## Capstone Idea: *AgriEcoTech – Smart Farming Platform for Climate-Resilient Agriculture in Rural Rwanda*

### Applying a Hidden Markov Model (HMM) in AgriEcoTech

AgriEcoTech aims to boost agricultural productivity and climate resilience by using AI to deliver real-time insights into soil health, crop status, and water usage. A Hidden Markov Model (HMM) can play a critical role in predicting crop health trends and managing environmental uncertainties, such as droughts or disease outbreaks.

### 1. Describe the Observations

The observable data (emissions) that the HMM would use include:

- Soil moisture levels (measured via sensors)
- Soil pH and nutrient content
- Daily temperature and rainfall records (from weather APIs)
- Satellite imagery indicating crop color and texture
- Crop growth stage or yield reports
- Irrigation and water usage data

These values are regularly measured or collected and serve as input for the model.

### 2. Type of HMM Problem

This is an unsupervised learning task. The true states (ex., "healthy crop growth", "early stress", "disease onset", "drought stress") are hidden, meaning we do not know them directly. We aim to infer these underlying conditions from the observable environmental and crop data.

### 3. Training Algorithm

**a. Known values:**

➢ Observed sensor and environmental data
➢ Sequence of observations over time
➢ Initial assumptions (ex., prior probabilities of each state)

**b. Unknown values to learn:**

❖ Transition probabilities between hidden states (ex., how likely a healthy crop shifts to stress)
❖ Emission probabilities (likelihood of certain sensor readings given a hidden state)
❖ Initial state probabilities if not predefined

The **Baum-Welch algorithm** (an Expectation-Maximization technique) would be used to estimate these unknown parameters.

### 4. Parameter Updates

The training process will update the following HMM parameters:

- **Transition matrix (A):** Probabilities of moving from one hidden state to another
- **Emission matrix (B):** Probabilities of each observation given a hidden state
- **Initial state distribution (π):** Probabilities of starting in each hidden state

Once trained, the HMM could be used with the Viterbi algorithm to infer the most likely sequence of hidden crop conditions based on ongoing sensor data. This insight would allow the platform to generate early warnings and adaptive recommendations for farmers, improving resilience and yield.