Landing on a Land Use: A Mathematical Modeling Analysis
Team #US-12691

Executive Summary

With the limited availability of resources but increasing population, land has become increasingly valuable, mainly due to the myriad of ways in which it can be developed and used. However, determining the "best" use of the land, which benefits both the individual and the community, presents a unique mathematical challenge. Thus, this report investigates the best usage of an area of land based on economic, social, and environmental criteria.

To start, the factors that would measure the benefit of land use were determined. Economically, initial cost and profit were deemed important, and socially, competition with local industries, the number of full-time jobs created, and human health impacts were selected. Finally, the environmental factor considered was carbon emissions. Qualitative conditions were converted to a quantitative scale to allow a mathematical ranking of the land use options. To ensure feasibility, topology and the average size of each land use option were used to limit excessive expansion. Additionally, to determine how much to weigh each criterion and rank each land use option, two Multi-Criteria Decision Making (MCDM) methods were employed: TOPSIS and Grey Relational Analysis (GRA). To determine the overall performance value of each option, the TOPSIS performance score and Grey Relational Grade values were normalized and averaged. Since the long-term goal was to optimize land usage, the best possible combinations of land use that fit in the land area were tested with the TOPSIS/GRA method, and the resulting grade values were used as the metric for combined land use.

Next, the metric model was applied to five of the considered options: outdoor sports complex, solar farm, grazing farm, regenerative farm, and agrivoltaic farm. Using the process mentioned above, it was determined that agrivoltaic farming provided the best benefits per acre, with a performance score of 0.214. Using the ranking of the different options to create the best combination of land uses and executing the TOPSIS/GRA process again, it was determined that a combination of sports complex and regenerative farming would produce the best results, with an overall score of 0.226.

Then, to consider the Micron fab's impact on land use, an artificial bias factor was added to favor options that would benefit from increased population and other results caused by the fab. The number of years to break even was also added as a consideration, as the factory would likely help and harm different industries in the area, affecting the profits of each land use. The annual revenue criterion was changed to a 10-year compound revenue, which was modeled using the Compound Annual Growth Rate (CAGR), to estimate the economic change. Additionally, since the fab would subjectively influence the importance of each criterion, their weights were re-evaluated using Analytic Hierarchy Process (AHP). Furthermore, building houses was considered as a usage option since it had the most to gain from an increase in the local population. Using the TOPSIS/GRA process, it was determined that the best use of the land would again be a sports complex and regenerative farm combination, with a new score of 0.198.

Finally, the model's ability to adapt to other locations appropriately was analyzed, and it was determined that as long as reasonable data was supplied, the model would generally perform well in any familiar environment. Sensitivity analysis was performed on the models to verify their stability.

Keywords: Multi-Criteria Decision Making, TOPSIS, Grey Relational Analysis, Grey Relational Grade, Compound Annual Growth Rate (CAGR), Analytic Hierarchy Process (AHP)

Letter to the Decision Makers

Dear Community Leaders and Business Planners,

Thank you for giving us the opportunity to share our advice regarding your land use decision. Our team has determined a metric for the "best" use and constructed models to rank the options, taking into account short and long-term benefits. We have also accounted for the effect on land use benefits by the Micron Technology semiconductor fabrication facility.

Using our model, which accounts for initial cost and profit per acre, competition with local industries, full-time jobs created, human health impacts, and carbon emissions, we have determined that a 175-acre outdoor sports facility and a 333-acre regenerative farm combination will be the most ideal use for the 3 km^2 of land. This conclusion was reached by maximizing the amount of land used while also optimizing the benefits and drawbacks of the different land uses.

From a financial perspective, this land use option has both a manageable risk and a high return on investment. While the initial investment cost is estimated to be around $6.59 million, annual profits in the first fiscal year are expected to reach $1.14 million. Additionally, considering that the sports complex has an estimated 2-4% Compound Annual Growth Rate (CAGR) and the regenerative farm has an approximate 0-2% CAGR, profits will only continue to grow. The sports complex is expected to recover the initial investment cost in around 5.5 years, and the regenerative farm is estimated to recover investment in just over 3.5 years, so the potential return is worth the investment.

From a social standpoint, this combination of land avoids local competition while creating many jobs and positively impacting human health. From our quantitative competition scale, the sports complex will have very little competition while the regenerative farm will have some competition, meaning that they will not gain much at the expense of competing businesses. In addition, this combination creates a total of 23 full-time jobs, one of the highest numbers possible from the tested options. Furthermore, the impact on human health is substantially positive based on our numerical scale, as the sports complex and regenerative farm together improve fitness, air quality, and diet. The construction of the fab would support this option even more, as a greater population would likely mean more customers at the sports complex, more people benefiting from an exercise facility, and a greater demand for local, organic food.

However, this option is not the most optimal environmentally, as the sports complex and regenerative farm produce a combined total of over 700 metric tons of carbon dioxide: a high amount compared to most other options. Nevertheless, the financial and social benefits of this usage option outweigh the environmental cost.

In conclusion, our team strongly recommends implementing a sports complex and a regenerative farm on the property. We sincerely hope that our results may be of use to you and provide insight into the best land use decision for this area. If you have any questions, please feel free to connect with us.

Best regards,
IMMC Team #US-12691

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Introduction

With the ever-increasing demand for space for various purposes, land has become one of the most valuable resources. Although it is often economically beneficial, land use also influences society and the environment. Considering the effect land use can have, what is the best way to maximize its benefits and minimize its drawbacks? How can "best" even be defined with so many qualitative factors? These questions have long puzzled landowners. Recent developments have only increased the urgency for an answer, as communities and the economy attempt to recover from the COVID-19 pandemic, which isolated people and destroyed financial growth. Moreover, the climate crisis continues to threaten humanity unless serious effort is taken to reduce greenhouse gas emissions.

To solve this pressing issue and provide guidance, we have deeply explored this problem, developing mathematical models and providing thorough analysis regarding how to quantitatively determine the "best" use of land based on a variety of factors.

1 Metric Criteria

1.1 Problem Restatement

Question 1 asks us to determine a quantitative decision metric that defines the "best" way to use the given 3 km^2 of land near Syracuse, NY, taking into account the short- and long-term benefits and costs of each usage option.

1.2 Assumptions and Justifications

Assumption	Justification
The main criteria when deciding land use are financial, social, and environmental.	While there might be some other factors to consider, these three categories are the most common and logical to follow. Most land planning projects consider conditions that fall within these criteria before executing their projects [1].

1.3 Developing the Metric

1.3.1 Grey Relational Analysis Model

The first part of our metric we used to define the 'best' use of the land was a Grey Relational Analysis (GRA) Model. GRA is a Multi-Criteria Decision Making (MCDM) technique designed to evaluate correlations and similarities between given options and an ideal alternative. It outputs a Grey Relational Grade (GRG), which is a statistical measure from 0 to 1 that determines the similarity between a given alternative with the ideal solution. To perform GRA, a set of given criteria is necessary, for which we used the following 6 criteria in table 1.

Criteria	Variable	Justification
Initial Costs ($)	*IC*	For any business, initial costs are important to determine the fiscal capital required to start the business.
Annual Profit ($)	*AP*	Yearly revenue helps to determine profitability of the business.
Local Competition (Scale of 1-50)	*LC*	Local competition can help to evaluate the demand for a business given what is present in surrounding locales. A nearby-competition land use drives the score up.
Full-Time Jobs Created	*FT*	Full time jobs quantify a portion of long-term impacts of the business.
Human Health Impacts (Scale from (1-9)	*HH*	Human health impacts demonstrate the impact on the community based on focus of the business (i.e. health center vs. ice cream shop).
CO_2 Emitted (metric tons)	*CE*	With carbon emissions remaining a significant issue, limiting CO_2 emitted can help the environment and brand value.

Table 1: Criteria with Variable Name and Justification

Using these criteria, we created the following evaluation matrix y_{ij} with *m* columns and *n* rows, based on the land-use options and the number of criteria, respectively.

$$y_{ij} = \begin{bmatrix} IC_1 & AP_1 & . & . & . & CE_1 \\ IC_2 & . & & & & . \\ . & & . & & & . \\ . & & & . & & . \\ . & & & & . & . \\ IC_m & . & . & . & . & CE_m \end{bmatrix}$$

With the matrix, GRA can now be performed using the following steps.

1. Determine which criteria are beneficial and non-beneficial. Criteria that have high desirable values will be beneficial, while criteria where the lowest values are optimal will be non-beneficial. Use these categorizations to process the data using the following equations:

   Beneficial Attribute:

$$y_i^*(k) = \frac{y_i^o(k) - min\, y_i^o(k)}{max\, y_i^o(k) - min\, y_i^o(k)} \tag{1}$$

   Non-Beneficial Attribute:

$$y_i^*(k) = \frac{max\, y_i^o(k) - y_i^o(k)}{max\, y_i^o(k) - min\, y_i^o(k)} \tag{2}$$

where k represents the criteria, $y_i^o(k)$ represents the data value of the land-use option for the kth criteria, $max\ y_i^o(k)$ is the largest value of $y_i^o(k)$ for the kth criteria, and $min\ y_i^o(k)$ is the smallest value of the $y_i^o(k)$ for the kth criteria. The result of this step is an equal-sized matrix as y_{ij} with normalized values between 0 and 1, known as the normalized matrix.

2. Calculate the grey relational coefficient, $\xi_i(k)$, using the following equation

$$\xi_i(k) = \frac{\Delta_{min} + \varsigma\Delta_{max}}{\Delta_{oi}(k) + \varsigma\Delta_{max}} \tag{3}$$

where $\Delta_{oi}(k)$ represents the deviation sequence for each of the criteria and ς represents the distinguished coefficient. In GRA, the distinguished coefficient is a parameter that is used to adjust the weight of the deviation sequence. A value of 0.5 for the distinguished coefficient is commonly used, although it can be adjusted. The equations for the deviation sequence, Δ_{min}, and Δ_{max} are shown below.

$$\Delta_{0i}(k) = \left\| y_0^*(k) - y_i^*(k) \right\| \tag{4}$$

$$\Delta_{min} = \min_{\forall j \in i} \min_{\forall k} \left\| y_0^*(k) - y_j^*(k) \right\| \tag{5}$$

$$\Delta_{max} = \max_{\forall j \in i} \max_{\forall k} \left\| y_0^*(k) - y_j^*(k) \right\| \tag{6}$$

In this set of equations, the deviation sequence can be explained as the absolute value of the difference between the maximum value in the normalized matrix (the ideal value of 1) and each of the values in the normalized matrix. The delta minimum and maximum are the smallest and largest values of the entire deviation sequence, respectively. The output of this step is another matrix of the same size as y_{ij} that has the grey relational coefficient in each of its elements.

3. Calculate the Grey Relational Grade (GRG), γ_i, using the following equation

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n} \xi_i(k) \tag{7}$$

where n is the number of criteria (in this case 6). The result of this step is a single column with individual GRGs for each option.

1.3.2 TOPSIS Decision Model

The second method we used to find the most optimal use of the land provided to us was the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) Model, which determines the best use of the land using Euclidean distances. TOPSIS is based on the concept that the best choice will have the shortest geometric distance from the positive ideal solution (PIS) and the longest geometric distance from the negative ideal solution (NIS). The result of the TOPSIS method is a performance score from 0 to 1 that demonstrates its distance from the NIS. The closer the value is to 0, the less optimal that choice is.

The same 6 criteria used in the GRA model above are used in this model. However, since TOPSIS requires the options to be independent, the amount of land used, in acres, plays a role. This is resolved by dividing the cost, profit, and CO_2 by the number of acres each facility uses so that the values are reliant on the space they take up. To determine the weights that each of these criteria should receive, we performed entropy, which is an algorithmic procedure to determine the relative weights of criteria based on their distributions. In entropy, the evaluation matrix is represented by the variable X_{ij}, where *i* and *j* represent an intersection in the matrix. The steps to calculate the weights based on entropy are:

1. Normalize the evaluation matrix to create the project outcomes p_{ij}, where

$$p_j = \frac{X_{ij}}{\sum_{i=1}^{m} X_{ij}} \tag{8}$$

2. Compute the entropy measure, E_{ij}, of the project outcomes.

$$E_j = \frac{-1}{ln(m)} \sum_{i=1}^{m} (p_{ij})(ln(p_{ij})) \tag{9}$$

3. Define the objective weight, w_j, based on the entropy measure.

$$w_j = \frac{1-E_j}{\sum_{j=1}^{n} (1-E_j)} \tag{10}$$

Note that entropy requires values greater than zero because the natural log of zero does not exist. Hence, we replaced zeros with one when performing entropy, which will have a negligible impact on the data. TOPSIS can now be performed with the following steps:

1. The same evaluation matrix as in entropy was reconstructed with *m* rows and *n* columns, based on the number of choices for the land and number of criteria, respectively. This matrix is represented by the variable $(X_{ij})_{m\times n}$, where each i and j represent an intersection in the matrix.
2. Next, the matrix was normalized through Normalization Under Root Summation, as shown in the equation below

$$\overline{X}_{ij} = \frac{X_{ij}}{\sqrt{\sum_{j=1}^{m} X_{ij}^2}} \tag{11}$$

   where each of the values in the matrix is normalized to a value between 0 and 1. This is done by dividing each value by the square root of the sum of the squares of all values in each column. This is crucial as many of the criteria are not measured on the same scale. If the matrix was not normalized, values such as profit and costs would be considered far more important than factors like Human Health Impacts or Local Competition, which are on a much smaller numerical scale. The bigger a normalized value is, the bigger it is relative to all the other values in that criteria.

3. The normalized matrix is then properly weighted, using the entropic weights explained above. The normalized matrix, $\overline{X}_{ij}$ is multiplied by the weight matrix w_j, creating the weighted normalized matrix V_{ij}.

$$V_{ij} = w_j \cdot \overline{X}_{ij} \tag{12}$$

4. The best and worst values for each criterion can then be determined by picking the lowest and highest values from each column. Since there is a multitude of factors in play, each land use option may have drawbacks. Finding the worst and best of all the choices in each criterion constructs a metric to compare the rest of the options. These "best" and "worst" values are expressed in row matrices V^+_j and V^-_j respectively, each the same length as the weighted matrix V_{ij}. For non-beneficial criteria, however, a lower value is more ideal, so V^+_j is actually the smallest numerical value. For example, when finding the ideal initial cost, a smaller value would be better than a larger value. This is dependent on the criteria, but for this scenario, Initial Cost (*IC*), Local Competition (*LC*), and CO_2 Emitted (*CE*) are all treated as non-beneficial.

5. After finding the best and worst values for each criterion, the total Euclidian distance from the PIS and NIS to each of the various options for land use can be calculated using the equations below

$$S^+_i = \sqrt{\sum_{j=1}^{n} (V_{ij} - V^+_j)^2} \tag{13}$$

$$S^-_i = \sqrt{\sum_{j=1}^{n} (V_{ij} - V^-_j)^2} \tag{14}$$

where S^+_i and S^-_i are the distances from the PIS and NIS for each option of land use. Essentially, using the standard distance formula for a geometrically Euclidean plane, the total distance from the optimal PIS and NIS for each criterion is determined and added together for each land use. Graphically, the coordinate point $(V^+_1, V^+_2, \cdot \quad \cdot \quad \cdot V^+_{n-1}, V^+_n)$ and $(V^-_1, V^-_2, \cdot \quad \cdot \quad \cdot V^-_{n-1}, V^-_n)$ represent the most and least ideal points in the *n*th dimensional plane since each criterion adds another plane in which distance is measured. We then measure the distance from each of the two points to the *m* number of choices listed, each represented by its own coordinate point.
The higher the S value, the farther it is away from the respective point. To find the most optimal of all choices given to us, we look for the smallest S^+_i value and the largest S^-_i. If there was one option that had the PIS for all of its criteria, its S^+_i would equal zero, showing that it contains all the best values from all rows, and therefore has a distance of zero to the PIS. Inversely, a point that shows a S^-_i of zero shows that it contains all the NIS values in all criteria, making it the worst choice possible.

6. However, these S values almost always return a number between 0 and 1. To find the choice close to S^{+}_{i} but still far from S^{-}_{i}, we determine the performance score P_i, represented by the equation

$$P_i = \frac{S^{-}_{i}}{S^{+}_{i} + S^{-}_{i}} \tag{15}$$

resulting in a normalized value between 0 and 1. This expression is unique as it takes into account not only the proximity to the best choice but also the distance from the worst. As we want the distance to the NIS to be large, the larger the performance score is, the better it performs.

1.3.3 Combined Model

Both GRA and TOPSIS have benefits and downsides. For example, GRA tends to be better at handling data with uncertain information (fuzzy data) and can deal with complex relationships between the data, but it assumes the criteria have a linear relationship with the alternatives. In contrast, TOPSIS remains unaffected by outliers and can accommodate varieties of alternatives, but it assumes independence and fixed weights. As such, our metric combines both MCDM methods into a system that weights them equally. Using γ_i and P_i,which represent the GRG from GRA and performance score from TOPSIS respectively, our metric, λ, is calculated as

$$\lambda_i = \left(\frac{1}{2}\right)\left(\frac{\gamma_i}{\sum_1^m \gamma_i} + \frac{P_i}{\sum_1^m P_i}\right) \tag{16}$$

where *m* is the number of options. Using this metric, each of the options can be ranked.

1.4 Strengths and Weaknesses

1.4.1 Strengths

- **Modeling Depth.** We took into account multiple factors that would influence land usage in our model. Our model can therefore better represent the situation and not oversimplify it. We also did not include excessive factors that would overly complicate the scenario and our model.
- **Objectivity.** Since TOPSIS and Grey Relational Analysis both determine weights and grades based on the data and not from subjective input, the metric will not be biased.

1.4.2 Weaknesses

- **Risk of Contradicting Models.** We used both TOPSIS and Grey Relational Analysis to determine the final grades of land uses, but the models rank options in slightly different ways, so there is no guarantee that they will corroborate each other.
- **Inconsistent Metric.** Since TOPSIS and Grey Relational Analysis produce different results based on the differences in data and the number of options, the metric is not standardized. That means that even if one option has the same data in two different tests, its metric value will be different based on the data of other options.

2 Testing Land Uses

2.1 Problem Restatement.

Problem 2 asks us to choose at least two of the already considered land use options and determine the values of those options using the "best" metric while defending the data and assumptions with valid reasoning.

2.2 Assumptions and Justifications

Assumption	Justification
The metric of the cost for clearing land is unnecessary in our model.	Since all of the uses for land require the clearing of trees in the 3 km^2 area, the cost of doing so is an unnecessary metric, as all the choices would have the same data in that criteria, having no weight on the overall decision.
Additional jobs created as a result of using the land is unnecessary in our model.	For all the options that we tested our decision metrics on, they all created more jobs around the area, not just on the land itself, in the form of suppliers, local businesses, etc. Since they all produce similar results in that criteria, it would form no weight on the decision, and can be omitted. Full-time jobs on the land, however, are accounted for.

2.3 Data For Modeling Process

To start, we selected five options for land use from those that were given: outdoor sports complex, solar farm, grazing farm, regenerative farm, and agrivoltaic farm.

2.3.1 Calculations and Justifications for Acre Data

The average size of each usage option was used to limit the number of acres each usage could take up except for the grazing farm (explained later). We assumed that a solar farm, for example, would not exceed the average solar farm size since it could create feasibility issues. The maximum acres for each land use option are shown below in table 2.

	Sports Complex	Solar Farm	Grazing Farm	Regenerative Farm	Agrivoltaic Farm
Acres	175	35	264*	333	35

Table 2: Acres for Each Land Use

For the sports complex, the number of acres was calculated as the sum of the acres of a parking lot, golf course, and all the sports courts, which were decided to be a baseball field, football field (which could be repurposed for lacrosse and other sports), quarter-mile track, softball field, and 4 tennis courts. The parking lot was assumed to be 1 acre and the average sizes of each sports field were used, so the golf course was 160 acres [2], the baseball field was 4.5 acres [3], the football field was 1.32 acres [4], the track was 2.75 acres (estimated using a quarter-mile drag strip) [5], the softball field was 1.5 acres [3], and the 4 tennis courts were about 0.25 acres total [6], for a total of 171.32 acres. Factoring in space between the fields, the final area used was increased to 175 acres.

For the solar farm, the average size was found to be 30-40 acres [7]. The median of the range was taken, so the solar farm was capped at 35 acres.

For the grazing farm, the maximum acres was not calculated based on average farm size but rather on what was feasible given the land area. From the topographic map, the area near the river made the most sense for a pasture because it had steep surrounding hills (from the topographic lines [8]) to act as a natural fence [9] and a source of water. The grazing area was calculated using a Riemann sum to approximate the number of acres below 120 meters (between the northern 120m boundary line and the southern 120m boundary line; if the southern 120m boundary line is outside the area, then use the road boundary). The visual for the approximation shown in figure 1 in the Appendix yields an area of about 264 acres. Therefore, the maximum grazing farm size is 264 acres.

For the regenerative farm, the average size was found to be 333 acres [10], and the average size of the agrivoltaic farm was estimated to be the same as the solar farm since they both use solar panels for commercial and/or utility purposes.

2.3.2 Calculations and Justifications for Data

The data for each land use method were obtained by making certain assumptions about its performance compared with values obtained through research. The data obtained are shown in table 3 below, and the calculation method and justification are shown below the table.

	Initial Cost ($) *IC*	Annual Profit ($) *AP*	Local Competition *LC*	Full-Time Jobs Created *FT*	Human Health Impact *HH*	Annual CO_2 Emitted (metric tons) *CE*
Sports Complex	6,318,020	1,066,971	10	20	8	589.88
Solar Farm	15,750,000	1,115,625	10	5	6	0
Grazing Farm	491,807.40	22,176	40	2	3	341.78
Regenerative Farm	268,736.54	71,475.64	30	3	7	136.85
Agrivoltaic Farm	12,340,063	925,757.50	10	3	7	0

Table 3: Data for Each Land Use

For the outdoor sports complex, the initial cost was calculated as the costs of building a parking lot and the sports fields: a baseball field, football field, quarter-mile track, softball field, golf course, and 4 tennis courts. Using the median costs, the baseball field cost $780,000 [11], the football field cost $1,050,000 [12], the track cost $750,000 [13], the softball field cost $535,000 [14], the golf course cost $2,717,000 (subtracting the cost to buy the land) [15], and the 4 tennis courts cost a total of $290,000 [16]. Adding in the cost for a 1-acre parking lot, which is 43,560 ft^2 x $4.5/$m^2$ = $196,020 [17] yields a total cost of $6,318,020. The annual profit was calculated as the revenue minus the upkeep cost. To get a rough estimate of the revenue, we used the pre-COVID revenue for Fulton Family YMCA, a nearby sports complex that earned $1,044,000 in 2019 [18], and added it to the average revenue of a golf course, or $1,252,000 [19]. Subtracting the costs of 5 fitness trainers each earning a salary of $40,700 [20], the expenses of labor and maintenance for the golf course, $971,029 [21], and the expenses of maintaining the sports fields, $54,500

[11] [12] [13] [14] [16], yields the annual cost of $1,229,029. Subtracting the costs from the revenue gives a profit of $1,066,971. The local competition rating is estimated at 10 (little competition) since there were no nearby sports complexes except the YMCA, which was indoor rather than outdoor. The number of full-time jobs created was 20 since it was assumed that 15 full-time golf course workers were sufficient for maintenance (numbers of golf course employees vary [22]). Since sports centers help support local events and encourage people to exercise, the health impact is 8 (beneficial). Finally, the carbon emissions in metric tons were calculated in two parts: the maintenance of the golf course and the artificial turf used in the other fields. For a standard golf course, there are approximately 4.28 metric tons of carbon emitted per hectare per year [23]. Taking into account the average size of 160 acres, or 64.75 hectares, the golf course produces 277.13 metric tons per year. Turf produces carbon emissions from the installation, production, and removal of natural grass. On average, a 2-acre field of turf leads to a total of 55.6 metric tons of carbon emissions [24]. Since we planned to add 11.25 acres of turf, that would lead to an emission of 312.75 metric tons of carbon every year. Adding the two together gives an emission of 589.88 metric tons per year.

For the solar farm, the initial cost was calculated as the average cost of an acre of a solar farm, $450,000 [7], multiplied by the average size, 35 acres [7], for a total of $15,750,000. Since the averages were provided as a range, the median value was chosen for consistency. This way of selecting data values was also used in the annual profit, which was calculated as the profit per acre, $31,875 [7], multiplied by the number of acres (35), for a total of $1,115,625. Similar to the sports complex, there was almost no local competition since there were no nearby solar farms. However, since electricity generated is not just used in the surrounding areas, there would still be some competition, so the competition rating was estimated at 10. The number of jobs created was assumed to be 5 since 2.1 jobs on average are created per megawatt of electricity produced [25] and the average number of acres of solar farm needed to produce a megawatt of electricity is 7.5 (taking the median) [26]. However, these include construction jobs, and in the long term, these do not count as creating a full-time job. In terms of health benefits, a solar farm tends to have little impact since it improves air quality by replacing fossil fuels, but the change is minimal. Therefore, its impact rating is 6, or slightly beneficial. Finally, since solar farms rely on sunlight, a renewable source of energy, in the long term it has no carbon emissions.

For the grazing farm, the initial cost was calculated by scaling up the cost for a cattle farm with 100 cows [27]. The area was estimated to be approximately 264 acres, which with 2 acres per cow can support 132 cows [28]. Thus, the cost of cows, feed bunk, and hay rack was scaled up by 1.32 times to match the 132 cows. The number of bulls used for reproduction was also scaled up, but costs were determined based on the nearest whole number (5 in this case). However, the cost of fencing was changed since the steep hills around most of the pasture area provided natural boundaries, so fencing was only necessary at the boundaries of the pasture and the Red Creek and Maroney roads. The length of fencing needed was approximated at 0.8 miles [8], which was used to scale down the fencing cost down to $63,673.40 [27]. All other costs, like the squeeze chute, corral, water tank, pump, 1-ton truck, stock truck, tractor, hay fork, rotary motor, and barn were kept the same since they would logically be able to service a slightly larger herd. All of these costs sum to $491,807.40. The profit was calculated by multiplying the annual profit per cow, $168 [29], by the number of cows, 132, which gives $22,176. The local competition rating given was 40 (competitive) since cattle is an extremely large and popular industry, so the farm would have to compete with imports and other farms. In terms of jobs, the cattle farm would create 2 full-time jobs since each worker can take care of 80 cows [30]. The grazing farm's human health rating was set as 3 (slightly harmful) since the products produced would be fresher and healthier but at the expense of the environment, as cows pollute water [31] and the air. Finally, the carbon emissions of the farm were calculated by converting the livestock methane emissions to a carbon equivalent. Each cow or bull produces 220 pounds of methane annually [32], which is 25 times more potent than CO_2 [33]. Converting to CO_2 and multiplying by the 137 cows and bulls gives 341.78 metric tons of CO_2.

For the regenerative farm, the initial cost was calculated by adding the cost of an average farm of 333 acres [10] to the cost of converting to a regenerative farm. Using the costs for an Iowa grain farm, most similar to the average crop farm, a combine cost $175,000, a large tractor cost $125,000, other equipment cost $420,000, and storage cost $275,000, for a total cost of $995,000 [34]. Scaling the cost down for 333 acres, the cost becomes about $220,890. The cost to implement regenerative practices is $355.05 per hectare [35], which is $47,846.54 for 333 acres (~135 hectares). Thus, the total initial investment is $268,736.54. The annual profit was calculated by multiplying the profit per hectare from regenerative farming, $530.39 [35], by the number of hectares, approximately 135, for an annual profit of $71,475.64. The local competition rating given was 30 (pretty competitive) since farming is a popular industry but regenerative practices and locality would give the farm an advantage over some other farms or imports. The number of full-time jobs created was estimated at 3 since the average farm has 1.3 workers [36][37] but is also larger at 445 acres [37] and therefore has more efficient equipment. For human health impact, the regenerative farm was rated 7 (beneficial) since it produces fresh, local food and pollutes the air less than traditional farming [38], although it still emits carbon dioxide. Finally, the annual carbon emissions were calculated by multiplying the carbon emissions per acre, 906 pounds [39], by the number of acres, 333, for a total of 301,698 pounds or 136.85 metric tons.

For the agrivoltaic farm, the initial cost was calculated as the sum of the cost of investment for the agrivoltaic and irrigation systems since we determined crop seed cost would be negligible. The agrivoltaic system costs about £802,100 per hectare [40], which converts to $12,249,938 for 35 acres. By taking the median of the average cost range, drip irrigation cost $2,575 per acre, or $90,125 for 35 acres. Adding the costs together gives a total cost of $12,340,063. The profit was calculated by adding crop sales and surplus sold electricity but subtracting worker salaries. Assuming the crop would be lettuce (a common, profitable crop in agrivoltaic farms), the revenue would be the revenue per acre, $10,400 [41], multiplied by the acres, 35, to get $364,000. Since agrivoltaic farms produce about 80% of the energy of solar farms [42] and also use some produced electricity to power irrigation and other systems, it was approximated that the remaining energy was approximately 70% of that produced by the solar farms, so the profit generated would also be 70% of solar farm profit, or $780,937.50. The revenue is therefore $1,144,937.50, and subtracting the cost of 3 full-time workers each paid $73,060 [43] gives the profit of $925,757.50. Since agrivoltaics are part of the solar industry, their local competition rating is therefore the same as the solar farm's at 10 (little competition). Although crops would be part of a more competitive industry, they have relatively little influence since they account for less revenue. Additionally, agrivoltaics also help shade-tolerant crops like lettuce grow and taste better since they provide shade [44], so there would be less competition. An agrivoltaic farm would create about 3 full-time jobs because there would be 30% less electricity and therefore 30% less management needed compared to the solar farm, and irrigation would allow almost autonomous agriculture. In human health impacts, agrivoltaics share both the impacts from solar farms and crop farms. Since this method of agriculture reduces water usage, provides better quality crops, and generates pollution-free electricity, it received a rating of 7 (beneficial). Finally, since an agrivoltaic farm uses renewable solar energy to power operations, in the long term it has no carbon emissions.

2.4 Applying the Models

2.4.1 Individual Options

With each of the following options' criteria having been quantified, the two metrics for determining the "best" use can be applied and combined, giving the final ranking for the uses of the land. Before finding the combinations that would be most optimal for the land, we first found the most optimal individual choice. Then, we used the rankings to find the best combination of land uses. For the original 5 choices given to us, using the combination of the two metrics from GRA and TOPSIS, we find that agrivoltaic farming is the most optimal based on the metrics used, followed by the sports complex and solar farm, which is seen in table 4 below, along with the λ values.

	GRG	TOPSIS Score	Calculated Metric (λ)	Rank
Sports Complex	0.8021565732	0.47486	0.2108787663	2
Solar Farm	0.7106481481	0.55047	0.2108246449	3
Grazing Farm	0.4614742472	0.53395	0.1695446821	5
Regenerative Farm	0.5861594486	0.56436	0.1942962924	4
Agrivoltaic Farm	0.6988966295	0.57985	0.2144556142	1

Table 4: Most Optimal Land Use Individually

2.4.2 Maximizing Land Space With Combinations

We must also take into account combinations of the different options, as just taking one option would not fill the space and would end up being less efficient for the space given. For example, the agrivoltaic farm would only take up 35 of the 741 acres (3 km^2) given for use. By adding the uses together, such as the sports complex, or other types of farms in another area of the land, we take full advantage of the area given to us, and in repeating the decision modeling for those data points, we may uncover a combination that would be more optimal. Because of this, we chose a wide range of combinations to maximize the use of the 3 km^2 given, based on the acre values derived earlier in the problem.

In deriving the data that we performed TOPSIS and GRA on, we added the costs (*IC*), profits (*AP*), jobs created (*FT*), and CO_2 emissions (*CE*) together while averaging the local competition (*LC*) and human health impacts (*HH*). The data for these combinations are shown in table 5 in the appendix. Using these new data points for each of the choices, we can calculate the rankings of the combinations, similar to the above. The combinations and subsequent metrics are calculated and ranked in table 6 below.

	GRG	TOPSIS Score	Calculated Metric (λ)	Rank
Graze + Regenerative	0.5555555556	0.57286	0.1954628215	4
Regenerative + Agrivoltaic + Solar + Sports	0.7539047686	0.42792	0.1995627331	3
Agrivoltaic + Grazing + Sports	0.5313890497	0.49081	0.1762219466	5
Algrivoltaic + Regenerative + Sports	0.6669530284	0.51901	0.2029440317	2
Sports + Regenerative	0.6563847228	0.64954	0.2258084672	1

Table 6: Most Optimal Land Use by Combination

From running these combinations through the same metrics, we determine that the best use of the land is by building both a sports complex and a regenerative farm on the land. This is mainly due to the high value TOPSIS places on this choice, as it seems to be the closest out of all of the choices to the ideal choice due to the entropic weights used. This follows our line of thinking, as those two combined produce a high profit relative to their costs, and is much less drastic than solar farms or agrivoltaic farming. Although it does produce some of the most carbon emissions, the model also places a strong emphasis on jobs created, which this combination excels at as well. GRA produced slightly different results, as it appeared to value annual profit the most, which is why the land use that combines four options was found to be the best by grey relational grade. In terms of placement on the land itself, we plan on placing the 175-acre sports complex on the northwest corner of the area, near the intersection of Maiden and County Line Road. This has plenty of coverage and produces a flat enough landscape for fields and a golf course. The farm, as it does not require cell coverage for much of its area and is not affected by changes in elevation, can be placed in a variety of areas, most likely along the east side of the land near Upton Road. A sample land distribution is shown in figure 2 in the Appendix.

2.5 Sensitivity Analysis

For our sensitivity analysis, we used a Monte Carlo simulation with 1000 iterations of both TOPSIS and GRA to test our calculated metric, allowing 10%, 25%, and 50% variability of the original data, meaning that the data would vary from 90% to 110% of the original data, 75% to 125%, and 50% to 150%. We looked for changes in the average λ scores compared to the score we obtained above and the variability in each option for land use. The results are shown in table 7 below.

	Calculated Metric (0%)	Calculated Metric (10%)	Calculated Metric (25%)	Calculated Metric (50%)	Consensus Rank
Graze + Regenerative	0.1954628215	0.1957093228	0.1946707628	0.1922580719	4
Regenerative + Agrivoltaic + Solar + Sports	0.1995627331	0.2000032277	0.1997429919	0.1957197354	3
Agrivoltaic + Grazing + Sports	0.1762219466	0.1769076866	0.179254653	0.1892468384	5
Algrivoltaic + Regenerative + Sports	0.2029440317	0.2040169258	0.2050207674	0.2003713165	2
Sports + Regenerative	0.2258084672	0.223362837	0.2213108249	0.2224040378	1

Table 7: Sensitivity Analysis for Changing Range of Data

Although the data never varied enough for the rankings to change, differences in variability were still noticeable. Options such as the sports complex with the regenerative farm had little variation, showing that changes to the original data do not affect its outcome overall. Meanwhile, the option of agrivoltaic farming, grazing, and a sports complex varied on an upward trend, showing that more often than not, a large change in the data supported the option to be more optimal, whether a decrease in costs or an increase in revenue. Overall, the model itself became more volatile as the range increased, yet when the average of the 1000 iterations was taken, it stayed at a similar value for many of the options. An example of this volatility is shown in figure 3 in the Appendix, which is the TOPSIS interactions for the 50% variability.

2.6 Strengths and Weaknesses

2.6.1 Strengths

- **Adaptive.** The TOPSIS and GRA models adapt based on the data given, so when data are added or removed, it is immediately reflected in the metric grades.

- **Efficient Selection of Land Use Combinations.** By using the results of the individual land uses to determine the land use combinations with the most potential, we decrease the number of combinations that need to be tested to determine the "best" one.

2.6.2 Weaknesses

- **Subjective Data.** Although we tried to be objective in our data, some parts, including the local competition and human health impacts, had to be subjectively converted from qualitative data to a quantitative scale. Because of the lack of satisfactory research data, we had to make more assumptions.
- **No Clear Way to Compare Single Use and Combination Use.** We assumed that combination use would be better than single use since that would take up more of the land space, but there is no way to compare the two since they are two separate data sets. If TOPSIS and GRA are performed on a collective data set with all 10 options, the results are skewed as the initial costs, annual profits, jobs created and carbon emissions are much higher for the combinations.
- **Left-Over Land.** Although our model attempts to maximize the land use, there are still roughly 233 unused acres when the Sports Facility and Regenerative Farms are created. Given more time, we could have performed linear programming to maximize all 3 square kilometers. Nevertheless, the remaining land can be sold, which will still be profitable since land is expensive in New York.

3 The Micron Fab and Other Land Uses

3.1 Problem Restatement.

Problem 3 asks us to re-evaluate the options determined by the "best" metric in Problem 2 in light of the construction of Micron Technology's new semiconductor fabrication facility (fab) in Clay, NY. It also invites us to consider alternative options for using the land or an additional option from the list of initial considerations.

3.2 Considering Other Land Uses.

For our model, we considered another alternative of a rural housing district since it would likely economically benefit most from the increase in population (workers from the fab). We also wanted to consider an alternative that had a less permanent benefit but likely more short-term benefits to see how it would compare to the other uses. We approximated that 230 homes would fit in the given land based on the population density of rural areas [45] and the intersection of areas with an elevation above 120m and the area with cell coverage. In this housing model, most houses would accumulate closer to the roads. The data for the criteria of a rural housing district are shown below.

	Initial Cost ($) *IC*	Annual Profit ($) *AP*	Local Competition *LC*	Full-time Jobs Created *FT*	Human Health Impact *HH*	Annual CO_2 Emitted (metric tons) *CE*
Rural Housing	41,745,000	5,359,000	40	0	5	531

Since the land is located in the state of New York, much of the housing prices and land values were skewed from the data of New York City, well-known for high housing prices and small house sizes. This, in addition to the rural nature of the surrounding land, made it difficult to find accurate data on the costs of building and buying homes. Thus, we looked at the housing prices from Cayuga county and compared them to housing prices in Kentucky, as both locations had similar population densities: 115.7 people/mi^2 [46] and 115 people/mi^2 [47] respectively. The median house price in Kentucky in February of 2023 is cited to be \$233,000 [48], and multiplying by the number of houses, 230, yields a profit of \$53,590,000 for all the houses on the land. However, not all houses will be sold in one year. To model this, we assumed that 10% of the original number of houses would be sold each year, for an annual profit of \$5,359,000. It was also assumed that houses will not require much upkeep before purchase, so the profit is equal to the sale price. The initial costs were derived in a similar way using Cayuga and Kentucky. The average size of a house in Cayuga is 1650 ft^2 [49], and we used Kentucky's average cost per ft^2 to build a house, around \$110/ft^2 [50], to estimate the cost. Multiplying these together, for 230 houses, the cost of building these houses is estimated at \$41,745,000. The local competition rating was valued at 40 (high competition) mainly due to a lower population, with not many houses being bought every year. Therefore, housing companies would have to compete for a home sale. No full-time jobs are created either, as after construction, there is not much maintenance needed. Housing produces no clear benefits or downsides to human health, so it received a rating of 5. Finally, the carbon emissions criteria were calculated. The average house uses around 5.8 kWh of electricity/ft^2/year [51], and each kWh of energy emits around 0.371 kg of CO_2 [52]. However, New York only gets 65% of its power from carbon-emitting sources [53], with the rest coming from renewable sources. Thus, the formula for the carbon emissions of one house in kilograms is

$$CE = 0.65(5.8kWh/ft^2 * A * 0.371kg/kWh) \tag{16}$$

where A is the area of the house in square feet. The average house size is 1650 ft^2, so multiplying by the 230 houses planned to be built gives an estimate of 531 metric tons of carbon dioxide emissions per year.

3.3 Adaptations to the Model

To incorporate the impact of the new semiconductor facility on land use, we made the following adaptations to our metric.

1. We added an "Artificial Bias" criteria. Since there were no quantitative and little qualitative data on a fab's impact on other industries, adding an artificial bias would allow us to consider which land usage options would be favored by the presence of the fab and a larger worker population. However, since the rating would be based on qualitative assumptions, the bias scale was only 1 to 9, where 9 meant the land usage would be heavily favored by the presence of a fab and 1 meant it would be heavily opposed. This would lessen the possible degree of error since there would be fewer numbers to choose from.
2. We evaluated ranges of profit growth rates for different options. Instead of evaluating a yearly profit, we determined that it would be best to investigate long-term impacts by measuring the total profit over 10 years with a compound annual growth rate (CAGR). This caused the "Annual Profit" criteria to be changed to a "10-Year Compound Profit Compounded Annually" (CP), which is a beneficial criterion. The calculation for this criterion, assuming that our annual profit statistic is year 0, is

$$CP = \int_0^{10} (AP)(1 + CAGR)^t dt \tag{17}$$

where t is the time in years. The high and low ends of the CAGR for each alternative, with justifications, are shown below in table 8.

Option	CAGR (%)	Justification
Sports Complex	2 to 4	Sports complexes often thrive from brand recognition, which can create significant growth rate. [55]
Solar Farm	4 to 6	At the leading edge of environmental technologies, it is likely systems for collecting and extracting solar energy will improve, giving the solar farm a high growth rate. This is a reason why the solar farm market is expected to have a CAGR of 20.1% from 2022-2030 [56].
Grazing Farm	-1 to 1	With grazing and farming revenues plummeting, it is possible for a grazing farm to lose yearly revenue. [57].
Rural Housing	1 to 3	The Micron fab in Clay will likely drive up home prices, but rural home prices have only recently begun to swing up due to COVID [58]. Hence a moderate growth rate is appropriate.
Regenerative Farm	0 to 2	As with grazing, profits from crops have shrunk in volume. However, regenerative practice helps to limit CO_2 emissions, which is helpful for revenue growth.
Agrivoltaic Farm	3 to 5	Agrivoltaic farms enjoy the benefits of the solar farm but retain drawbacks of crop farms, placing them at a moderate CAGR rate.

Table 8: CAGR Values and Justifications

3. We added a non-beneficial "Years-to-Break-Even" (*YBE*) criterion. Another way to understand long-term economic impacts is through a statistic that determines the number of years that each option takes to earn back its initial investment. The calculation for this criteria, using the CAGRs presented above, is

$$IC = \int_0^y (AP)(1 + CAGR)^t dt \tag{18}$$

where t is the time in years and y is the years to break even.

4. For TOPSIS, instead of calculating the weights via entropy, we calculated them via Analytic Hierarchy Processes (AHP). AHP is another decision-making technique that helps to analyze options based on a set of criteria, however, it can also be used to derive weights for criteria based on a pairwise comparison matrix. Although entropy is a more objective method to derive the weights, AHP allows us to better incorporate the impact of the fab on the importance of the criteria. The process for AHP is as follows.

a) Construct the pairwise comparison matrix, where the criteria are listed across the top and the bottom. The methodology for determining elements a_{ij} is as follows.

   i) If $i = j$, $a_{ij} = 1$.
   ii) If $i \neq j$, a_{ij} will equal the intensity importance of the criteria in the row (i) relative to the criteria in the column (j). The AHP scale for importance is shown in figure 4 [54].
   iii) For all a_{ij}, a_{ji} will be equal to the reciprocal of a_{ij}. In other words, if the pairwise matrix is labeled matrix A, then taking the reciprocal of each element should create the matrix A^T.

b) Normalize the columns by dividing each individual value by the sum of the entire column. The calculation for the normalized values, b_{ij}, is as follows

$$b_{ij} = \frac{a_{ij}}{\sum_{j=1}^{n} a_{ij}} \tag{19}$$

where n is the number of criteria.

c) Calculate the arithmetic mean of the rows of the normalized matrix using the following equation

$$w_i = \frac{1}{n}\sum_{j=1}^{n} b_{ij} \tag{20}$$

where w_i represents the weight of criterion i.

3.4 Applying the Models

3.4.1 AHP Weight

Much like in the second problem, we first determined the "best" use of the land through the ranking of the λ values for individual options while implementing our adaptations to the metric. We gave the sports complex, solar farm, grazing farm, rural housing, regenerative farm, and agrivoltaic farming artificial bias scores of 6, 4, 5, 7, 5, and 4, respectively. For the sports complex, the fab would likely be beneficial since more workers would increase the number of potential customers. However, the change would not be drastic since the factory is not very close to the location of the land. The fab would likely slightly disfavor the solar farm since they are in different industries, but jobs would both be in the tech sector, which would lead to some competition. Since the solar farm only requires 5 jobs, though, there would be relatively little impact. For the grazing farm, there would be almost no impact since the industries are different, and the beef and dairy industries are already popular, so a small increase in population would not change much. For rural housing, the increase in population from the fab would lead to greater demand and economic growth, so it would be more favored. For the regenerative farm, the fab would likely not impact it since they are in different industries, and a slight increase in population would not noticeably impact demand. Finally, agrivoltaic farming, like solar farming, would be slightly disfavored by the fab since it requires tech jobs.

This criterion, along with Years-To-Break-Even (YBE) and compound profit, were added with compound profit replacing annual profit. In the TOPSIS model, compound profit was divided by the number of acres used to ensure independence. Both compound profit and artificial bias were listed as positive traits in the models, while YBE was added as a negative trait. The 10-Year Compound Revenue and Years to Break Even criteria were calculated using equations 17 and 18 above. The adapted data for both the maximum and minimum CAGRs are presented in tables 9 and 10 below.

	Initial Cost ($) *IC*	10-Year Compounded Profit ($) *CP*	Years to Break Even YBE	Local Competition *LC*	Full-Time Jobs Created *FT*	Human Health Impact *HH*	Annual CO_2 Emitted (metric tons) *CE*	Artificial Bias AB
Sports Complex	6,318,020	11,799,479	5.60	10	20	8	589.88	6
Solar Farm	15,750,000	13,660,448	11.23	10	5	6	0	4
Grazing Farm	491,807.40	210,980	25.09	40	2	3	341.78	5
Rural Housing	41745000	56,346,876	7.50	40	0	5	530.80	7
Regenerative Farm	268,736.54	714,756	3.76	30	3	7	136.85	5
Agrivoltaic Farm	12,340,063	10,771,179	11.24	10	3	7	0	4

Table 9: Data with Adaptations for Low-End CAGRs

	Initial Cost ($) *IC*	10-Year Compounded Profit ($) *CP*	Years to Break Even YBE	Local Competition *LC*	Full-Time Jobs Created *FT*	Human Health Impact *HH*	Annual CO_2 Emitted (metric tons) *CE*	Artificial Bias AB
Sports Complex	6,318,020	13,064,696	5.32	10	20	8	589.88	6
Solar Farm	15,750,000	15,141,685	10.30	10	5	6	0	4
Grazing Farm	491,807.40	233,168	20.04	40	2	3	341.78	5
Rural Housing	41745000	62,351,913	7.01	40	0	5	798	7
Regenerative Farm	359,149.83	1,056,292	3.63	30	3	7	182.87	5
Agrivoltaic Farm	12,340,063	11,932,813	10.27	10	3	7	0	4

Table 10: Data with Adaptations for High-End CAGRs

For AHP, we constructed the pairwise matrix without artificial bias shown in table 11, which gave us the weights shown in table 12 (both tables are found in the appendix). Artificial bias was given a fixed weight of 5% to boost options that were more favored without crowding out other criteria or receiving a negligible weight.

In the pairwise comparison matrix, carbon emissions and human health impacts are given more relative importance compared to other statistics because semiconductor facilities are known to contribute to roughly 31% of global greenhouse gas emissions [59]. Thus, it is of utmost importance to tamp down other sources of pollution in the upstate New York area. In addition, the economic aspects were weighed more because the addition of a semiconductor facility can help to boost profitability by driving more people to the area, which increases demand for food, housing, entertainment, etc.

3.4.2 Individual Choices

With the new AHP weights known, we can calculate the new optimal use of land, with the fabricator built. In addition, we have added two criteria and edited annual profit to be compounded profit, showing the long-term effects of each use of the land, along with a new option of rural housing for land use. The table for GRG, TOPSIS Score, and λ is found in table 13 below, for both the high-end and low-end CAGRs:

	GRG(Low)	TOPSIS Score (Low)	Calculated λ (Low)	Rank	GRG (High)	TOPSIS Score (High)	Calculated λ (High)	Rank
Sports Complex	0.7433680969	0.41431	0.160297739	5	0.6331880886	0.4119	0.1475631091	6
Solar Farm	0.6042311092	0.61489	0.1687133481	3	0.6137359526	0.61388	0.1727121392	3
Grazing Farm	0.4450300403	0.56825	0.1401976567	6	0.5011296867	0.57104	0.1506753004	5
Rural Housing	0.5690017349	0.64168	0.1675294197	4	0.5091780111	0.64009	0.1613760134	4
Regenerative Farm	0.61869268	0.71668	0.1847790714	1	0.6152354985	0.7158	0.1870214945	1
Agrivoltaic Farm	0.6258945688	0.66387	0.1784827652	2	0.6219348172	0.66281	0.1806519434	2

Table 13: Rankings for Altered Individual Choices (Low and High)

In using both the low-end and high-end CAGRs, the best choice did not change, but some of the lower rankings were affected by the different growth rates. The sports complex's ranking fell to 6th while the grazing farm's increased to 5th from a small change in each CAGR. Comparing these results to the ones seen in problem 2, there are some major changes, most notably with regenerative farming being much more optimal, rising from fourth to first in the rankings. With the influence of a semiconductor fabrication facility nearby, the metric significantly changed, mainly due to the change in weighting method from entropy to a more tailored AHP system. With a heavy emphasis on carbon emissions and human health but less emphasis on jobs, the regenerative and agrivoltaic farms are individually the best, while other options fall due to their weaknesses in these criteria.

3.4.3 Optimal Combinations

Similar to our process in 2.4.2, we evaluated combinations of various options to determine the best use of the land by maximizing space. In addition to the options we selected previously, we added a sports and housing option, which would create a development in the area where the homeowners can readily access the sports facilities. To obtain the values for these combinations, we added the total costs (*IC*), jobs created (*FT*), and CO_2 emissions (*CE*), averaged the local competition (*LC*), human health impacts (*HH*), and artificial bias (*AB*), and calculated compound profit (*CP*) and years to break even (*YBE*) based on the total annual profit and total initial costs. To calculate *CP* and *YBE*, we summed the average value of the high and low CAGRs for each option. For example, for the Grazing Farm and Regenerative Farm option, the CAGR was $\frac{(-1\%+1\%)}{2} + \frac{(0\%+2\%)}{2} = 1\%$. Table 14 in the Appendix demonstrates the data values for the combinations while the results for GRG, TOPSIS, and λ are shown in table 15 below.

	GRG	TOPSIS Score	Calculated Metric (λ)	Rank
Graze + Regenerative	0.5043859649	0.62229	0.1759095067	2
Sports + Housing	0.6018751257	0.37964	0.1489698292	5
Regenerative + Agrivoltaic + Solar + Sports	0.6396235765	0.46372	0.1684329387	4
Agrivoltaic + Grazing + Sports	0.4950958135	0.38299	0.1344127042	6
Agrivoltaic + Regenerative + Sports	0.6037356682	0.5309	0.1746316477	3
Sports + Regenerative	0.6864321102	0.59821	0.1976433735	1

Table 15: Rankings for Combinations After Alteration

The results of our new metric show that with the construction of a new fabricator, a combination of a sports complex and regenerative field is still the best. The rankings below it, however, undergo changes when comparing these results to problem 2. This is most likely due to the additional weight on carbon emissions and costs and the lower weight on jobs created. The high initial cost of some of the uses, including housing, agrivoltaic farms, and solar farms bring down their ranking based on our metric.

3.5 Sensitivity Analysis

Similar to the sensitivity analysis for problem 2, we used a Monte Carlo simulation with 1000 iterations, testing the variability of the results by having the data (except *YBE*) be a random number first within 10%, then 25% and finally 50% of the original value. The results for the 6 choices, calculated using our metric, are listed in table 16 below.

	Calculated Metric (0%)	Calculated Metric (10%)	Calculated Metric (25%)	Calculated Metric (50%)	Consensus Rank
Graze + Regenerative	0.1759095067	0.1751615491	0.1763045025	0.1739319064	2
Sports + Housing	0.1489698292	0.1499051551	0.1475579165	0.1502931453	5
Regenerative + Agrivoltaic + Solar + Sports	0.1684329387	0.1688994368	0.1672791093	0.169288062	4
Agrivoltaic + Grazing + Sports	0.1344127042	0.1342945709	0.1377806121	0.1426469077	6
Algrivoltaic + Regenerative + Sports	0.1746316477	0.1742850977	0.1753295436	0.1717530208	3
Sports + Regenerative	0.1976433735	0.1974541904	0.195748316	0.1920869579	1

Table 16: Sensitivity analysis for Problem 3 Combinations

The rankings did not differ from the original results, but there was more variation among the options. The data's range increased, though some combination uses changed more than others. Most notably, we found that the combination of agrivoltaic farm, grazing farm, and sports complex experienced a similar growth as the variability increased, parallel to its increase in the second problem's analysis. Even with different weights, it continued to increase, although at a slower trend than in the second problem. Overall, the ranking is not very volatile, and although there will be certain situations in which the change in data results in a change in ranking, the average λ value remains somewhat consistent.

3.6 Strengths and Weaknesses

3.6.1 Strengths

- **Analysis of Long-Term Fab Effect.** We implemented multiple changes that examined the effect of the Micron fab on revenue, jobs, and demand. This ensures that the fab will have a noticeable effect on the metric grades and rankings and demonstrates our consideration of the long term.
- **Consideration of Other Land Uses.** By taking into account housing, which benefits greatly from the fab compared to other uses, the data becomes more varied. Therefore, it shows our wide range of considerations for finding the most optimal land use.

3.6.2 Weaknesses

- **More Subjectivity.** In order to take into account the fab's effect, the weight for TOPSIS was manually set using AHP, making the metric more subjective than it was in Part 2. Additionally, some added data sections, like the Artificial Bias, also contributed to subjectivity since it also converted qualitative information to a quantitative scale.

4 Broader Application of the Model

Since our model relies on a variety of inputs, as long as we are able to find data regarding the surrounding land, our calculations can be generalized to a wide range of locations. Finding the data for the location is the main difficulty of the metric, and in places where data are not readily available, we must make assumptions to model the characteristics of the land. For example, our housing data, especially costs and profits, are based on the average square footage and the average price per square foot, which is hard to gather, especially for a rural area. However, we adapted by assuming that the housing prices would be similar to those of Kentucky, which shares close to the same population density as the county of Cayuga where the land plot is. We were also forced to make other assumptions on different criteria due to a lack of data. The more specific the model, the more information is needed to be gathered before the metric can mathematically predict the "best" use. In places with little information, it becomes difficult to accurately measure important criteria like profits, demand, and long-term effects.

However, under the assumption that we are in a familiar environment, our model is engineered for ease of use and can be generalized not only to other locations but different uses of land as well, as seen with the addition of a housing option in problem 3. For example, in a place where the winter seasons tend to last longer, such as Alaska, more winter-based uses such as a skiing and snowboarding facility or a winter lodge may be considered. In contrast, we may look to creating a hotel or private park in warmer climates. Our criteria can also be changed, much like it was in problem 3. By adding a criterion like 10-year compound profit, we also begin considering the long-term impacts of using the land. The weight of the modeling can also be edited, like how we changed our weight from an objective entropic weight to the more subjective AHP, which is dependent on what criteria are deemed important. The adaptivity of our model ensures that different locations can still be modeled as long as data can either be provided or found. In this problem, we have also gathered much of the conversions needed for adapting this model for a new area, such as the carbon emissions per kWh of electricity, acreages and costs for different sports fields, and much more. This database will be very useful in locations we model in the future.

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6 Appendix

6.1 Data Tables and Figures

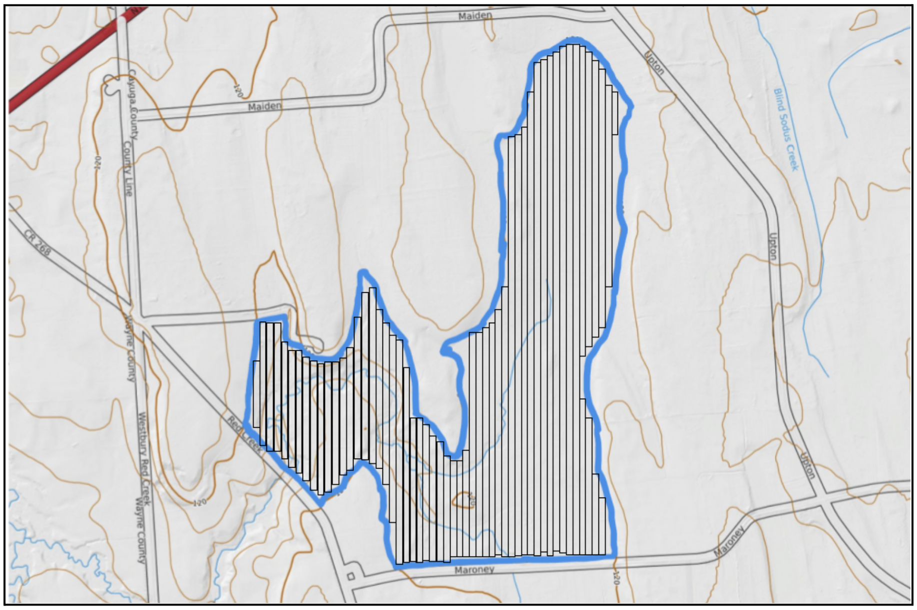

Figure 1: Riemann Diagram for Grazing Area Approximation

	Initial Cost ($) *IC*	Annual Profit ($) *AP*	Local Competition *LC*	Full-time Jobs Created *FT*	Human Health Impact *HH*	Annual CO_2 Emitted (metric tons) *CE*
Graze + Regenerative	760543.94	93651.63634	35	5	5	478.63185
Regenerative + Agrivoltaic + Solar + Sports	34676819.54	3179829.136	15	31	7	726.73
Agrivoltaic + Grazing + Sports	19149890.4	2014904.5	20	25	6	931.66185
Algrivoltaic + Regenerative + Sports	18926819.54	2064204.136	16.6	26	7.33	726.73
Sports + Regenerative	6586756.54	1138446.636	20	23	7.5	726.73

Table 5: Data for Combinations Question 2

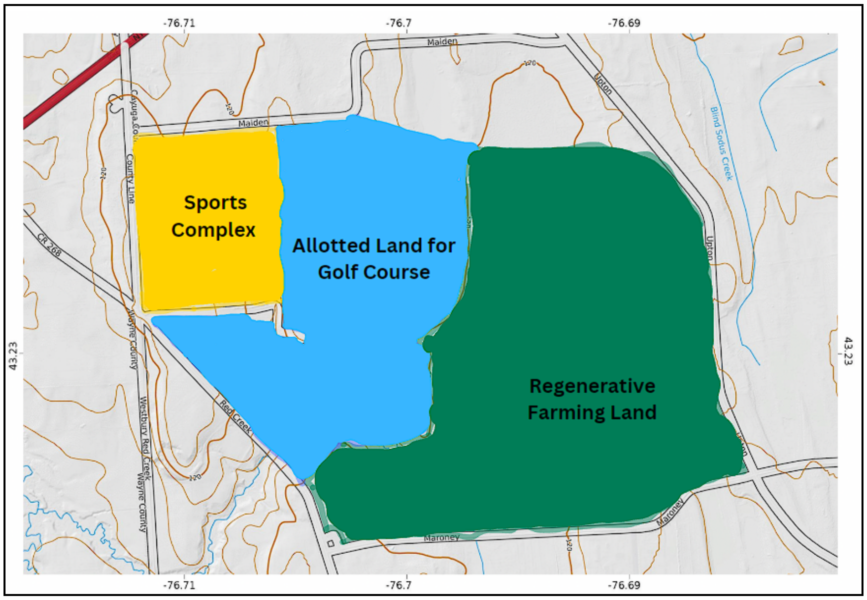

Figure 2: Example Land Distribution

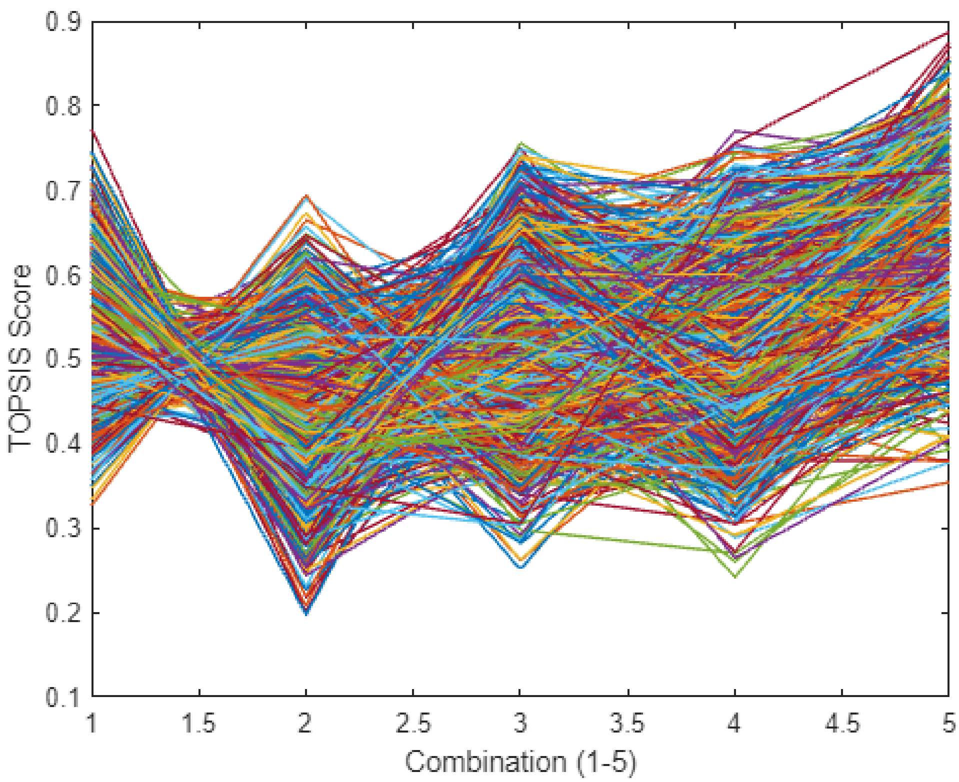

Figure 3: Monte Carlo Simulation for TOPSIS Problem 2, 50% Range

Intensity of importance	Definition	Explanation
1	Equal importance	Two criteria contribute equally to the objective of waste reduction
3	Moderate importance	Judgment slightly favor one over another
5	Strong importance	Judgment strongly favor one over another
7	Very strong importance	A criterion is strongly favored and its dominance is demonstrated in practice
9	Absolute importance	Importance of one over another affirmed on the highest possible order
2,4,6,8	Intermediate values	Used to represent compromise between the priorities listed above

Figure 4: AHP Importance Explanation

	IC	CP	YTR	LC	FT	HH	CE
IC	1	1/2	1	3	7	2	3/2
CP	2	1	3	1/3	3	1/2	1/5
YBE	1	1/3	1	1	5	1/3	1/5
LC	1/3	3	1	1	3	1/4	1/5
FT	1/7	1/3	1/5	1/3	1	1/4	1/7
HH	1/2	2	3	4	4	1	1
CE	2/3	5	5	5	7	1	1

Table 11: AHP Pairwise Comparison Matrix

Criterion	Weight
IC	0.197
CP	0.124
YBE	0.084
LC	0.087
FT	0.028
HH	0.176
CE	0.255
AB	0.05

Table 12: AHP Weights for Each Criterion

	Initial Cost ($) *IC*	10-Year Compound Profit ($) *CP*	Years to Break Even YBE	Local Competition *LC*	Full-time Jobs Created *FT*	Human Health Impact *HH*	Annual CO_2 Emitted (metric tons) *CE*	Artificial Bias AB
Graze + Regenerative	760543.9431	984694.2164	7.80945	35	5	5	478.63185	5
Sports + Housing	48063020	82829371.5	6.37628	25	20	6.5	1120.675265	6.5
Regenerative + Agrivoltaic + Solar + Sports	34676819.54	62301281.61	6.93087	15	31	7	728.73	4.75
Agrivoltaic + Grazing + Sports	19149890.4	28802195.52	7.33898	20	25	6	932.66185	5
Algrivoltaic + Regenerative + Sports	18926819.54	31084010.01	6.93796	16.66	26	7.33	727.73	5
Sports + Regenerative	6586756.54	13939891.62	5.21427	20	23	7.5	726.73	5.5

Table 14: Data for Combinations Question 3

6.2 Metric Calculations for Question 2

6.2.1 Sample GRA Calculation

Options	Initial Costs	Yearly Profit	Local Competition	FT Jobs Created	Human Health Impacts	CO2 Emitted (metric tons)
Sports Complex (1 football field, 1 track, 4 tennis courts, 1 baseball field, 1 softball field, 1 golf course)	6318020	1066971	10	20	8	589.88
Solar Farm	15750000	1115625	10	5	6	0
Grazing Farm	491807.4031	22176	40	2	3	341.78185
Regenerative Farm	268736.54	71475.63634	30	3	7	136.85
Agrivoltaic Farming (lettuce)	12340063	925757.5	10	3	7	0
Max	15750000	1115625	40	20	8	589.88
Min	268736.54	22176	10	2	3	0
Beneficial and Non-Beneficial Values						
Sports Complex (1 football field, 1 track, 4 tennis courts, 1 baseball field, 1 softball field, 1 golf course)	0.6092513072	0.9555040976	1	1	1	0
Solar Farm	0	1	1	0.1666666667	0.6	1
Grazing Farm	0.9855909136	0	0	0	0	0.4205908829
Regenerative Farm	1	0.04508636099	0.3333333333	0.05555555556	0.8	0.7680036618
Agrivoltaic Farming (lettuce)	0.2202621904	0.8263590712	1	0.05555555556	0.8	1
Max	1					
Min	0					
Deviation Sequence						
Sports Complex (1 football field, 1 track, 4 tennis courts, 1 baseball field, 1 softball field, 1 golf course)	0.3907486928	0.04449590242	0	0	0	1
Solar Farm	1	0	0	0.8333333333	0.4	0
Grazing Farm	0.01440908642	1	1	1	1	0.5794091171
Regenerative Farm	0	0.954913639	0.6666666667	0.9444444444	0.2	0.2319963382
Agrivoltaic Farming (lettuce)	0.7797378096	0.1736409288	0	0.9444444444	0.2	0
Max	1	DC-	0.5			
Min	0					
Grey Relational Coefficient						
Sports Complex (1 football field, 1 track, 4 tennis courts, 1 baseball field, 1 softball field, 1 golf course)	0.5613255501	0.918280556	1	1	1	0.3333333333
Solar Farm	0.3333333333	1	1	0.375	0.5555555556	1
Grazing Farm	0.9719890515	0.3333333333	0.3333333333	0.3333333333	0.3333333333	0.463216395
Regenerative Farm	1	0.3436630097	0.4285714286	0.3461538462	0.7142857143	0.6830635263
Agrivoltaic Farming (lettuce)	0.3907050306	0.7422351858	1	0.3461538462	0.7142857143	1
Options		**Grey Relational Grade**				
Sports Complex (1 football field, 1 track, 4 tennis courts, 1 baseball field, 1 softball field, 1 golf course)	4.812939439	0.8021565732				
Solar Farm	4.263888889	0.7106481481				
Grazing Farm	2.76853878	0.4614742472				
Regenerative Farm	3.515737525	0.5861594486				
Agrivoltaic Farming (lettuce)	4.193379777	0.6988966295				

6.2.2 Matlab Code for TOPSIS Method with Entropy

```
%Shannon Entropy: Define Data

X = [1273.942953 156.8704126 35 5 5 0.801728392

59994.49747 5501.434492 15 36 7 1.260778547

40400.61266 4250.853376 20 30 6 1.967641034

34856.02125 3801.480914 16.66666667 26 7.333333333 1.340202578

12966.05618 2241.036686 20 28 7.5 1.430570866]

% Normalize the Values in Matrix

[n, m] = size(X);

normalized_data = zeros(n, m);

for i = 1:m

   column_sum = sum(X(:,i));

   normalized_data(:,i) = X(:,i) ./ column_sum;

end

% Calculate sum of X*lnX and then find Ej

log_normalized = normalized_data .* log(normalized_data);

new_sum = sum(log_normalized);

Ej = -1/log(n) .* new_sum;

%Finding Objective Weight for data

Ej_comp = 1 - Ej;

Ej_sum = sum(Ej_comp);

W = Ej_comp ./ Ej_sum

% TOPSIS Method

Wcriteria = [0,1,0,1,1,0];

% Based on the assumption that costs, competition, and emissions are
non-beneficial

Xval=length(X(:,1));

Y = zeros([Xval,length(W)]);

%% calculating the normalized matrix
```

```
for j=1:length(W)
   for i=1:Xval
   Y(i,j)=X(i,j)/sqrt(sum((X(:,j).^2)));
   end
end
Normalized_Matrix = num2str([Y]);
%% calculating the weighted normalized matrix
for j=1:length(W)
   for i=1:Xval
       Yw(i,j)=Y(i,j).*W(j);
   end
end
Weighted_Normalized_Matrix = num2str([Yw]);
%% calculating the positive and negative best
for j=1:length(W)
   if Wcriteria(1,j)== 0
       Vp(1,j)= min(Yw(:,j));
       Vn(1,j)= max(Yw(:,j));
   else
       Vp(1,j)= max(Yw(:,j));
       Vn(1,j)= min(Yw(:,j));
   end
end
Positive_best = num2str([Vp])
Negative_best = num2str([Vn])
%% Euclidean distance from Ideal Best and Worst
for j=1:length(W)
   for i=1:Xval
```

```
        Sp(i,j)=((Yw(i,j)-Vp(j)).^2);
        Sn(i,j)=((Yw(i,j)-Vn(j)).^2);
    end
end
for i=1:Xval
    Splus(i)=sqrt(sum(Sp(i,:)));
    Snegative(i)=sqrt(sum(Sn(i,:)));
end
%% calculating the performance score
P=zeros(Xval,1);
for i=1:Xval
    P(i)=Snegative(i)/(Splus(i)+Snegative(i));
end
Performance_Score =  num2str([P])
```

6.2.3 Apps Script Code to Auto-Update GRG For Sensitivity Analysis

```
function gra_Monte_Carlo_Auto_Update() {
  var rangeToLog = 'GRA Problem 2 Combos!C55:C60';
  var sheetToLogTo = 'GRA Combos 10 Percent';
  var ss = SpreadsheetApp.getActive();
  var valuesToLog = ss.getRange(rangeToLog).getValues();
  var logSheet = ss.getSheetByName(sheetToLogTo);
  if (!logSheet) {
    logSheet = ss.insertSheet(sheetToLogTo);
    logSheet.appendRow(['Date time', 'Data']);
  }
  var rowToAppend = [new Date()].concat(
    valuesToLog.reduce(function (a, b) { return a.concat(b); })
  );
  logSheet.appendRow(rowToAppend);
}
```

6.2.4 Matlab Code for Sensitivity Analysis

```
%Sensitivity Analysis Problem 2

%Define Data

Data = [1273.942953 156.8704126 35 5 5 0.801728392

59994.49747 5501.434492 15 36 7 1.260778547

40400.61266 4250.853376 20 30 6 1.967641034

34856.02125 3801.480914 16.66666667 26 7.333333333 1.340202578

12966.05618 2241.036686 20 28 7.5 1.430570866];

%Monte Carlo Simulation

num_iterations = 1000;

Low = 0.5 * Data

High = 1.5 * Data

X = zeros(5, 6)

Performance_score = 0;

for i = 1:num_iterations

for j = 1:5

   X(j, 1) = Low(j,1) + (High(j,1)-Low(j,1)).*rand;

   X(j, 2) = Low(j,2) + (High(j,2)-Low(j,2)).*rand;

   X(j, 3) = Low(j,3) + (High(j,3)-Low(j,3)).*rand;

   X(j, 4) = Low(j,4) + (High(j,4)-Low(j,4)).*rand;

   X(j, 5) = Low(j,5) + (High(j,5)-Low(j,5)).*rand;

   X(j, 6) = Low(j,6) + (High(j,6)-Low(j,6)).*rand;

end

% Normalize the Values in Matrix

[n, m] = size(X);

normalized_data = zeros(n, m);

for i = 1:m

   column_sum = sum(X(:,i));
```

```
   normalized_data(:,i) = X(:,i) ./ column_sum;
end
% Calculate sum of X*lnX and then find Ej
log_normalized = normalized_data .* log(normalized_data);
new_sum = sum(log_normalized);
Ej = -1/log(n) .* new_sum;
%Finding Objective Weight for data
Ej_comp = 1 - Ej;
Ej_sum = sum(Ej_comp);
W = Ej_comp ./ Ej_sum;
% TOPSIS Method
% Negative and Positive Criteria
Wcriteria = [0,1,0,1,1,0];
Xval=length(X(:,1));
Y = zeros([Xval,length(W)]);
%% calculating the normalized matrix
for j=1:length(W)
   for i=1:Xval
   Y(i,j)=X(i,j)/sqrt(sum((X(:,j).^2)));
   end
end
Normalized_Matrix = num2str([Y]);
%% calculating the weighted normalized matrix
for j=1:length(W)
   for i=1:Xval
       Yw(i,j)=Y(i,j).*W(j);
   end
end
```

```
Weighted_Normalized_Matrix = num2str([Yw]);
%% calculating the positive and negative best
for j=1:length(W)
   if Wcriteria(1,j)== 0
       Vp(1,j)= min(Yw(:,j));
       Vn(1,j)= max(Yw(:,j));
   else
       Vp(1,j)= max(Yw(:,j));
       Vn(1,j)= min(Yw(:,j));
   end
end
Positive_best = num2str([Vp]);
Negative_best = num2str([Vn]);
%% Euclidean distance from Ideal Best and Worst
for j=1:length(W)
   for i=1:Xval
       Sp(i,j)=((Yw(i,j)-Vp(j)).^2);
       Sn(i,j)=((Yw(i,j)-Vn(j)).^2);
   end
end
for i=1:Xval
   Splus(i)=sqrt(sum(Sp(i,:)));
   Snegative(i)=sqrt(sum(Sn(i,:)));
end
%% calculating the performance score
P=zeros(Xval,1);
for i=1:Xval
   P(i)=Snegative(i)/(Splus(i)+Snegative(i));
```

```
end
% Calculating sum of all Performance Scores in iteration
Performance_score =  Performance_score + P;
% Plotting the 1000 iteration on one plot
plot(P)
hold on
end
hold off
% Determine average performance score
Average_Performance = Performance_score / 1000
plot(Average_Performance);
```

6.3 Code for Question 3

6.3.1 Matlab Code for AHP Weights

```
% input matrix of data
data = [1 1/2 1 3 7 2 3/2
2 1 3 1/3 3 1/2 1/5
1 1/3 1 1 5 1/3 1/5
1/3 3 1 1 3 1/4 1/5
1/7 1/3 1/5 1/3 1 1/4 1/7
1/2 2 3 4 4 1 1
2/3 5 5 5 7 1 1]
% normalize the matrix to create a pairwise comparison matrix
[n, m] = size(data);
normalized_data = zeros(n, m);
for i = 1:m
   column_sum = sum(data(:,i));
   normalized_data(:,i) = data(:,i) ./ column_sum;
```

```
end
% calculate the weighted sum of each row
weights = sum(normalized_data, 2) ./ n;
% calculate the consistency index and ratio
consistency_index = (max(eig(normalized_data)) - n) / (n - 1);
random_index = [0 0 0.58 0.9 1.12 1.24 1.32 1.41 1.45 1.51];
consistency_ratio = consistency_index / random_index(n);
% rank the items
[sorted_weights, rank] = sort(weights, 'descend');
% display the results
disp('Pairwise Comparison Matrix:');
disp(normalized_data);
disp('Weights:');
disp(weights);
disp('Consistency Ratio:');
disp(consistency_ratio);
disp('Ranking:');
for i = 1:n
   fprintf('%d. Item %d (weight = %.3f)\n', i, rank(i), sorted_weights(i));
end
```

6.3.2 Matlab Code for TOPSIS Method with AHP Weights

```
% Matrix for Problem 3 Individual
X = [36102.97143 13064696/175   5.32465 10 20 8 3.370742857 6
450000 15141685/35 10.3018 10 5 6 0.02857142857   4
1862.90683 233168/264 20.03977 40 2 3 1.29462822  5
83490 62351913/500   7.01046 40 1 5 1.06159053  7
807.0166366 790438.8286/333    3.62644 30 3 7 0.410960961 5
```

```
352573.2286 11932813/35   10.2683 10 3 7 0.02857142857   4]

% This weight is for AHP

W = [0.197505,0.12369,0.084075,0.08664,0.027645,0.17556,0.25498,0.05]

% TOPSIS Method

% Negative and Positive Values: 0 is negative, 1 is positive

Wcriteria = [0,1,0,0,1,1,0,1];

Xval=length(X(:,1));

Y = zeros([Xval,length(W)]);

%% calculating the normalized matrix

for j=1:length(W)

   for i=1:Xval

   Y(i,j)=X(i,j)/sqrt(sum((X(:,j).^2)));

   end

end

Normalized_Matrix = num2str([Y]);

%% calculating the weighted normalized matrix

for j=1:length(W)

   for i=1:Xval

       Yw(i,j)=Y(i,j).*W(j);

   end

end

Weighted_Normalized_Matrix = num2str([Yw]);

%% calculating the positive and negative best

for j=1:length(W)

   if Wcriteria(1,j)== 0

       Vp(1,j)= min(Yw(:,j));

       Vn(1,j)= max(Yw(:,j));

   else
```

```
        Vp(1,j)= max(Yw(:,j));
        Vn(1,j)= min(Yw(:,j));
    end
end
Positive_best = num2str([Vp])
Negative_best = num2str([Vn])
%% Euclidean distance from Ideal Best and Worst
for j=1:length(W)
    for i=1:Xval
        Sp(i,j)=((Yw(i,j)-Vp(j)).^2);
        Sn(i,j)=((Yw(i,j)-Vn(j)).^2);
    end
end
for i=1:Xval
    Splus(i)=sqrt(sum(Sp(i,:)));
    Snegative(i)=sqrt(sum(Sn(i,:)));
end
%% calculating the performance score
P=zeros(Xval,1);
for i=1:Xval
    P(i)=Snegative(i)/(Splus(i)+Snegative(i));
end
Performance_Score =  num2str([P])
```

6.3.3 Matlab Code for TOPSIS Sensitivity Analysis with AHP Weights

```
% Matrix for Problem 3 Combo
Data = [1273.942953 984694.2164/597 7.80945 35 5 5 0.801728392 5
71204.47407 82829371.5/675    6.37628 25 26 6.5 1.660259652 6.5
```

```
59994.49747 62301281.61/578    6.93087 15 36 7 1.260778547 4.75
40400.61266 28802195/474   7.33898 20 30 6 1.967641034 5
34856.02125 31084010.01/543    6.93796 16.66666667 26 7.333333333 1.340202578 5
12966.05618 13939891.62/508    5.21427 20 28 7.5 1.430570866 5.5]
% Monte Carlo Simulation
num_iterations = 1000;
% Range of Data matrices
Low = 0.9 * Data
High = 1.1 * Data
X = zeros(6, 8);
Performance_score = 0;
for i = 1:num_iterations
% Randomizing the matrix for a value between Low and High for each data point
for j = 1:6
   X(j, 1) = Low(j,1) + (High(j,1)-Low(j,1)).*rand;
   X(j, 2) = Low(j,2) + (High(j,2)-Low(j,2)).*rand;
   X(j, 3) = Data(j,3);
   X(j, 4) = Low(j,4) + (High(j,4)-Low(j,4)).*rand;
   X(j, 5) = Low(j,5) + (High(j,5)-Low(j,5)).*rand;
   X(j, 6) = Low(j,6) + (High(j,6)-Low(j,6)).*rand;
   X(j, 7) = Low(j,7) + (High(j,7)-Low(j,7)).*rand;
   X(j, 8) = Low(j,8) + (High(j,8)-Low(j,8)).*rand;
end
% This weight is for AHP
W = [0.197505,0.12369,0.084075,0.08664,0.027645,0.17556,0.25498,0.05];
% TOPSIS Method
% Weights, either positive or negative
Wcriteria = [0,1,0,0,1,1,0,1];
```

```
Xval=length(X(:,1));
Y = zeros([Xval,length(W)]);
%% calculating the normalized matrix
for j=1:length(W)
   for i=1:Xval
   Y(i,j)=X(i,j)/sqrt(sum((X(:,j).^2)));
   end
end
Normalized_Matrix = num2str([Y]);
%% calculating the weighted mormalized matrix
for j=1:length(W)
   for i=1:Xval
       Yw(i,j)=Y(i,j).*W(j);
   end
end
Weighted_Normalized_Matrix = num2str([Yw]);
%% calculating the positive and negative best
for j=1:length(W)
   if Wcriteria(1,j)== 0
       Vp(1,j)= min(Yw(:,j));
       Vn(1,j)= max(Yw(:,j));
   else
       Vp(1,j)= max(Yw(:,j));
       Vn(1,j)= min(Yw(:,j));
   end
end
Positive_best = num2str([Vp]);
Negative_best = num2str([Vn]);
```

```
%% Euclidean distance from Ideal Best and Worst
for j=1:length(W)
   for i=1:Xval
       Sp(i,j)=((Yw(i,j)-Vp(j)).^2);
       Sn(i,j)=((Yw(i,j)-Vn(j)).^2);
   end
end
for i=1:Xval
   Splus(i)=sqrt(sum(Sp(i,:)));
   Snegative(i)=sqrt(sum(Sn(i,:)));
end
%% calculating the performance score
P=zeros(Xval,1);
for i=1:Xval
   P(i)=Snegative(i)/(Splus(i)+Snegative(i));
end
% Adding sum of all performance scores
Performance_score =  Performance_score + P;
plot(P)
hold on
end
hold off
% finding average performance score for all iterations
Average_Performance = Performance_score / num_iterations
plot(Average_Performance);
```