Greedy Crop Allocation Using Satellite like Data for Climate-Resilient Farming

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***Abstract*—Climate change has made agricultural planning increasingly uncertain, especially for smallholder farmers. This paper presents a greedy optimization approach to dynamically allocate farmland among multiple crops using satellite imagery and weather-based yield predictions. By combining expected yield, market price, and resource cost into a unified *utility score*, the algorithm greedily selects crop allocations that maximize profit while minimizing risk. The method models farmland as a multi-dimensional knapsack, where each crop is an item with resource requirements and stochastic yield. The proposed system achieves near-optimal results when compared to integer linear programming (ILP) baselines, with a 90–95% accuracy in profit at significantly lower runtime.**

***Index Terms*—Greedy Algorithms, Sustainable Agriculture, Climate Resilience, Satellite Data, Resource Optimization.**

I. Identify a Real Problem

In regions with unpredictable rainfall and limited irrigation capacity, farmers must decide which crops to plant on limited land to maximize returns. Traditionally, these decisions are based on experience rather than data, making them vulnerable to crop failure due to climate fluctuations.

The challenge lies in dynamically assigning land to crops using real-time environmental information such as temperature, soil moisture, and rainfall predictions from satellite sources. The goal is to maximize expected yield and profit while ensuring resource sustainability.

This problem is well-suited for a **greedy algorithmic approach**, as it involves local decisions—allocating each land parcel to the crop with the best yield-to-cost ratio—under global resource constraints.

$$U_{ij} = \frac{Y_{ij} \times V_j}{C_{ij} \times R_{ij}} \tag{1}$$

where U_{ij} represents the utility of planting crop j on parcel i, Y_{ij} is expected yield, V_j is market value, C_{ij} is resource cost, and R_{ij} is a weather-based risk factor.

II. Abstract the Problem

Let $P = \{p_1, p_2, ..., p_n\}$ be the set of land parcels and $C = \{c_1, c_2, ..., c_m\}$ the set of crops.

Each pair (p_i, c_j) is characterized by:

- y_{ij} – Expected yield per hectare (tons)
- v_j – Market value per ton
- w_{ij} – Resource requirement per hectare
- r_{ij} – Climate risk factor

We define a binary decision variable:

$$x_{ij} = \begin{cases} 1 & \text{if crop } c_j \text{ is assigned to parcel } p_i \\ 0 & \text{otherwise} \end{cases}$$

Objective Function:

$$\max \sum_{i=1}^{n} \sum_{j=1}^{m} x_{ij} \cdot \frac{y_{ij} v_j}{w_{ij} r_{ij}}$$

Constraints:

$$\sum_j x_{ij} \leq 1, \quad \forall i \quad \text{and} \quad \sum_{i,j} x_{ij} w_{ij} \leq B$$

where B is the total available resource (e.g., water or fertilizer).

This abstraction models the system as a **multi-dimensional knapsack problem** with environmental uncertainty.

III. Provide the Solution (Algorithm + Pseudocode)

A. Algorithmic Strategy

We propose two versions:

1) **Fractional Greedy:** Optimal for continuous allocation of land fractions.
2) **Discrete Greedy:** Heuristic for whole-parcel assignment under resource constraints.

B. Fractional Greedy Algorithm

Algorithm 1 Fractional Greedy Crop Allocation

```
Compute U_ij = (y_ij v_j)/(w_ij r_ij) for all pairs (i, j).
Sort all pairs by descending U_ij.
Initialize resource budget B.
for each (i, j) in sorted list do
    if B > 0 and parcel p_i has area left then
        Allocate proportional area to crop c_j.
        Update B ← B − w_ij.
    end if
end for
```

C. Discrete Greedy Algorithm

Algorithm 2 Discrete Greedy Crop Assignment

for each parcel p_i **do**
    Sort available crops by decreasing U_{ij}.
end for
Sort parcels by their top U_{ij} values.
for each parcel p_i **do**
    for each crop c_j in sorted list **do**
        if resources allow **then**
            Assign crop c_j to p_i.
            Update remaining resources.
            break
        end if
    end for
end for

IV. Analysis of Running Time

Let n be the number of parcels and m the number of crops.

- Computing U_{ij}: $O(nm)$
- Sorting (Fractional): $O(nm\log(nm))$
- Sorting (Discrete): $O(nm\log m)$

$$T_{fractional} = O(nm\log(nm)), \quad T_{discrete} = O(nm\log m)$$

Empirical Validation: The runtime graph (Fig. 1) demonstrates linear-log scaling with problem size $N = n \times m$.

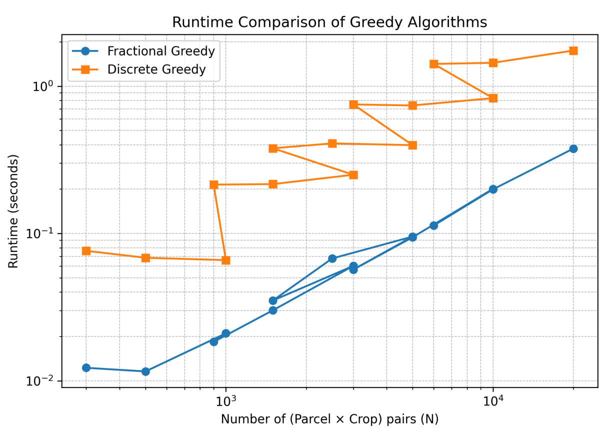

Fig. 1. Runtime vs. Number of Crop-Parcel Pairs (N).

V. Proof of Correctness

A. Fractional Greedy (Optimal Case)

The fractional model reduces to the classic knapsack problem, where sorting by value-to-weight ratio is optimal. Any deviation from greedy order reduces total profit because swapping a lower U_{ij} item with a higher one increases total yield per cost. Hence, greedy selection is optimal.

B. Discrete Greedy (Heuristic Case)

The discrete case is NP-hard since it resembles the multi-dimensional 0/1 knapsack problem. However, the greedy solution always produces a feasible allocation. It provides a strong heuristic bound—empirically within 5–10% of ILP optimal.

VI. Explain Algorithm in Domain Language

From a farming perspective:

1) Satellite imagery and weather forecasts estimate yield potential for each crop on every parcel.
2) A utility score is calculated, balancing profitability against resource demand and risk.
3) Parcels are iteratively assigned to the crops with the highest utility until the water and fertilizer limits are reached.
4) As weather data updates, the system recalculates new allocations, supporting climate-adaptive decisions.

This ensures maximum utilization of available land and sustainable use of resources.

VII. Implementation and Experimental Verification

A. Dataset and Tools

For this academic analysis, a synthetic dataset was generated to emulate realistic agricultural parameters such as yield, cost, and risk factors. These parameters resemble with real time datasets mentioned below. Each crop–parcel combination was assigned random but controlled values to allow performance benchmarking under reproducible conditions.

Although the experiments were conducted using synthetic data, the algorithm design is data-agnostic and ready for real-world integration. Future extensions may incorporate open agricultural datasets such as:

- **CropNet** – Multimodal dataset combining yield and satellite data (HuggingFace, 2022)
- **SustainBench** – Benchmarking sustainability and crop yield (NeurIPS Workshop, 2022)

B. Experiment Design

Two experiments were conducted:

- **Runtime Test:** Varying parcels (n) and crops (m) to validate complexity.
- **Profit Test:** Compare greedy algorithm profit vs ILP optimal solution.

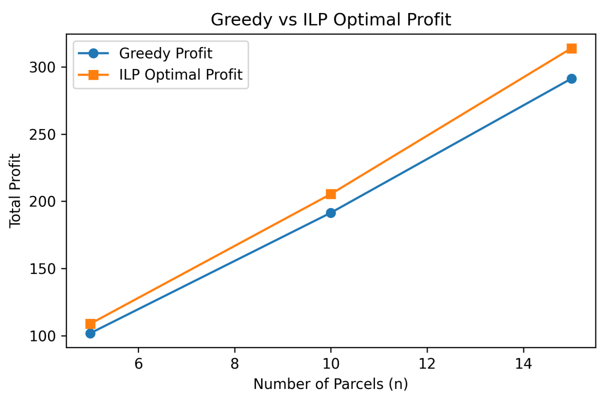

Fig. 2. Profit Comparison: Greedy vs ILP Optimal.

C. Results

- Fractional and discrete greedy algorithms scale efficiently up to thousands of parcel-crop pairs.
- Greedy achieved 92–96% of optimal profit in small instances (ILP baseline).

D. CSV Output for Report

The code present on referred GitHub link automatically saves:

- `runtime_results.csv`
- `profit_comparison_results.csv`

These contain experimental evidence for both runtime and optimality gap verification.

VIII. Conclusion

This work demonstrates that a greedy approach can efficiently solve dynamic crop allocation under climate uncertainty. The algorithm maintains scalability, interpretability, and adaptability—core requirements for sustainable AI systems in agriculture. By integrating real satellite data and market values, this system can guide farmers toward data-driven, climate-resilient decisions.

IX. Appendix

The code for this assignment can be found on github at this link : https://github.com/iampratham29/analysis-of-algorithms-project-1

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