**Efficient Logistics for Minimizing Costs and Spoilage** 

### AgriRoute

Optimized Multi-Stage Agriculture Supply Chain Design

Group - AG12

# PROBLEM STATEMENT

### Data Structures and Inputs

### Farm

- id: Unique identifier.
- location:
   Coordinates.
- produce\_quantity
- perishability\_window

### StorageHub

- id: Unique identifier.
- location: Coordinates
- capacity
- storage\_cost\_per\_unit
- fixed\_usage\_cost

## Distribution Center

- id: Unique identifier.
- location:Coordinates
- demand
- deadline

### Data Structures and Inputs

### Network Routes

- Polyline : dictionary of route coordinates
- Cost matrix (optional or derived): If fuel cost or tolls vary per route.

### Vehicle

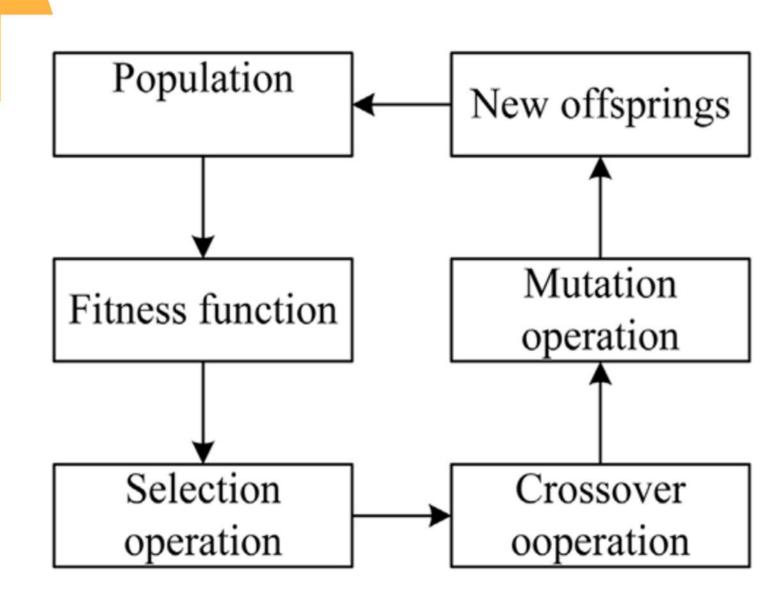
- type: "small" or "large"
- capacity
- variable\_cost\_per\_distance:

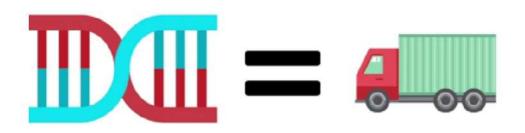
# Dynamic Disruptions

- Road closures
- Traffic conditions
- Variable fuel costs

# Glimpse of Genetic Algorithm

#### Introduction



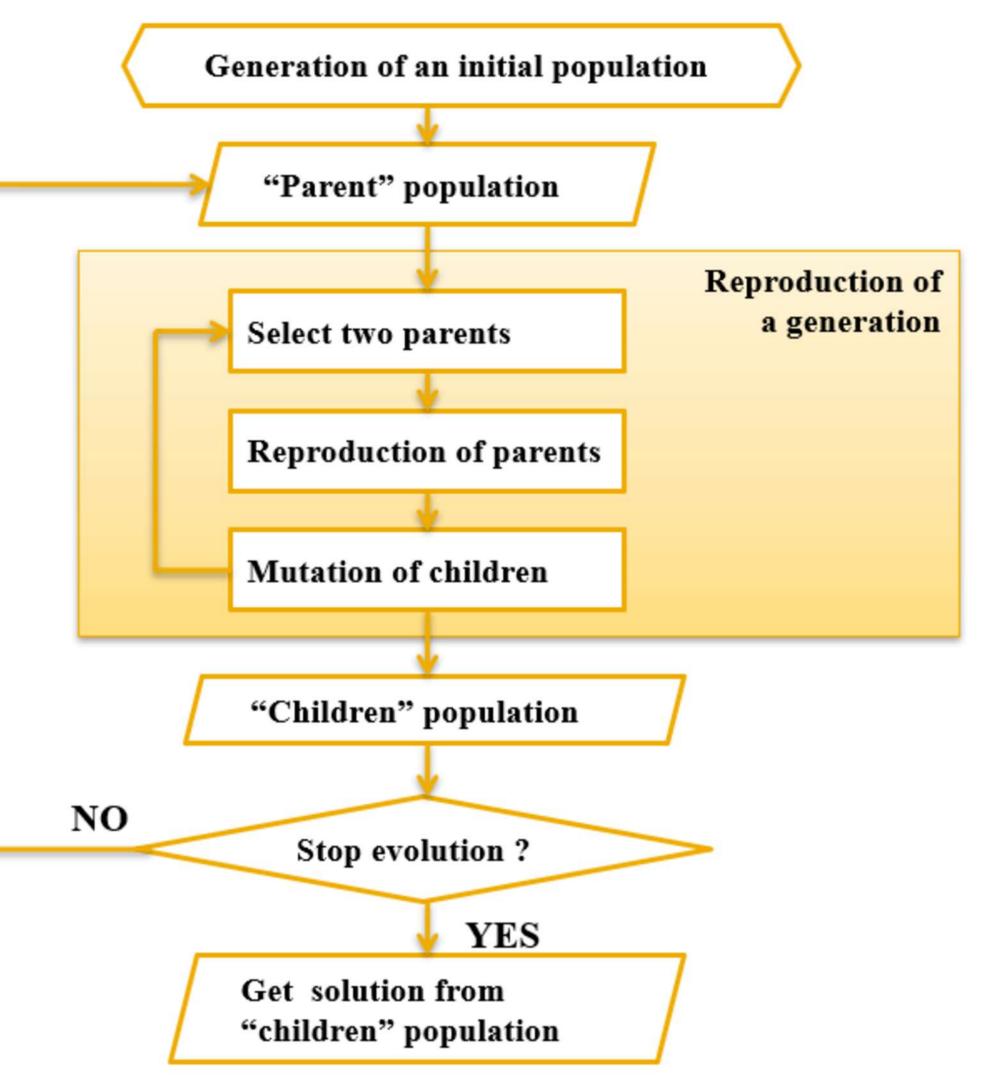


### chromosome ~ A Truck

..And the Genes in the chromosome is suppliers to be visited by the truck

Generation of a new "parent" population from "children" population

We Initialize a population and select few of the strongest parents to generate offspring. Until we reach a certain number of generation.





# Adaptive Genetic Algorithm

- Adaptive Crossover and Mutation Rates
- Roulette Wheel Selection
- Encoding & Population Initialization
- Constraint Handling

#### **Adaptive Crossover and Mutation Rates**

- If an individual's fitness is above average (a good solution):
  - A lower mutation rate is used to preserve its promising structure.
- If an individual's fitness is below average:
  - A higher mutation rate is employed to encourage exploration of new possibilities

#### **Roulette Wheel Selection Based on Reciprocal Fitness**

#### Improved GA:

Uses a reciprocal construction of the cost function, ensuring that lower–cost (higher–quality) solutions have higher fitness values and hence a greater chance of being selected. This method improves convergence toward lower-cost solutions.

#### **Encoding & Population Initialization**

- The improved GA uses natural number encoding for each shipment
- The initial population is generated randomly to cover a wide range of possibilities, which is crucial for diverse search in the solution space.

```
4:{ 🚉
 "farm_id": 6
 "hub_id": 1
 "vehicle_id": 3
 "assigned_qty": 532
 "distance": 0.13697732724140071 🚉
 "cost_multiplier": 1.2
 "transport_cost": 0.16437279268968086
5:{
 "farm_id": 7
 "hub_id": 1
 "vehicle_id": 0
 "assigned atv": 130
```

## Simulation and Dataset Generator

### 1) Data Input Options

Choose Input Mode:

- Manual
- Simulate

#### **Enter Numbers of Entities**

Number of Farms

3 - +

**Number of Hubs** 

2 **- +** 

**Number of Centers** 

2 - +

**Number of Vehicles** 

3 - +

### Purpose:

Simulate real-world agricultural supply chain scenarios.

### Features:

Adjustable parameters: Farm locations, vehicle capacities, perishability rates, demand levels.

Dynamic disruptions: Traffic conditions, road closures.

**Deliverable:** 

Flexible tool for generating test datasets of varying complexity.

### **Farms** Farm #0 Farm ID 0 Latitude 28.70 Longitude 77.10 **Produce Quantity** 500 Perishability Window 3 Farm #1

#### **Manual Mode**

In this mode, users can input data manually by specifying the following parameters:

Entities: Number of farms, hubs, distribution centers, and vehicles.

Farm Details: Farm ID, latitude, longitude, produce quantity, and perishable window.

The provided data is utilized to generate a comprehensive map of farms, hubs, and centers, alongside constructing a distance matrix for further analysis.

### 1) Data Input Options



#### Simulate Mode

This mode allows users to generate realistic data sets using adjustable parameters:

Sliders: Define the number of farms, hubs, distribution centers, small vehicles, and large vehicles.

Data Generation: On selecting the "Simulate Data" option, the system generates realistic data sets, including farm details, distribution centers, storage hubs, and vehicle assignments.

The simulation mode simplifies the process of creating large-scale scenarios for testing and analysis, ensuring realistic and actionable data generation.

### 2) Current Data

#### **Farms**

	id	location	produ
0	0	28.7 77.1	
1	1	28.71 77.11	
2	2	28.72 77.1199999999999	

### **Storage Hubs**

	id	location	capa
0	0	28.6 77	2,
1	1	28.61000000000000 77.01	2,

### **Distribution Centers**

	id	location	dema
0	0	28.9 77.2	8
1	1	28.91 77.21000000000001	8

### **Vehicles**

	id	type	capacity	fixed_cost	variable
0	0	small	1,000	200	
1	1	small	1,000	200	
2	2	large	3,000	350	

```
Distance Matrix (sample):
```

```
▼0:[
  0 : "farm"
  1:0
  2: "hub"
  3:0
1:[
  ▼0:{
     "route_id": 1
     "distance_km": 46.623
     "geometry":
        [0 - 100]
        [ 100 - 200 ]
        [ 200 - 300 ]
        [ 300 - 400 ]
        [ 400 - 500 ]
        [ 500 - 600 ]
```

# Data Generation with Azure Maps Integration of Azure Maps API:

Generates coordinates for possible paths between farms, storage hubs, and distribution centers which are further fetched by our optimisation model to analyze possible routes based on dynamic constraints such as road closures and traffic conditions.

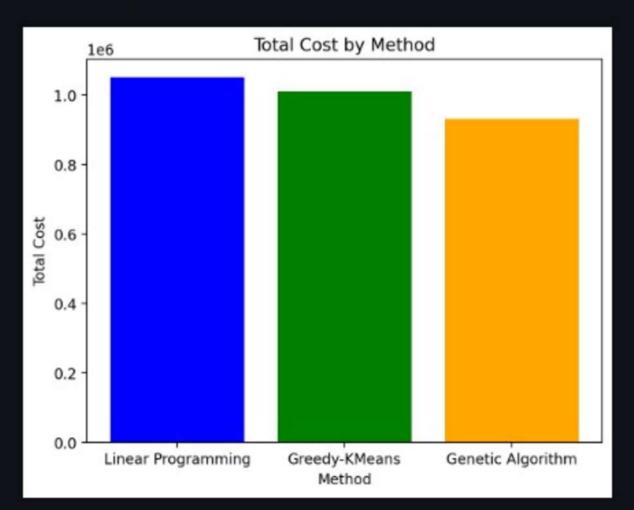
### **Comparison Data**

	Method	Total Cost	Total Spoilage Cost
0	Linear Programming	1,050,350	690,750
1	Greedy-KMeans	1,011,271.4	539,400
2	Genetic Algorithm	932,023.8	269,700

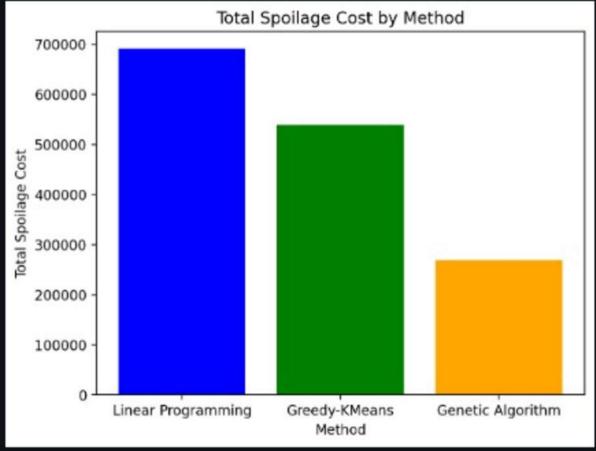
### Performance Analysis

### **Cost Comparisons**

### **Total Cost**



### **Total Spoilage Cost**

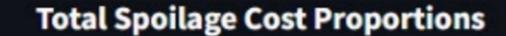


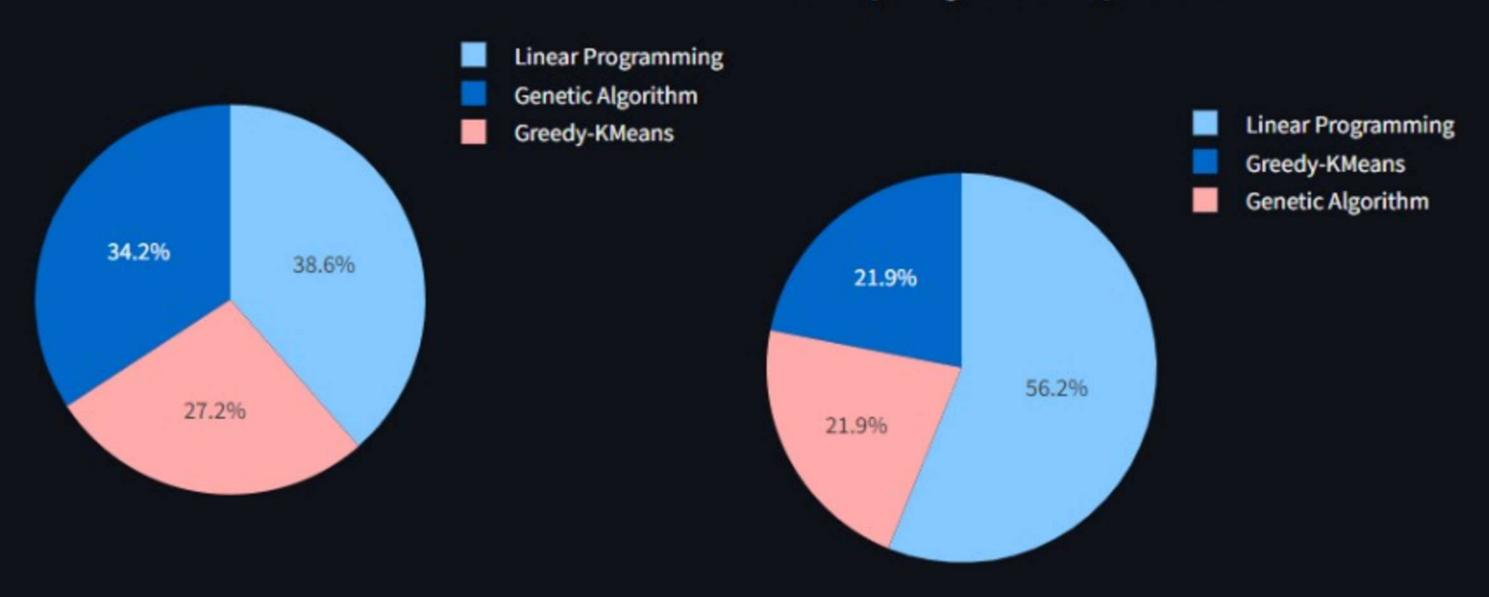
### Proportional Breakdown 🖘

### **Proportion of Total Cost**

### Proportion of Spoilage Cost

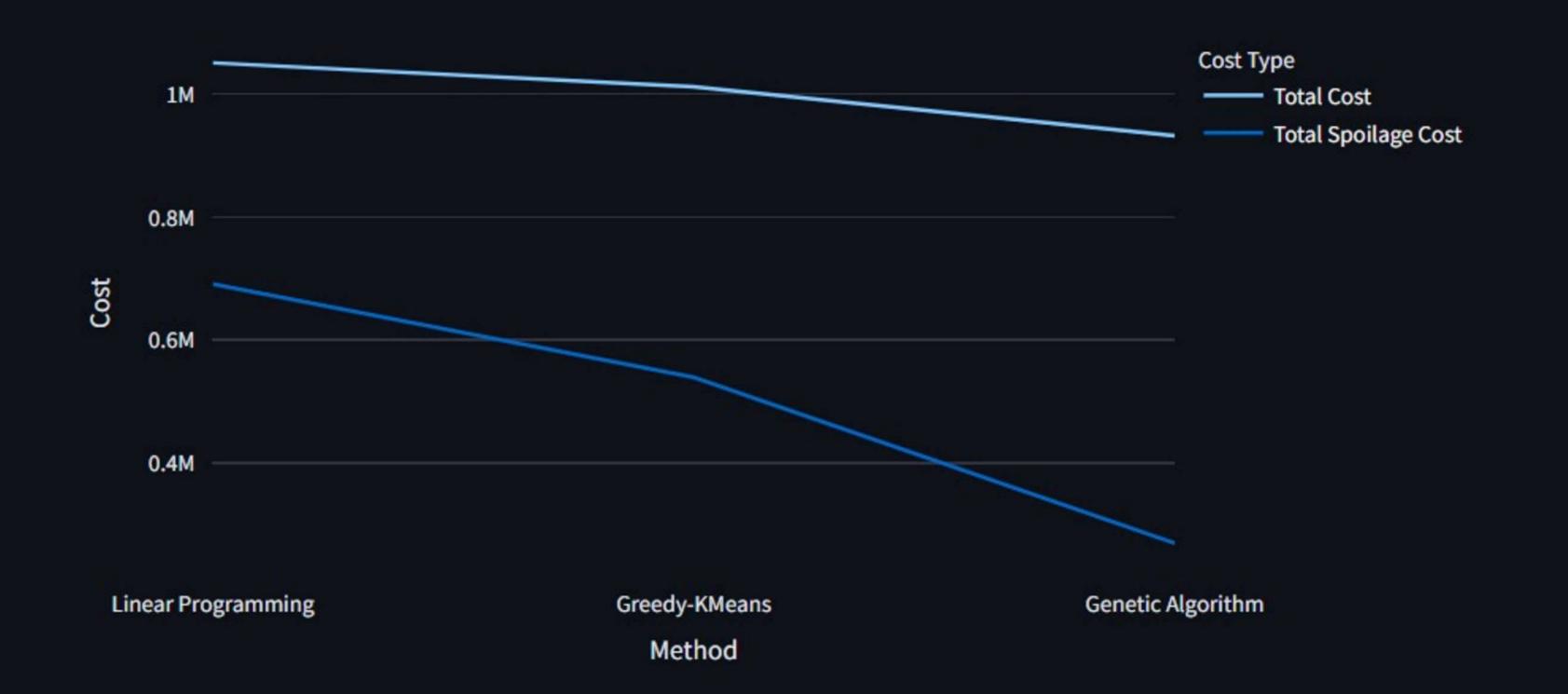
#### **Total Cost Proportions**





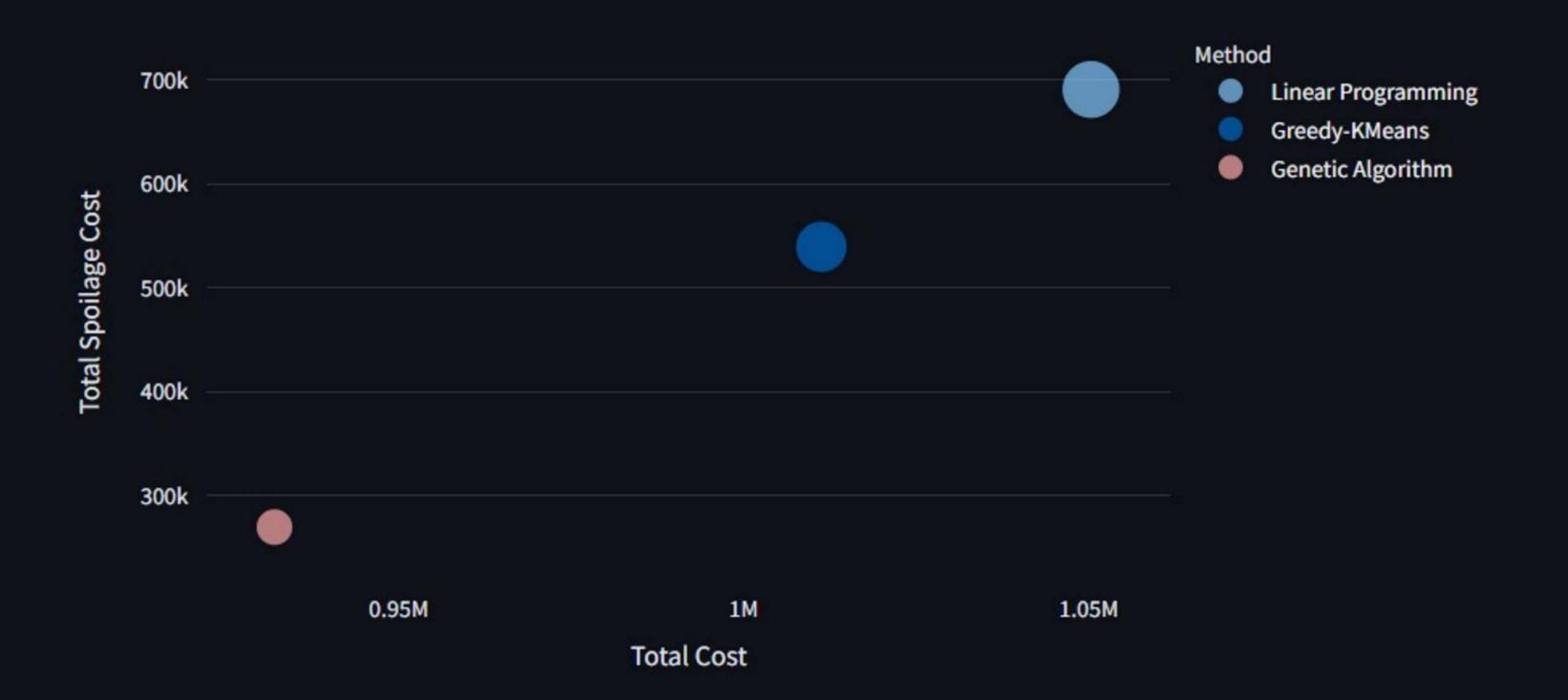
### **Trends Across Methods**

#### Trends: Total Cost vs Total Spoilage Cost



### **Cost Relationships**

#### **Total Cost vs Total Spoilage Cost**



- Method: Genetic Algorithm
- Cost: 932023.8

### Lowest Total Spoilage Cost: 🖘

- Method: Genetic Algorithm
- Spoilage Cost: 269700.0

### **Highest Total Cost:**

- Method: Linear Programming
- Cost: 1050350.0

### **Highest Total Spoilage Cost:**

- Method: Linear Programming
- Spoilage Cost: 690750.0



### **Greedy Solution JSON:**

```
{ ê
 "method": "Greedy-KMeans"
 "best_cost" : 1011271.4
 "total_spoilage_cost": 539400
 "detailed_routes":
    [0 - 100]
     100 - 200
      200 - 300
```

### Results



### Visualisation

### Greedy LP GA

### LP Solution JSON:

```
"method": "LinearProgramming"
"best_cost" : 1050350
"total_spoilage_cost": 690750
"detailed_routes": [] 
"runtime_sec": 0.01
```

### Results



### Visualisation

### **GA Solution JSON:**

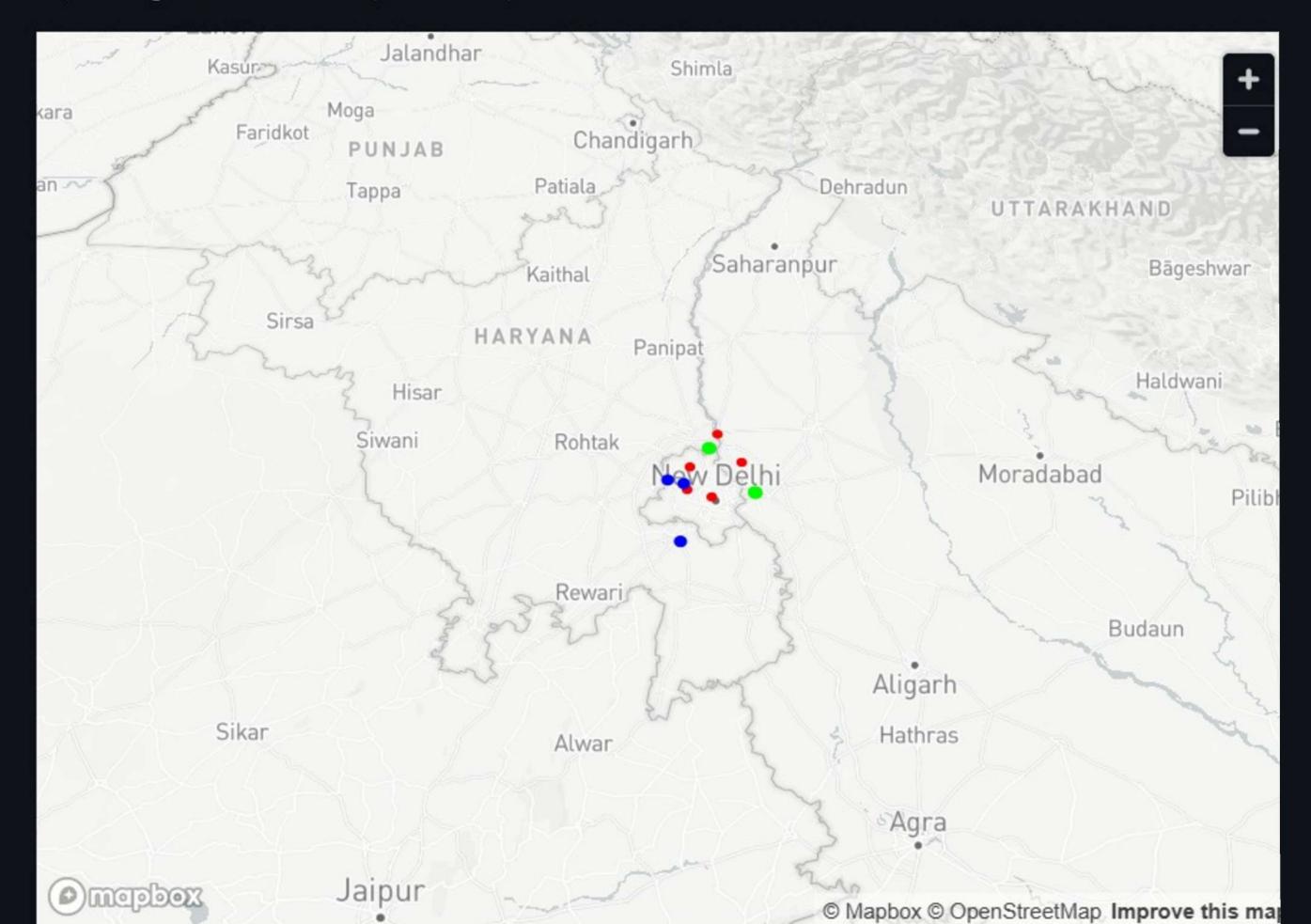
```
"method": "GeneticAlgorithm"
"best_cost": 932023.8
"total_spoilage_cost" : 269700
"detailed_routes":
  [0 - 100]
  100 - 200
  [ 200 - 300 ]
  300 - 400
    400 - 500
```

### Results



### Visualisation

### 3) Map of Farms, Hubs, and Centers



### **Optional: Display Distance Map**

**Show Distances on Map** 83 Muzaffarnagar Panipat Jind Baraut Sonipat Meerut Rohtak Bahadurgach New Delhi Matenhail Greater Noida Guruaram Bulandshahr Faridabad Gautam Manesar Haileymandi Budda Nagar

### E-GA Visualisation

