector towards the center of the area to ensure it doesn't fly into restricted airspace or crash into a neighboring sector.

## 4 Implementation Analysis

### 4.1 Expected vs. Actual Implementation

The initial design specifications (outlined in `expected_work.md` and the reference paper *Drought-Cast*) proposed an end-to-end ML pipeline. Below is a comparison of the theoretical design versus the current simulated implementation.

Feature	Expected Design	Current Implementation
<b>Drought Prediction</b>	LSTM Neural Network trained on historical Kaggle meteorological data (SPI, SMI, VCI).	<b>Probabilistic Simulation:</b> Uses a stochastic model to generate realistic probability distributions ( <code>drought_probability_model.py</code> ) mimicking real-world variance.
<b>Data Sources</b>	Real-time satellite imagery (MODIS) and weather station APIs.	<b>Simulated Environments:</b> Synthetic data generation to allow testing without live internet dependencies.
<b>Coverage Optimization</b>	<code>scipy.optimize</code> for perfect non-overlapping circles.	<b>Greedy Allocation:</b> Dynamic assignment based on immediate risk priority and proximity ( <code>area_allocation.py</code> ).
<b>Fault Detection</b>	Statistical hypothesis testing ( $2\sigma$ deviation).	<b>Implemented exactly as designed.</b> Compares sensor readings against the model's baseline prediction.

Table 1: Design vs. Implementation Comparison

### 4.2 Key Code Implementations

The core logic for our **Sensor Fusion** and **Fault Detection** is critical to the system's reliability. Below are the specific functions driving these behaviors.

#### 4.2.1 Sensor Fusion Logic

We use **Inverse-Variance Weighting** to merge conflicting probability estimates. This ensures that a drone with a noisy sensor (high variance) has less influence on the final decision than a drone with a precise sensor.

```
1 def fuse_probabilities(prob_a, var_a, prob_b, var_b):
2     """
3     Merges two probability estimates using inverse-variance weighting.
4     Formula: (w1*x1 + w2*x2) / (w1 + w2) where w = 1/variance
5     """
6     weight_a = 1.0 / var_a
7     weight_b = 1.0 / var_b
8
9     fused_prob = (weight_a * prob_a + weight_b * prob_b) / (weight_a + weight_b)
10    fused_var = 1.0 / (weight_a + weight_b)
11
```

```
12     return fused_prob, fused_var
```

Listing 1: Inverse-Variance Fusion Logic

#### 4.2.2 Fault Detection Threshold

The system flags a sensor as "Faulty" if its reading deviates from the expected model prediction by more than dynamic threshold (driven by the sensor's known noise profile).

```
1 def detect_fault(sensor_val, model_val, sensor_noise_std):
2     # Threshold is 2 * standard_deviation (95% confidence interval)
3     # plus a small base margin (0.15)
4     dynamic_threshold = (2 * sensor_noise_std) + 0.15
5
6     deviation = abs(sensor_val - model_val)
7
8     if deviation > dynamic_threshold:
9         return True # FAULT DETECTED
10    return False
```

Listing 2: Adaptive Fault Detection

## 5 Future Work & Limitations

### 5.1 Current Limitations

- **Simulated Weather:** The system currently does not ingest live weather API data; it relies on a sophisticated probability generator.
- **2D Movement:** Drones currently operate at a fixed altitude. True 3D terrain following is not yet implemented.
- **Simplified Physics:** Battery consumption is modeled as a linear drain, ignoring wind resistance and varied payload mass.

### 5.2 Future Roadmap

1. **Live LSTM Integration:** Replace the `drought_probability_model.py` with the pre-trained PyTorch LSTM model referenced in the *DroughtCast* paper.
2. **Swarm Communication:** Implement mesh networking so drones can share "Auditor" roles locally without routing every request through a central base station.
3. **Hardware Deployment:** Port the ROS nodes to physical PX4-based drones for real-world field testing.