Problem Title	2023	Team Number
Using Land: A Valuable Resource	**IMMC Challenge Summary Sheet**	**12519**

How do land developers decide what to build? In a small town near Syracuse, New York, there is a roughly 3-square-kilometer plot of land being considered for the development of a new business. The local "decision-makers" need help determining the best use of land given several business options, such as sports facilities and various types of farms. To help them decide, we designed a quantitative metric to define the "best" use of the land.

As a part of the problem, we were provided with the land characteristics and specific location of the plot. Additionally, we were instructed to assume that the plot of land has adequate water, power supplies, and soil that is sufficiently rich for crop farming or grazing animals.

To begin, we determined the most significant characteristics affecting land developers' decisions, leading us to divide the decision process into three main factors: (a) project feasibility, (b) long-term environmental conditions, and (c) economic potential. By evaluating these factors alongside individualized importance rankings, we were able to create a model that allows the decision-makers to balance community values and business profits in their final decision.

To determine the project's feasibility, our model considers usable surface area, average changes in elevation, and proximity to local bodies of water. Next, we used predictive modeling to anticipate the future conditions of the land, ensuring that our decision model is viable in the long run. Finally, we evaluated economic potential using financial indicators that account for profitability and community interests for each business option.

Since the decision-makers are willing to divide the property into different sections, we utilized the sliding-window method, which applies our decision-making process to multiple sizes of "windows" or subplots. Specifically, we divided the land into either four windows, two vertical windows, two horizontal windows, or one window that encompasses the whole piece of land. Through this process, every business receives a "best" fit score for each subplot, allowing us to identify the optimal choice for each section of land.

Initially, our model determined that a grazing farm is the most optimal choice when looking at the plot of land as one piece. When divided vertically into two subplots, the left and right sides best suit an agrivoltaic farm and outdoor sports complex, respectively. If the land is horizontally divided into two pieces, a grazing farm would best suit the top half, while a skiing facility would utilize the mountainous land on the southern part of the plot. Finally, when partitioned into four sections, grazing farms would best fit the top two sections, an agrivoltaic farm would best suit the bottom left corner, and an outdoor sports complex would best fit the bottom right corner of the plot.

After determining our model's "best" business choices, we evaluated the impact of a soon-to-be-built semiconductor fabrication facility on our recommendation. When constructed, the facility is estimated to create 9,000 local jobs and 40,000 external jobs. As a result, we revised our economic model to account for changes in the job market associated with the presence of other companies. These final results and recommendations are detailed in our letter to the decision-makers.

We concluded that our model is highly adaptable because the process does not need to be modified for additional business options, enabling users to apply it to virtually any plot of land.

Letter to the Decision Makers

March 12, 2023

Dear Decision Makers,

We are writing to inform you of our most recent research on the business that "best" fits the given plot of land. We are pleased to present our model's results, which take into account various factors to most accurately determine the best business for the plot of land.

We first determined each business's feasibility by analyzing the plot's topographical data. Next, we considered long-term environmental factors to determine how well the land would continue to fit the business we chose in the future. Additionally, we examined financial indicators for the economic success of each business relative to the surrounding community. Finally, we incorporated the economic effects of constructing a new semiconductor fabrication facility into our model.

To analyze these factors, we developed a sliding window model to allocate optimal business choices to specific sub-regions of the plot. In addition to considering the plot of land as a whole, we partitioned the land into two vertical halves, two horizontal halves, and four quadrants.

From our thorough, detailed, and adaptable mathematical model that considers both feasibility and community values, we propose the following suggestions for your review:

— If willing to split the land into four sections, the upper left and bottom right quarters should be allocated towards a sports complex, the lower left should house an agritourist center, and the upper right should belong to a grazing farm.

— If the land is to be vertically split into halves, the left-hand side should be designated to an agritourist center and the right-hand side should belong to an outdoor sports complex.

— If the land is to be horizontally split into halves, a cross-country skiing facility would best fit the top portion while a grazing farm would best fit the bottom portion.

— Lastly, if the land is not to be partitioned, but rather considered as a whole, a grazing farm would be the best fit.

Our suggestions were determined from a complete review of short-term and long-term factors, including community views and competitors in the local region. Additionally, if the priorities of each business option change, the decision model can be easily adapted to any business needs. Furthermore, our decision model generalizes to other plots of land with the need of location-specific data only.

We anticipate that our research and suggestions will aid in the decision process to develop this plot of land.

Best regards,

Team 12519

Contents

1 Introduction 4
- 1.1 Background 4
- 1.2 Problem Restatement 4
- 1.3 Assumptions 4

2 Part 1: Creating a "Best" Metric 5
- 2.1 Problem Analysis 5
- 2.2 Variables 6
- 2.3 Topographical Factors: What Makes a Project Feasible? 6
  - 2.3.1 Usable Surface Area 6
  - 2.3.2 Average Elevation Change 7
  - 2.3.3 Bodies of Water . . . 7
- 2.4 Sustainability Factors: Long-Term Environmental Conditions 8
  - 2.4.1 Sunshine Levels . . 8
  - 2.4.2 Precipitation Levels . 9
  - 2.4.3 Deforestation 11
- 2.5 Economic Factors: Time to Make Money 11
  - 2.5.1 Revenue and Expenditures 11
  - 2.5.2 Growth 12
  - 2.5.3 Risk 12
  - 2.5.4 Competitors 12
  - 2.5.5 Combined Economic Score 13
  - 2.5.6 Collected Financial Data 13
- 2.6 Calculating a "Best" Score . 13
  - 2.6.1 Combined Scores Matrix 13
  - 2.6.2 High-Low Matrix . . 13
  - 2.6.3 Importance Matrix . 15
  - 2.6.4 Final Score Calculation 15

3 Part 2: Applying Our Model to Specific Scenarios 16
- 3.1 Sliding Window Analysis . . 16
- 3.2 Results 17
  - 3.2.1 Two Partitions . . . 17
  - 3.2.2 A Singular Vertical Partition 18
  - 3.2.3 A Singular Horizontal Partition 19
  - 3.2.4 Zero Partitions . . . 19
- 3.3 Model Discussion 20
  - 3.3.1 Strengths 20
  - 3.3.2 Limitations 20

4 Part 3: Understanding Potential External Factors 21
- 4.1 Problem Analysis 21
- 4.2 Revised Model Scores 21
  - 4.2.1 Strengths 22
  - 4.2.2 Limitations 22

5 Part 4: Generalizability of our Model 23

6 References 24

7 Appendices 26
- 7.1 Appendix 1. Fourier Series Parameters 26
- 7.2 Appendix 2. Collected Financial Data Table 27
- 7.3 Appendix 3. ML Sunlight Level Prediction 28
- 7.4 Appendix 4. Fourier Series Precipitation Prediction . . . 30
- 7.5 Appendix 5. (Part 2) Economic Factor Calculation . . 32
- 7.6 Appendix 6. Sliding Windows Implementation 34
- 7.7 Appendix 7. Importance Matrix Justification 39
- 7.8 Appendix 8. (Part 2 and 3) Score and Spearman's Coefficient Calculations 43

1 Introduction

1.1 Background

Community leaders and business planners are constantly trying to work together to find the best use of local land. This often requires balancing community values and business profits by taking into account factors such as geography, climate, business options, community needs, and local culture to make important decisions.

1.2 Problem Restatement

Located near Syracuse, New York, is a 3 km^2 plot of land available for development. We are tasked with developing a process to aid local decision-makers in determining the "best use" of this plot of land.

The decision-makers have already considered multiple options for the land: an outdoor sports complex, a cross-country skiing facility, a crop farm, a grazing farm, a regenerative farm, a solar array, an agrivoltaic farm, and an agritourist center. The decision-makers are also open to considering other options or dividing the property into sections with different uses.

Overall, we have four tasks:

1. We are asked to develop a **quantitative decision metric** that defines what the "best use" of land is. This metric should consider long and short-term benefits and costs.
2. We should use our "best" metric to **score at least two of the options** the decision-makers are currently considering.
3. It was recently announced that a large semiconductor factory will be built in a town near the plot of land. We need to determine how **the construction of this factory will affect our "best" metric**, and additionally, re-evaluate the options using the new "best" metric.
4. We need to **explore the generalizability of our model** and understand how it applies and what might change if used elsewhere.

1.3 Assumptions

1. **The plot of land has sufficient irrigation.**

   Justification: We assume that the plot of land has a sufficient minimum level of irrigation. However, the quality of irrigation can be improved when considering rain levels and proximity to bodies of water.

2. **The Mercator Projection yields an accurate rectangular surface.**

   Justification: The Mercator Projection is a rectangular-based mapping system. Because the plot of land (3 km^2) is relatively small when compared to other continents, the Mercator Projection for latitude and longitude will not affect accuracy by a significant margin [1].

3. **Soil fertility and nutrient levels are uniform throughout the whole plot of land.**

   Justification: The village of Red Creek (where the plot of land is located) has historically had high soil fertility [2] [3] [4].

4. **Natural disasters are not a major concern for this region.**

Justification: Since the parcel of land is near the Atlantic Seaboard, flooding is the area's primary type of natural disaster. However, there have historically been few floods many floods, and the local county has implemented policies to mitigate the risk of flooding. Thus, natural disasters are not a significant concern for the development of this plot [3] [5].

5. **Deforestation refers to the total removal of trees and foliage.**

   Justification: For calculating deforestation and its effects on our model, we assume that if deforestation is necessary for a specific business, then deforestation will occur over the whole plot of land. As stated in the problem, only 38% of land is forest; therefore, it is assumed that businesses that value tree coverage will keep all trees while businesses that need additional usable surface area will remove all trees.

6. **Similar businesses are representative of proposed business options**.

   Justification: In order to conduct competitor analysis and understand the financial abilities of each land-use case, we assumed that the economic characteristics of similar external corporations and businesses are representative of the companies in this problem.

2 Part 1: Creating a "Best" Metric

2.1 Problem Analysis

Our first step in developing a metric to "best" fit a business to the plot of land was to determine the most essential contributors to a successful business. Because the decision-makers want to balance business profits with community values, we evaluated economic factors, community sustainability, and the feasibility of a project—which is affected by the topography of the land.

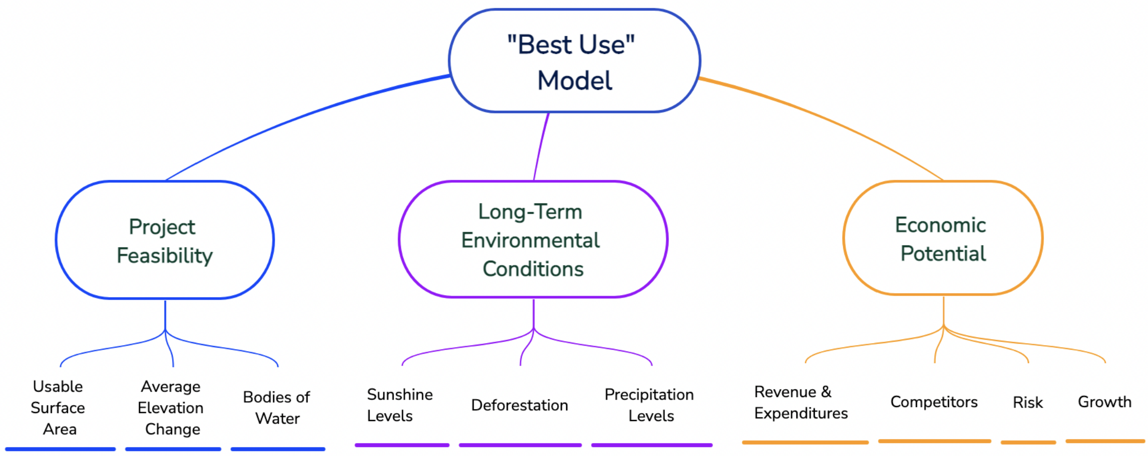

Figure 1: **Impacting factors hierarchy tree**. A tree of all factors we considered in our decision model for choosing the "best" business.

2.2 Variables

Variable	Symbol	Description
Longitudinal Coordinate	x	Longitudinal degree at point (x, y).
Latitudinal Coordinate	y	Latitudinal degree at point (x, y).
Region of Choice	c_i	Sliding window analysis region.
Area of Water Body	A_{water}	Area of nearest water body to region c_i
Tree Coverage	T	Percentage of tree coverage at (x, y).
EBITDA	$EBITDA$	The yearly earnings of a company prior to interest, tax, depreciation, and amortization to calculate profitability [6].
Earnings Per Share	EPS	The earnings per market share in the most recent yearly report of a company [7].
Sales Growth Percentage	SG	The percentage growth in total sales revenue over the past five years [8].
Gross Profit Growth Percentage	GPG	The percentage growth in total gross profit over the past five years of a company adjusted for inflation [8].
Standard Deviation	σ	The standard deviation of company's market prices [9].
Relative Strength Index	RSI	A financial indicator of the validation of a stock [10].
Operating Cash Flow Ratio	OF	The availability of cash flow in a company [11].

2.3 Topographical Factors: What Makes a Project Feasible?

One of the main concerns among land developers is the feasibility of a project. This is mainly affected by the initial state of the land, or *topography*. Thus, we considered three key topographical factors: (1) Usable Surface Area, (2) Average Elevation Change, and (3) Distance to Bodies of Water. For example, flatter land may be more suited for farming, whereas mountainous land would better suit a ski resort. Likewise, distances from bodies of water may also affect land use.

2.3.1 Usable Surface Area

Usable surface area is an important factor to consider because different businesses prioritize the amount of usable land differently. The usable surface area includes all land area, excluding bodies of water, as trees can be cut down to increase usable space but water cannot be removed.

In general, the surface area varies with elevation; therefore, we need to determine the elevation of specific points on the plot of land. We used ArcGIS, an online geographic information system, to discretely sample elevation data on the property, which we then used to create a continuous elevation function $E(x, y)$ where x and y are the longitude and latitude components, respectively [12]. Given a point (x, y) on the plot of land, the elevation function returns the altitude, or z-coordinate, in kilometers at that point. Note that we previously assumed the longitudinal and latitudinal coordinates of the Mercator Projection are rectangular.

For a region of choice c_i, we calculated the surface area $SA(c_i)$ using a three-dimensional surface integral to account for sloped land. The elevation data was discretely obtained, such that each (x, y) coordinate is spaced 0.174 km or $1.56 \cdot 10^{-3}$ degrees longitude and $1.04 \cdot 10^{-3}$ degrees latitude apart. Let $\frac{\partial E}{\partial x}$ be the change in elevation along the longitudinal axis and $\frac{\partial E}{\partial y}$ be the change along the latitudinal axis, where (x, y) are coordinates. Then, we parameterized each surface differential as a rectangle, so that the area is the product of the lengths of the sides. Finally, we sum the *usable*, or non-water, surface differential areas over the latitudinal and longitudinal axes to find the surface area of the land (Figure 2).

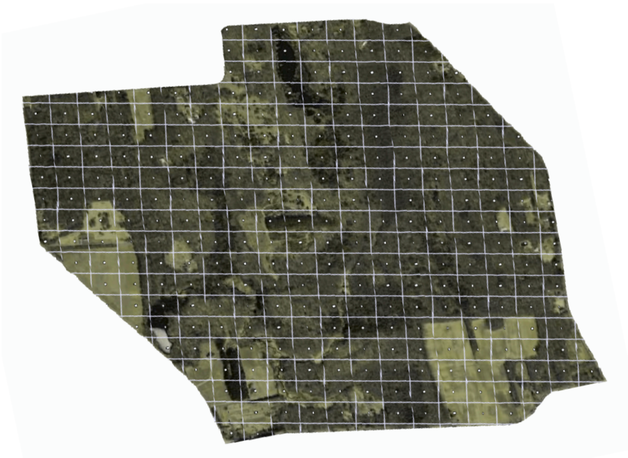

Figure 2: **A bird's eye view of the parcel of land**. Grid drawn to represent points for our discrete (x, y) coordinates.

$$SA(c_i) = \sum_{i=0}^{n} \sqrt{x_i^2 + \left(\frac{\partial E}{\partial x}_i\right)^2} \cdot \sqrt{y_i^2 + \left(\frac{\partial E}{\partial y}_i\right)^2} \qquad \forall \text{ usable } (x_i, y_i) \in c_i \tag{1}$$

2.3.2 Average Elevation Change

Next, we created a function to determine the average elevation change given a specific area. Knowing the average change in elevation is crucial for businesses such as ski facilities, which require hills for ski trails, and for farms, which benefit from minimal elevation change.

Similar to the surface area, in order to find average elevation change, it is necessary to use the elevation function defined previously. For elevation function $z = E(x, y)$, we find the average of the gradients along the region of choice. To calculate a gradient at point (x, y), we find the magnitude of the gradient in the latitudinal and longitudinal directions. Finally, we sum and calculate the mean of all of the gradients along the region of choice c_i.

$$\bar{\Delta E}(c_i) = \frac{1}{n} \sum_{i=0}^{n} \nabla E_i = \frac{1}{n} \sum_{i=0}^{n} \sqrt{\left(\frac{\partial E}{\partial x}_i\right)^2 + \left(\frac{\partial E}{\partial y}_i\right)^2} \qquad \forall (x_i, y_i) \in c_i \tag{2}$$

2.3.3 Bodies of Water

Next, we created a metric to quantify the impact of the nearest body of water on a given region. Proximity to bodies of water is crucial, as it can significantly impact certain businesses. For

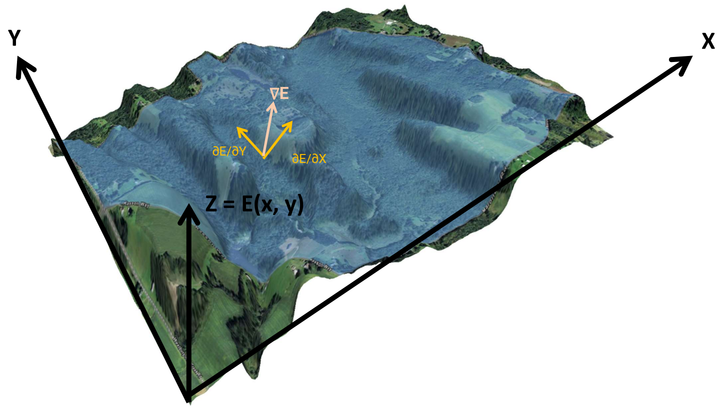

Figure 3: **An isometric view of the parcel of land, representative of the plot elevation.** The visual representations for gradients by component are also shown.

example, farms can benefit from being near a body of water to aid crop growth, while outdoor sports complexes may be less affected.

To calculate the impact of the nearest body of water on the region of choice c_i, we calculate this impact score function $W(c_i)$ as the root of distance in kilometers from the center of the region of choice c_i and the nearest point to a river or lake as defined by the topography graphs. We chose the root function to scale the penalty for greater distances and not make their penalty disproportionate. Furthermore, define the nearest water body to have area A_{water}. Thus, we defined the impact score as follows in Equation 3.

$$W(c_i) = \frac{A_{\text{water}}}{\sqrt{\sqrt{(\bar{x_{c_i}} - x_{\text{water}})^2 + (\bar{y_{c_i}} - y_{\text{water}})^2}}} \tag{3}$$

2.4 Sustainability Factors: Long-Term Environmental Conditions

In addition to the initial feasibility factors, we evaluated long-term environmental impacts on the land. To achieve this, we examined three climate and sustainability components that could impact business models, namely: (1) levels of sunshine, (2) levels of precipitation, and (3) the extent of deforestation.

2.4.1 Sunshine Levels

Sunshine levels can be a critical factor in the success of certain businesses, particularly in agriculture, where sufficient sunlight is essential for optimal crop growth. To forecast future sunshine levels in the region, we utilize a function $S(t)$, which measures sunlight in hours per month, with t representing the number of months after March 2023. The total amount of sunlight over the next n months can be calculated using this function as follows:

$$\text{Total Sunlight} = \int_0^n S(t)dt \tag{4}$$

To ensure that our model accounted for the long-term effects of global warming, such as increasing cloud cover, we aimed to move beyond a simple cyclic model of sunshine levels based on seasonal changes [13].

We trained a Tensorflow deep learning model using over a hundred samples of sunshine data collected from Central NY, which includes several hidden layers, LSTM layers, and a prediction layer. Unlike predictive Markov models, deep learning models can handle complex patterns in data and produce more accurate predictions [14] [15]. We utilized Long Short-Term Memory nodes in the model to process temporal data and maintain predictions throughout the model (Figure 4).

LSTMs, as shown in Figure 4, are often used in temporal data processing and deep learning applications. In this case, we used LSTMs to use a previous window of sunlight data to predict the next month's sunlight level.

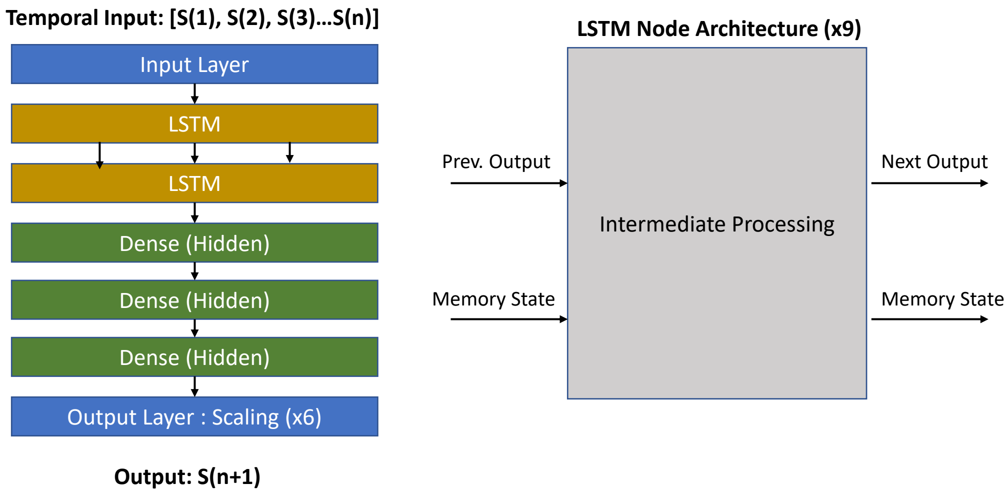

Figure 4: **Deep learning model architecture.** We utilized temporal-based nodes within our network to make better temporal predictions. By using a memory state, we can achieve higher accuracies [14].

To optimize the prediction model's performance, we trained it on historical sunlight data for 100 iterations using the Mean Absolute Error (MAE) metric described in Equation 5 [16]. The training resulted in a robust sunlight prediction model with an MAE of 15.2. See Figure 5 for future prediction results.

$$\text{MAE} = \frac{1}{n}\sum_{i=0}^{n} |S_{\text{true}} - S_{\text{pred}}| \tag{5}$$

2.4.2 Precipitation Levels

Precipitation levels, like sunshine levels, can also significantly impact the success of businesses on the proposed land, depending on the objectives of individual companies.

To account for future precipitation levels and potential future outlooks for rain-dependent business models, we developed a sinusoidal regression model of best fit to represent the cyclical nature of precipitation. First, we collected historical precipitation data of monthly precipitation in inches from the past 150 years [17].

Using the window from the past 25 months, we fit a Fourier series, $R(t)$ to the data to predict future precipitation levels. We chose a Fourier series to model the cyclical data because of the varying amplitudes and periods of the data. $R(t)$ measures the monthly precipitation level in inches for month t after March 2023. The typical Fourier series is in the form of Equation 6. Our program to fit a Fourier series utilized a χ^2 Goodness of Fit test to determine the accuracy

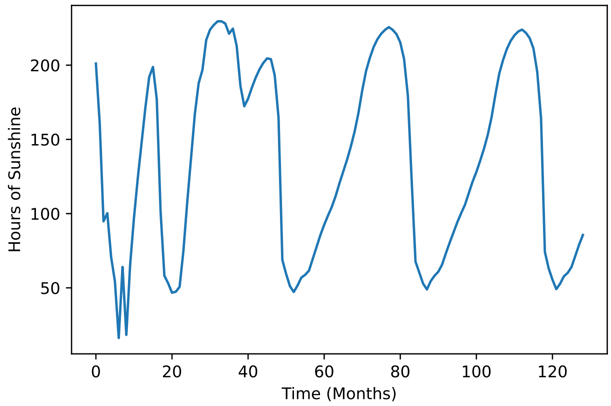

Figure 5: **Predicted sunshine levels.** Amount of sunshine per month after March 2023.

of the calculated sinusoidal function in our model. Additionally, we set the degree of the series, n, to 10 to account for the variable nature of the series as well as the unique qualifications needed for a statistically relevant model. More specifically, 10 serves as the minimum degree number that can be statistically analyzed.

$$R(t) = a_0 + \sum_{i=1}^{n} a_i + \cos(\omega x) + b_i \sin(\omega x) \tag{6}$$

Using technical computing software as shown in Appendix 4, we determined the values of the parameters of the Fourier series as shown in Table 5 in Appendix 1.

Using our model, we can predict the total precipitation level over the next n years using Equation 7. The rain prediction chart is shown in Figure 6.

$$\text{Total Rain} = \int_0^n R(t)dt \tag{7}$$

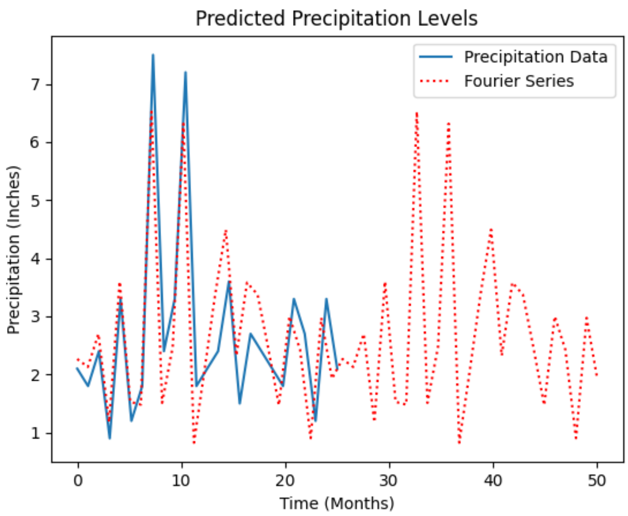

Figure 6: **Rain prediction graph over time.** The Fourier series uses the periodic attribute to project rain levels over the next several months.

2.4.3 Deforestation

Next, we created a deforestation factor to accommodate individual business needs. For example, while some businesses prefer keeping trees, such as a ski resort for ski trails, some rely on deforestation to gain usable surface area, such as farms. Moreover, deforestation has social and cultural implications that can impact a company's revenue, as seen with agritourism centers that rely on community tourism.

To consider the impact of deforestation on community views, we define a function $D(c_i)$ for the region of interest c_i, which measures the number of trees and natural foliage removed while starting a business. We assume that as the number of removed trees increases, the business's impact on community views also increases. The tree cover percentage at a specific coordinate (x, y) is denoted as $T(x, y)$.

We express the deforestation function as Equation 8, which integrates the percentage forest coverage over the region of interest to determine the total forest coverage removed in km^2.

$$D(c_i) = \iint_{c_i} T(x, y)dxdy \qquad \forall(x, y) \in c_i \tag{8}$$

2.5 Economic Factors: Time to Make Money

Lastly, we determined that economic factors, such as potential revenue, growth, expenditures, risk, and nearby competitors, will affect how well a business will "fit" in the plot of land.

In order to fully account for these factors we conducted a thorough market analysis for each business option. In our analysis, we determined the two most *similar* publicly-held companies for each business option, denoted as sb_k. We determined similarity between businesses and business choice b_i by company location and, most importantly, company mission. From each similar company, we collected yearly financial statements, stock prices, and financial indicators to determine company health.

In each of the sub-factors below, we normalized the output values to be near 0 to 1. The normalization was performed to allow addition of the scores without heavy skew caused by large discrepancies or outliers.

2.5.1 Revenue and Expenditures

We predict business model b_i's potential revenue and expenditures, and consequentially, profit. In Equation 11, we developed a profit score $P(b_i)$ of business choice b_i as a function of *similar* business profit performances. First, we calculated $EBITDA$ margins of the n *similar* businesses for business choice b_i, which are an evaluation of earnings per total revenue. The formula for $EBITDA$ margin can be found in Equation 9, which indicates the potential profitability of *similar* businesses. Next, we calculated Price to Earnings PE ratios per n *similar* businesses to factor in the value of the company. These financial indices are collected from the most recent yearly report. The formula for the PE ratio can be found in Equation 10.

$$\text{EBITDA Margin} = \frac{\text{Earnings Before Interest, Tax, Depreciation, Amortization}}{\text{Total Revenue}} \tag{9}$$

$$PE \text{ Ratio} = \frac{\text{Market Value Per Share}}{EPS} \tag{10}$$

Since a higher $EBITDA$ margin and lower PE ratio (near 10) is desirable for a profitable and high-earning company, we developed the following weighted average function for profit score $P(b_i)$ in Equation 11. Since $EBITDA$ margin is a percentage between 0-1, we were able to make sure that the score was normalized. Furthermore, an optimal PE ratio would be near 5 to 10 since a lower PE ratio is better, so we divided 10 by the PE ratio to create a normalized score.

$$P(b_i) = \frac{1}{n}\sum_{k=0}^{n} EBITDA\,\text{Margin}_{sb_k} + \frac{10}{PE\,\text{Ratio}_{sb_k}} \tag{11}$$

2.5.2 Growth

Next, we developed a growth score $G(b_i)$ to assess the potential growth in a company. This was used to further evaluate the long-term goals of a business model b_i. First, we considered *similar* company sales and inflation-adjusted gross profit growth over the past five years as percentages. Next, we denote sales growth as SG_{sb_k} and gross profit growth as GPG_{sb_k}, both of which are expressed as percentages. Then, we normalized these percentage scores by dividing them by one hundred and setting their weights as 0.3 and 0.7 to scale the scores between 0 and 1. These growth percentages were included to measure potential growth in our business choice.

We defined our growth score to be Equation 12 as a weighted average of sales growth and gross profit growth over all n *similar* businesses sb_k. Thus, the higher the growth score, the greater potential growth this company has. Since we decided that profitability depends on gross profit growth more than sales growth, our weighted average leaned towards GPG.

$$G(b_i) = \frac{1}{n}\sum_{k=0}^{n} \frac{1}{100}\left(0.3SG_{sb_k} + 0.7GPG_{sb_k}\right) \tag{12}$$

2.5.3 Risk

We define the *risk* function as the score $\zeta(b_i)$ of company failure. The greater the ζ score, the greater the probability of company bankruptcy or failure and the lower the ζ score, the lower the probability of company failure.

To analyze the *risk* of a potential company b_i, we find a weighted average of current risk-indicators such as the Standard Deviation of Market Prices σ, Relative Strength Index RSI, and Operating Cash Flow Ratio OF financial indicators in *similar* businesses, sb_k. Standard deviation, or σ, is an indicator of volatility, or instability, of a company. Furthermore, indicators such as RSI and OF are measures of risk and stability, respectively. More specifically, these financial indices are collected from the most recent yearly report. We define risk score as a weighted mean over the n *similar* businesses of the risk indicators in Equation 13.

$$\zeta(b_i) = \sum_{k=0}^{n} \frac{1}{100}\sigma_{sb_k} + \frac{1}{80}RSI_{sb_k} - \frac{1.1}{OF_{sb_k}} \tag{13}$$

Furthermore, we scaled the RSI index by 80 since greater RSI indicates overvalued companies, and thus a greater risk. Lastly, we divided 1.1 by the OF ratio and subtracted this factor. Ratios greater than 1.1 would signify a decreased risk, since a greater cash flow suggests stability in a company. A lower or negative OF would signify greater risk, thus we used the reciprocal of OF.

2.5.4 Competitors

If a potential business model has nearby competitors within a radius of 25 miles, it will negatively impact the potential business model b_i. The farther the competing business is, the less of an impact the competitor will have. Thus, we define our competitor function (within 25 miles)

$\Upsilon(b_i)$ of business model b_i as the sum of the root of the distance in kilometers between the 3 km^2 plot of land and the n competitor(s) as seen in Equation 14.

$$\Upsilon(b_i) = \sum_{k=0}^{n} \frac{1}{\sqrt{\text{distance}_k}} \tag{14}$$

This score is normalized as the distances are in the denominator, thus the individual score per competitor will be near or less than 1.

2.5.5 Combined Economic Score

Since each score is normalized, we can add the scores to achieve a total economic score E_c (Equation 15). We subtracted negatively-affecting scores such as risk and competitors and added the positively-affecting scores such as profitability and growth.

$$E_c(b_i) = P(b_i) + G(b_i) - \zeta(b_i) - \Upsilon(b_i) \tag{15}$$

2.5.6 Collected Financial Data

For input values to the financial model scores, all collected data was obtained from publicly held companies who maintained companies and sites similar to our land plot. The full table of values can be found in Table 6 [18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31].

2.6 Calculating a "Best" Score

In order to account for the three major areas in our decision-making for planning the use of the land, we designed a decision matrix. The proposed decision matrix calculates each topographical, sustainability, and economic factor for each region of choice and business model. Then, we scale using a normal distribution to the resulting values of each factor to find out which factors are stronger in each region of interest. Lastly, we choose the business model with rankings of factors that best align with the region of interest.

2.6.1 Combined Scores Matrix

For each region of interest c_i and business model b_i, a *raw* combined score matrix **RS** will be calculated as a vector of values from each individual factor.

$$\mathbf{RS} = \begin{array}{r} \\ \text{Sports Complex } (b_1) \\ \text{Ski Facility } (b_2) \\ \text{Crop Farm } (b_3) \\ \text{Grazing Farm } (b_4) \\ \text{Regen. Farm } (b_5) \\ \text{Solar Array } (b_6) \\ \text{Agrivoltaic Farm } (b_7) \\ \text{Agritourist Center } (b_8) \end{array} \begin{array}{c} \begin{array}{ccccccc} SA & \Delta E & W & S & R & D & Ec \end{array} \\ \begin{bmatrix} SA(c_i) & \Delta E(c_i) & W(c_i) & \int_0^n S(t)dt & \int_0^n R(t)dt & D(c_i) & E_c(b_i) \\ \cdots & & & & & & \\ & \cdots & & & & & \\ & & \cdots & & & & \\ & & & \cdots & & & \\ & & & & \cdots & & \\ & & & & & \cdots & \\ & & & & & & \cdots \end{bmatrix} \end{array}$$

2.6.2 High-Low Matrix

The criteria considered in this matrix were categorized into three major groups: Topography, Sustainability, and Economic Factors. We defined the *High-Low Matrix* based on the priorities of each business model for the feasibility factors. For each value HL_{ij} in *High-Low Matrix* **HL**, we assign a 1, 0, or -1. We assign a 1 to HL_{ij} if business choice in row i desires a high output in the score of column j. Consequentially, we assign a -1 to HL_{ij} if business choice in row i desires a low output in the score of column j. Lastly, we assign a 0 if the business desires a middle-ground output in the score column or if there is no relevance of the score to the business.

$$\mathbf{HL} = \begin{array}{r} \\ \text{Outdoor Sports Complex} \\ \text{Ski Facility} \\ \text{Crop Farm} \\ \text{Grazing Farm} \\ \text{Regenerative Farm} \\ \text{Solar Array} \\ \text{Agrivoltaic Farm} \\ \text{Agritourist Center} \end{array} \begin{array}{c} \begin{array}{ccccccc} SA & \Delta E & W & S & R & D & Ec \end{array} \\ \begin{bmatrix} 1 & -1 & 0 & 1 & 0 & 0 & 1 \\ 1 & 1 & 1 & 0 & -1 & -1 & 1 \\ 1 & -1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 0 & 1 & 1 & 1 & 1 & 1 \\ 1 & 0 & 0 & 1 & 1 & -1 & 1 \\ 1 & 0 & 0 & 1 & 0 & 1 & 1 \\ 1 & -1 & 1 & 1 & 1 & 1 & 1 \\ 1 & -1 & 1 & 1 & 0 & -1 & 1 \end{bmatrix} \end{array} \tag{16}$$

The factors for **topography** are as listed and each *High-Low* value is discussed below.

1. Usable Surface Area (SA)

   In this case, all businesses want to utilize as much space as they can; therefore, all companies want a high usable surface area or a score of 1.

2. Elevation Change (ΔE)

   Ski facilities benefit from significant elevation changes for ski trails, while outdoor sports complexes and crop farms benefit from less elevation change or flat land. Grazing farms, regenerative farms, and solar arrays are indifferent to elevation change.

3. Water (W)

   The two primary businesses that benefit from being near a body of water are agricultural farms and ski facilities; proximity to water increases irrigation quality, and water can be used to create fake snow. Other listed businesses do not require close proximity to a body of water, thus receiving lower values in the matrix.

The factors for **sustainability** are as listed and each *High-Low* value is discussed below.

1. Sunshine Amounts (S)

   In most cases, high sunshine levels are beneficial for crop growing, harvesting energy from solar panels, or attracting tourists with good weather. The only company that would not need sunshine is a ski facility since it is possible to ski when it is lightly snowing as well as later in the evening once the sun has set.

2. Rain Levels (R)

   All farms benefit from rain to aid crop growth. However, a solar array farm and an agritourist center are indifferent to rain since the former does not include any crop growing. The latter requires a balance between rain for crops and good weather to attract tourists. Conversely, a ski facility would not benefit from rain since it could cause snow on its trails to melt.

3. Deforestation Levels (D)

   For most farms, deforestation is necessary for additional crop growth as it increases usable surface area. Regenerative farms and agritourist centers are exceptions, as they prioritize sustainability and community views. Ski facilities also do not benefit from deforestation, as trees are beneficial to ski trails. Outdoor sports complexes are generally indifferent to deforestation since their land is not heavily forested, but they may cut down trees if needed.

Lastly, since all business models b_i would desire a greater economic score, we set the *High-Low* value to be 1 for all companies.

2.6.3 Importance Matrix

We created an importance matrix to assess the significance of different factors for each company, taking into account their unique values and objectives. For instance, sunshine is crucial for solar arrays to generate energy, making it the top priority. In contrast, elevation and economy are more essential for ski facilities. We conducted this evaluation for all eight types of businesses in our model, and the resulting importance matrix can be found in Figure 7.

More specifically, we ranked each factor for each business on a scale of 1 to 7, 1 being most important for that company and 7 being least important. We did this by considering the values of each company and what would be most important for the success of each business. Detailed derivations of each rank for each company are discussed in Appendix 7.

We decided that an importance matrix would be the most suitable approach for our model and would minimize bias when scaling each factor for each company. Unlike a weighted scale of importance, a ranking system considers the varying significance of different factors to different businesses.

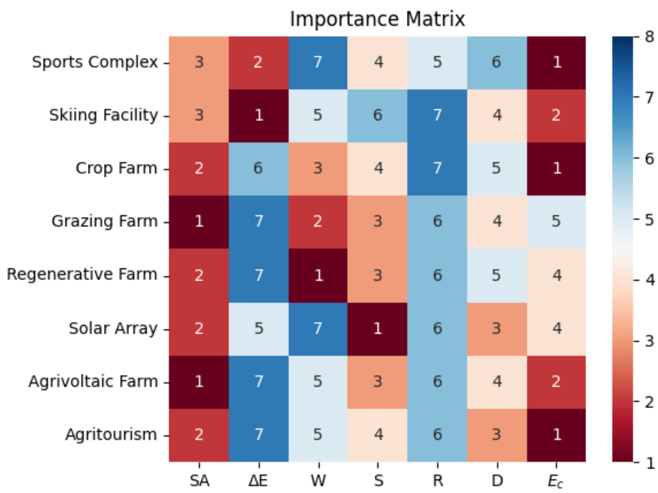

Figure 7: **Importance Matrix**. Approximated rankings of importance for matrix **I** for each business model b_i.

2.6.4 Final Score Calculation

Because the Raw Score calculation is challenging to compare and analyze, we devised a new method for calculating the final score. Our approach employs a normal distribution, z-scores, and rank correlation analysis techniques. Figure 8 visually depicts our final score calculation.

First and foremost, we normalized the raw scores from matrix **RS** by column, such that value RS_{ij} would be normalized by the values of column j and corresponding column j's in other raw score matrices from the sliding window analysis in Part 2. We conducted normalization in order to analyze factors with respect to mean values, so we normalized the raw score using the z-score of RS_{ij}.

Thus, for raw score matrix **RS**, we are to obtain a new matrix **RS'** of z-scores for each score RS_{ij}. However, since some scores are more desirable as negative or lower values while others are more desirable as higher values, we utilized the *High-Low Matrix* to account for these stark differences. For each row i in z-score matrix **RS'**, we perform element-wise multiplication to row i of matrix **HL**. Thus, we are able to obtain appropriately scaled values with respect to desirable outcomes.

Lastly, our model considers rank correlation in order to find the business model best fit for our final scores. In order to compare our z-scores from matrix **HL'**, we used the Spearman's Rank Correlation Coefficient (ρ) to find a business model that best fits the rankings from the Importance Matrix **I** (Figure 7). We rank the z-scores from matrix **RS'** to compare to matrix **I**. The Spearman's Rank Correlation Coefficient finds the correlation from a scale of -1 to 1, with 1 representing the highest correlation in rankings, and thus the best business model choice has the greatest coefficient [32]. The formula for the Spearman's Rank Correlation Coefficient (ρ) is described in Equation 17 where d_i is the difference in rankings between the ith pair of rankings and n is the total number of rankings.

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)} \tag{17}$$

Therefore, the business model b_i that has the **greatest Spearman Correlation Coefficient is the optimal choice**.

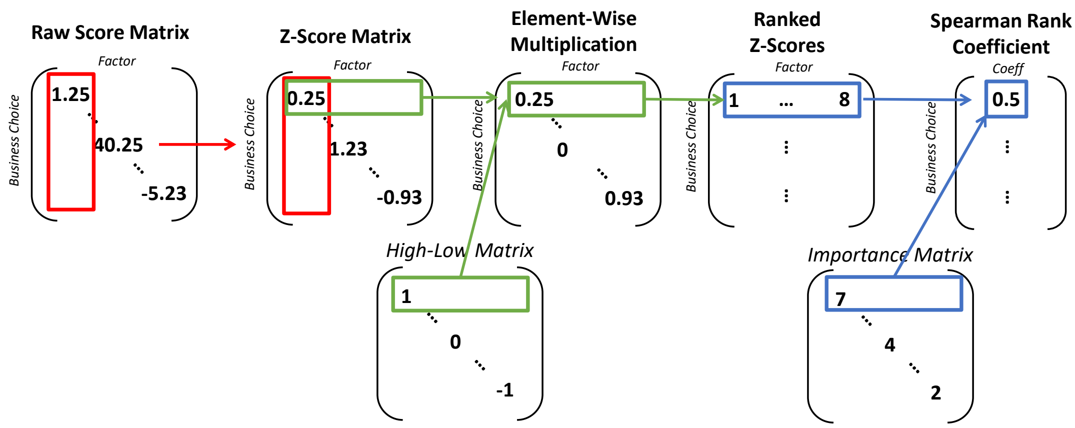

Figure 8: **Flowchart for final score calculation.** Utilizes z-scores, the *High-Low Matrix*, and Rank Correlation analysis techniques.

3 Part 2: Applying Our Model to Specific Scenarios

3.1 Sliding Window Analysis

We utilized a sliding window analysis technique to assess our decision model on the plot of land. This approach involved applying the decision model to various windows throughout the land. Using a sliding window, we could determine the best business model for each section of the land.

As shown in Figure 9, we partitioned the plot of land with two, one, one, and no partition. From each partition, we applied our decision model onto the window to calculate the raw score, z-scores, and conduct rank correlation analysis. The implementation for our sliding window analysis can be found in Algorithm 1. In order to collect data on the topographic variables; surface area, elevation change, and distance from water, we decided to work with ArcGIS.

Additionally, once each window is analyzed separately using our model, we compared all the windows using our previously discussed decision method in order to finalize which business choice best fits each window.

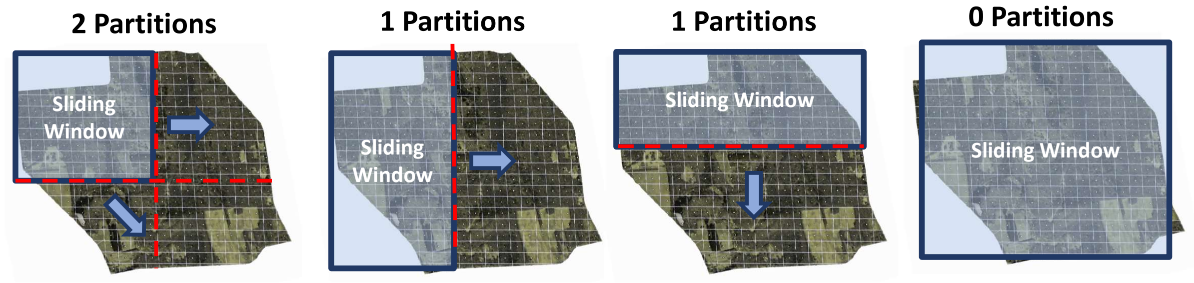

Figure 9: **Sliding window visualization.** Displays four sliding window considerations with 2, 1, 1, and 0 partitions, respectively.

Algorithm 1: An algorithm to implement sliding windows. X is the score matrix, HL is the *High-Low Matrix*, I is the importance matrix, and Y is the vector of the final Spearman's Coefficients.

$X \leftarrow [[0...0]...[0...0]]$;
$HL \leftarrow [[1..0..-1]...[0..-1..1]]$;
$I \leftarrow [1..3..8]...[5..2..7]]$;
$Y \leftarrow [0...0]$;
for $W \in$ *WINDOWS* **do**
  for $B \in$ *BUSINESSES* **do**
    for $row \in [0, 9]$ **do**
      $X[row, :] \leftarrow$ RAW SCORE$^T_{W,B}$;
      $X[row, :] \leftarrow$ Z-Score$(X[row, :])$;
      $X[row, :] \leftarrow X[row, :] * HL[row, :]$;
      $Y[row] \leftarrow$ SPEARMAN$(I[row, :], X[row, :])]$;
    end
  end
end

3.2 Results

3.2.1 Two Partitions

When the plot of land is partitioned twice into four regions, we calculated the final Spearman's Coefficients for each region of choice c_i. The results from the previously discussed decision model can be found in Table 1. Thus, the optimal business choice for each region is the business b_i with the highest Spearman's Coefficient. The optimal business choice for dividing the region into 4 parts is a **grazing farm, agrivoltaic farm, and sports complex** in the formation of Figure 10.

Business Model	Spearman Rank Correlation Coefficient Top Left	Top Right	Bottom Left	Bottom Right
Sports Complex	0.161	0.125	−0.054	**0.482**
Skiing Facility	−0.143	−0.321	−0.179	−0.036
Crop Farm	−0.250	−0.357	−0.036	−0.214
Grazing Farm	**0.286**	**0.679**	0.000	0.393
Regen. Farm	−0.518	−0.339	−0.268	−0.089
Solar Array	−1.268	−0.839	−0.696	−0.268
Agrivoltaic Farm	−0.786	−0.643	**0.071**	−0.214
Agritourist Center	−0.571	−0.643	0.070	−0.250

Table 1: **Final Spearman's Coefficients for 2x2 partitioned land.** Raw scores and intermediate scores can be found in Appendix 8.

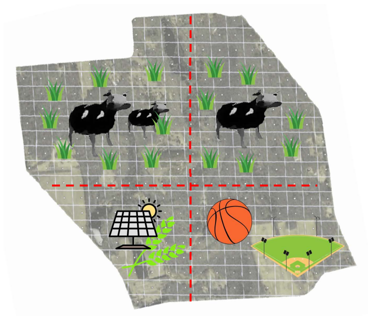

Figure 10: **Visual representation of optimal business choices.**

3.2.2 A Singular Vertical Partition

After dividing the plot of land into two vertical regions, we calculated the final Spearman's coefficients for each region of choice c_i. Table 2 displays the decision model results, which reveal that the **best business choice for the left region would be an agrivoltaic farm and for the right region would be an outdoor sports complex**. See Figure 11 for the corresponding business allocation visualization.

Business Model	Spearman's Rank Correlation Coefficient Left	Right
Sports Complex	−0.054	**0.554**
Skiing Facility	−0.179	−0.036
Crop Farm	−0.036	−0.286
Grazing Farm	−0.179	0.464
Regen. Farm	−0.268	−0.161
Solar Array	−0.696	−0.304
Agrivoltaic Farm	**0.071**	−0.536
Agritourist Center	0.070	−0.5

Table 2: **Final Spearman's Coefficients for vertically partitioned land.** Raw scores and intermediate scores can be found in Appendix 8.

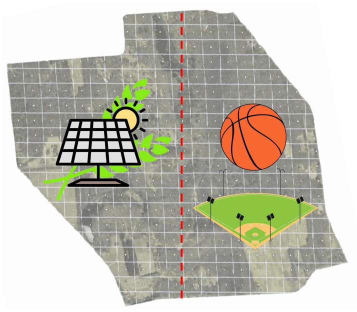

Figure 11: **Visual representation of optimal business choices.**

3.2.3 A Singular Horizontal Partition

When the plot of land is partitioned into two horizontal regions, we calculated the final Spearman's Coefficients for each region of choice c_i. The results from the previously discussed decision model can be found in Table 3. Thus, the optimal businesses for this partitioning would be a **grazing farm and a cross-country skiing facility**, as shown in Figure 12.

	Spearman's Rank Correlation Coefficient	
Business Model	**Top**	**Bottom**
Sports Complex	0.125	0.018
Skiing Facility	−0.214	**0.107**
Crop Farm	−0.357	−0.107
Grazing Farm	**0.321**	0.106
Regen. Farm	−0.446	−0.268
Solar Array	−0.839	−0.696
Agrivoltaic Farm	−0.786	−0.321
Agritourist Center	−0.679	−0.000

Table 3: **Final Spearman's Coefficients for horizontally partitioned land.** Raw scores and intermediate scores can be found in Appendix 8.

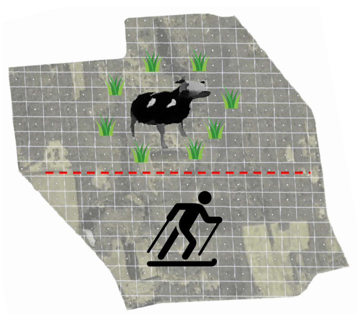

Figure 12: **Visual representation of optimal business choices.**

3.2.4 Zero Partitions

When the plot of land is not partitioned and the window contains the entire region, we calculated the final Spearman's Coefficients for the entire region. The results from the previously discussed decision model can be found in Table 4. Thus, the optimal business choice if the land was not divided would be a **grazing farm**.

Business Model	Spearman's Rank Correlation Coefficient
Sports Complex	-0.054
Skiing Facility	-0.250
Crop Farm	-0.214
Grazing Farm	**0.500**
Regen. Farm	-0.089
Solar Array	-0.304
Agrivoltaic Farm	-0.250
Agritourist Center	-0.179

Table 4: **Final Spearman's Coefficients non-partitioned land.** Raw scores and intermediate scores can be found in Appendix 8.

3.3 Model Discussion

3.3.1 Strengths

1. Our model yields relevant and accurate results by **considering a variety of factors**.

   With the consideration of numerous parameters, our model is able to analyze which company best fits the plot of land more accurately. Additionally, by considering many different types of factors, including topographical, sustainability, and economic factors, we are able to better understand the overall fit of each company based on the plot of land itself, as well as possible external influences.

2. Our model allows for **tailorable and easily-adaptable decision-making** for a plot of land.

   Due to the "sliding window" methodology used in this model, users can define the desired size of the window subplots, effectively creating any number of windows. This adaptability allows business owners to consider one or more businesses in the plot of land as well as where each one would best fit.

3. Our model considered both **short-term and long-term** factors.

   Of the factors we decided to include in our model, some determined the company of best fit over a short period of time while other factors considered best fit over a long period of time. Within our model, rain levels, sunshine levels, and economic growth considered best fit over a long period of time since those factors considered the company fit in the future.

3.3.2 Limitations

1. Our model requires **a lot of external data**.

   Due to the complexity of the parameters utilized in our model, background research, financial data, and topographical data were **essential** for the precision of this model. Although all of the data used in our model development was publicly available, applying this model to different regions or business choices would require additional data.

2. Our model focuses on the **bigger-picture fit of a business** on the plot of land.

    The focus of our model was to understand a company's fit in the plot of land by considering various factors. This was done by normalizing and combining all individual factor scores to understand the business's fit. However, our model would not be able to account for a scenario where a business owner focuses closely on just a singular parameter.

4 Part 3: Understanding Potential External Factors

4.1 Problem Analysis

According to the given problem, we need to consider how a new semiconductor fabrication facility (fab) built about 25 miles from the plot of land will affect the output of our model. Once built, the facility can provide employment to almost 9,000 people. Additionally, the construction of this facility would provide an additional 40,000 jobs to suppliers, construction firms, and other additional businesses.

In order to evaluate how this new facility would affect our original results, we first determined that we must re-evaluate the competitor analysis of our economic factor since this business would affect jobs around the area. Our original model did not account for competitors as our background research indicated there were no competitors related to the businesses we were considering within a 25-mile radius. Thus, we decided to focus on the effect of additional jobs in the area on our model output now that there is a nearby competitor.

4.2 Revised Model Scores

We revised the competitor score as a part of the economic score to account for all local *similar* companies with mutualistic and non-mutualistic goals (Equation 18). In order to keep the decision model streamlined, we maintained the same decision model process.

In creating this **new competitor score** $\Upsilon(b_i)$, we considered both the distance to a competitor as well as the internal and external effects of this competitor. For each competing company, we added the proportion of internal jobs created to total jobs created by the business to represent the negative effects of the competitor to the total *similar* business job market. However, we also modeled the positive benefits of the competitor such that they create new jobs for related industries. Thus, we subtracted a proportion of the external jobs created from the total jobs created to represent the positive externalities, or good byproducts, of this company. Furthermore, we scaled this factor by 10 to represent the greater societal impact of these positive externalities.

$$\Upsilon(b_i) = \sum_{i=0}^{n} \frac{1}{\sqrt{\text{distance}_i}} \left(\frac{\text{Internal Jobs Created}_i}{\text{Total Jobs Created}_i} - 10 \cdot \frac{\text{External Jobs Created}_i}{\text{Total Jobs Created}_i} \right) \tag{18}$$

Note that we subtracted the external job proportion because the total competitor score is subtracted from the total economic score, thus the external job proportion would have a positive effect on the final economic score. Lastly, we reran the decision model with this new competitor scoring metric for Raw Scores, z-scores, and Spearman's Rank Correlation Coefficients. We found that the new fab business positively impacted economic scores in *similar* businesses. A detailed score breakdown can be found in Appendix 8. A visualization of the optimal business choices can be found in Figure 13.

The optimal business choices for the following partitions are listed below. Business allocations that *did change* are italicized.

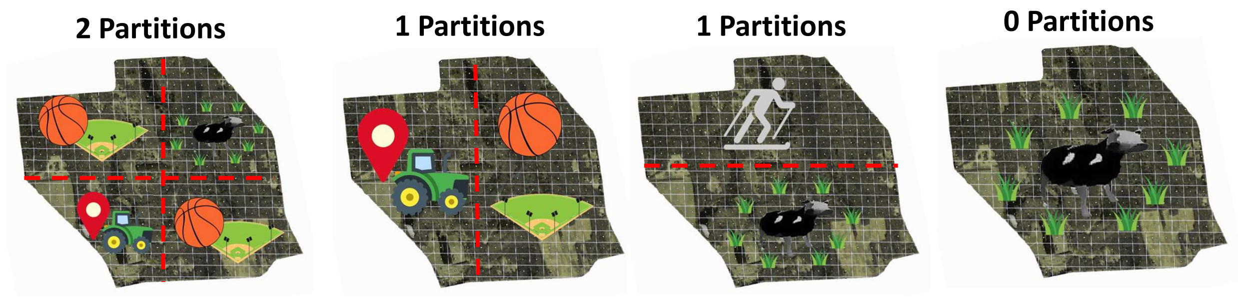

Figure 13: **Visualization of optimal business choices *after* competitor score revision.**

- **2 Partitions**: (Top Left) ***Outdoor Sports Facility***, (Top Right) **Grazing Farm**, (Bottom Left) ***Agritourist Center***, (Bottom Right) **Outdoor Sports Complex**.
- **1 Vertical Partition**: (Left) ***Agritourist Center***, (Right) **Outdoor Sports Complex**.
- **1 Horizontal Partition**: (Top) ***Cross Country Skiing Facility***, (Bottom) ***Grazing Area***.
- **No Partitions**: The optimal business choices is a **Grazing Area**.

It is important to note that some results changed while others stayed the same. This is due to the changing economic factors when we considered the additional company a competitor in our analysis. Additionally, since each business considered the importance of each factor differently (Figure 7), the change in economic factors had contrasting effects in our model to better align with each company's values.

4.2.1 Strengths

1. This model accounts for both **negative and positive effects** from company competition.

   When competing companies develop in an area, the hiring market diversifies for local businesses, benefiting both competing and non-competing companies. Our economic model was modified to better account for nearby companies and the associated increase in the employee pool, thus improving the decision process as well.

4.2.2 Limitations

1. The new competitor score would be **difficult to measure**.

   As more companies are included in this competitor score, the effect of additional companies on the workforce becomes harder to measure due to the dependent nature of *similar* businesses. Additionally, since many companies form mutualistic relationships with other local companies, it can become difficult to quantify the impact of those relationships on our economic score as the number of relationships increases.

2. The new competitor score does not consider **competition beyond *similar* industries**.

   Our revised model did not measure adverse effects beyond jobs, such as pollution, community happiness, and overall county economic conditions, which would affect not only *similar* businesses, but also other business options. We decided that the job metric would be the most significant out of these effects, thus we only included the job effects in our model.

5 Part 4: Generalizability of our Model

Our model considers numerous parameters, making it possible to customize it to other regions with greater accuracy. By incorporating more relevant information specific to the region, we can better predict the optimal business. As all data used by our model is publicly available, similar information can be obtained for other plots of land.

To analyze other business choices on another plot of land **both within and outside the United States**, we would require the following data:

- **Regional data**
  - Elevation and detailed topographical data throughout the plot of land.
  - Previous sunlight data within the new region to predict future sunlight levels.
  - Historical precipitation data for the region to predict future amounts of precipitation.
  - Forest coverage percentages throughout the plot of land.
- **Business choice data**
  - Economic indicators from *similar* companies for all business choices.
  - Competitors and their impacts on jobs in the local region of the new region.

The business options considered in this model may vary, however, the only *initial* piece of data necessary is the location of the plot of land. All other data and factors can be identified using online sources and geographic information systems, such as ArcGIS. Thus, our model is **highly versatile** and can be easily adapted to virtually any region of the Earth.

6 References

[1] The Editors of The Encyclopaedia Britannica, "Mercator Projection."

[2] "Red Creek, New York," Sept. 2022. Page Version ID: 1111369057.

[3] "Wayne County New York," 2017.

[4] "WAYNE COUNTY, NY: PROFILE," 2015.

[5] Young Strategies, Inc., "Visit Syracuse Onondaga County, New York Travel Market Research," Sept. 2015.

[6] Adam Hayes, "EBITDA: Meaning, Formula, and History."

[7] Jason Fernando, "Earnings Per Share (EPS): What It Means and How to Calculate It."

[8] James Chen, "Growth Rates: Formula, How to Calculate, and Definition."

[9] Marshall Hargrave, "Standard Deviation Formula and Uses vs. Variance."

[10] Jason Fernando, "Relative Strength Index (RSI) Indicator Explained With Formula."

[11] Marshall Hargrave, "Operating Cash Flow (OCF): Definition, Types, and Formula."

[12] Esri, "ArcGis."

[13] P. Ceppi and P. Nowack, "Observational evidence that cloud feedback amplifies global warming," *Proceedings of the National Academy of Sciences*, vol. 118, p. e2026290118, July 2021. Publisher: Proceedings of the National Academy of Sciences.

[14] H. Sak, A. W. Senior, and F. Beaufays, "Long short-term memory based recurrent neural network architectures for large vocabulary speech recognition," *CoRR*, vol. abs/1402.1128, 2014.

[15] Mart Abadi, Ashish Agarwal, Paul Barham, Eugene Brevdo, Zhifeng Chen, Craig Citro, Greg S. Corrado, Andy Davis, and Jeffrey Dean, "Tensorflow."

[16] "CNYWeather.com - Sunshine Hours."

[17] Aladin, "Wolcott, NY - Climate & Monthly weather forecast."

[18] "Vail Resorts, Inc. (MTN."

[19] "Adecoagro S.A. (AGRO)."

[20] "JBS S.A. (JBSAY)."

[21] "Grupo Bimbo, S.A.B. de C.V. (BIMBOA.MX)."

[22] "First Solar, Inc. (FSLR)."

[23] "CubicFarm Systems Corp. (CUB.TO)."

[24] "Carnival Corporation & plc (CCL)."

[25] "American Outdoor Brands, Inc. (AOUT)."

[26] "Farmland Partners Inc. (FPI)."

[27] "Hormel Foods Corporation (HRL) Stock Price."

[28] "Maxeon Solar Technologies, Ltd. (MAXN)."

[29] "Hydrofarm Holdings Group, Inc. (HYFM)."

[30] "General Mills, Inc. (GIS)."

[31] "Academy Sports and Outdoors, Inc. (ASO)."

[32] "18.2 - Spearman Correlation Coefficient," in *Design and Analysis of Clinical Trials*.

7 Appendices

7.1 Appendix 1. Fourier Series Parameters

Parameter	Value	Parameter	Value
a_0	$-2.17 \cdot 10^1$	b_1	$-6.79 \cdot 10^0$
a_1	$4.89 \cdot 10^1$	b_2	$-1.62 \cdot 10^2$
a_2	$9.23 \cdot 10^2$	b_3	$-1.58 \cdot 10^2$
a_3	$3.24 \cdot 10^1$	b_4	$3.19 \cdot 10^2$
a_4	$-9.15 \cdot 10^2$	b_5	$1.69 \cdot 10^2$
a_5	$-2.40 \cdot 10^1$	b_6	$-7.50 \cdot 10^0$
a_6	$2.37 \cdot 10^1$	b_7	$1.19 \cdot 10^1$
a_7	$-2.29 \cdot 10^1$	b_8	$4.82 \cdot 10^0$
a_8	$-2.80 \cdot 10^2$	b_9	$-7.59 \cdot 10^0$
a_9	$-3.32 \cdot 10^1$	b_{10}	$-1.05 \cdot 10^2$
a_{10}	$-2.71 \cdot 10^2$	ω	$1.00 \cdot 10^0$

Table 5: **Fourier parameters and their values.** From Fourier series fitting in Appendix 4.

7.2 Appendix 2. Collected Financial Data Table

Business Model	***Similar* Company Symbol**	**$EBITDA$ Margin**	**PE Ratio**	**Sales Growth**	**Gross Profit Growth**	6	**RSI Index**	**OCF Ratio**
Outdoor Sports Complex	AOUT	-0.25	-2.16	40%	37%	1.0	52	-0.24
Outdoor Sports Complex	DKS	0.16	13.17	38.5%	71.4%	16	80	1.60
Outdoor Sports Complex	ASO	0.15	8.58	33.7%	55.4%	2	59	1.59
Grazing Field	JBSAY	0.11	2.37	85.4%	113%	0.4	53	1.29
Grazing Field	HRL	0.13	22.50	30.4%	34.8%	5	20	1.03
Ski Resort	MTN	0.09	27.11	16%	9.3%	6	31	1.095
Crop Farm	AGRO	0.36	5.40	47.7%	59.9%	0.3	42	0.839
Crop Farm	FPI	0.58	64.44	14.4%	5.2%	1.5	25	0.95
Regen Farm	GIS	0.21	16.46	14.9%	17.4%	2	50	1.08
Regen Farm	BIMBOA	0.15	18.07	35.2%	32.3%	2	40	1.54
Solar Array	FSLR	0.11	40.3	-14.4%	-87.3%	45	76	5.01
Solar Array	MAXN	-0.17	-1.17	-20%	-330%	7	76	0.48
Agrivoltaic	CUB	-9.25	15.68	-20%	-129.8%	0.0	52	7.15
Agrivoltaic	HFYM	-0.57	-3.15	79%	79%	0.4	40	0.91

Table 6: **Collected financial data for *similar* companies to business options.**

7.3 Appendix 3. ML Sunlight Level Prediction

./sunshinepredictor.py

```
# -*- coding: utf-8 -*-
"""sunshinepredictor.ipynb

Automatically generated by Colaboratory.

Original file is located at
    https://colab.research.google.com/drive/1lv-xI9FzcAkKOid_dfCRgrZ9Dj5SDGCa
"""

import csv
import numpy as np
import tensorflow as tf
import matplotlib.pyplot as plt

dataset = tf.data.Dataset.from_tensor_slices([45,85.8,119,138.9,105.2,177.1,137.1,122.9,78.8,83.6,60.6,55.2,74.1,60,129,97.5,184.7,180,195.3,115.8,98.2,46.4,30.1,36.7,54.3,69,133.8,79.5,82.7,158.2,186.9,144.9,85.4,49.3,55.1,51,53.3,77.8,111.5,120.9,161.7,186,201.2,190.4,85.8,44.7,69.8,22.1,86.5,99.3,110.4,127.7,167.2,178.3,201.1,161,94.8,100.3,70.8,54.3,16.2,64.1,18.3])

#Initialize windows
dataset = dataset.window(10, shift = 1, drop_remainder = True)

#Create batched windows
dataset = dataset.flat_map(lambda window: window.batch(10))

#Create windows
dataset = dataset.map(lambda window: (window[:-1], window[-1:]))

#Shuffle Dataset
dataset = dataset.shuffle(buffer_size = 10)

#Batch dataset
dataset = dataset.batch(2).prefetch(1)

for X, y in dataset:
    print("Input:", X.numpy(), "Target:", y.numpy())

tf.keras.backend.clear_session()

model = tf.keras.models.Sequential([
    tf.keras.layers.Input(shape=(None, 1)),
```

```
    tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(9, return_sequences = True)),
    tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(9)),
    tf.keras.layers.Dense(32, activation='relu'),
    tf.keras.layers.Dense(16, activation='relu'),
    tf.keras.layers.Dense(1),
    tf.keras.layers.Lambda(lambda x: x * 200)
])

model.summary()

model.compile(optimizer='adam', loss=tf.keras.losses.Huber(), metrics=['mae'])

model.fit(dataset, epochs=50)

initial = [201.1,161,94.8,100.3,70.8,54.3,16.2,64.1,18.3]

# n is months after March, 2023
def predict_sunshine(n):
  for i in range(n):
    result = model.predict([initial[i:]], verbose=0)
    initial.append(float(result[0][0]))
  return(initial[-1])

from matplotlib.backends.backend_pdf import PdfPages

def function_plot(X, pp):
    plt.figure()
    plt.clf()
    plt.plot(X)
    graph = plt.title('y vs x')
    plt.xlabel("Time (Months)")
    plt.ylabel("Hours of Sunshine")
    pp.savefig(plt.gcf())


with PdfPages('test.pdf') as pp:
    function_plot(initial, pp)
```

7.4 Appendix 4. Fourier Series Precipitation Prediction

./fourierregression.py

```python
from symfit import parameters, variables, sin, cos, Fit
import numpy as np
import matplotlib.pyplot as plt

plt.ion()

def fourier_series(x, f, n=0):
    """
    Returns a symbolic fourier series of order `n`.

    :param n: Order of the fourier series.
    :param x: Independent variable
    :param f: Frequency of the fourier series
    """
    # Make the parameter objects for all the terms
    a0, *cos_a = parameters(','.join(['a{}'.format(i) for i in range(0, n + 1)]))
    sin_b = parameters(','.join(['b{}'.format(i) for i in range(1, n + 1)]))
    # Construct the series
    series = a0 + sum(ai * cos(i * f * x) + bi * sin(i * f * x)
                     for i, (ai, bi) in enumerate(zip(cos_a, sin_b), start=1))
    return series

x, y = variables('x, y')
w, = parameters('w')
model_dict = {y: fourier_series(x, f=w, n=10)}
print(model_dict)

# Make step function data
xdata = np.linspace(0, 25, 25)
ydata = np.array([2.1,1.8,2.4,0.9,3.3,1.2,1.8,7.5,2.4,3.3,7.2,1.8,2.1,2.4,3.6,1.5,2.7,2.4,2.1,1.8,3.3,2.7,1.2,3.3,2.1])
print(xdata.shape)
print(ydata.shape)
# Define a Fit object for this model and data
fit = Fit(model_dict, x=xdata, y=ydata)
fit_result = fit.execute()
print(fit_result)

# Plot the result
plt.plot(xdata, ydata)
plt.plot(xdata, fit.model(x=xdata, **fit_result.params).y, color='green', ls=':')
```

```
plt.pause(1000)
```

7.5 Appendix 5. (Part 2) Economic Factor Calculation

./EconomicalFactorCalculation.py

```
# Import required modules
import numpy as np
import os
import csv

# Define a class called EconomicFactor
class EconomicFactor:
    # Constructor method that initializes instance variables
    def __init__(self, symbol, ebitda_margin, pe_ratio, sales_growth,
    gross_profit_growth, std, rsi, ocf, competitors=[]):
        self.symbol = symbol
        self.ebitda_margin = ebitda_margin
        self.pe_ratio = pe_ratio
        self.sales_growth = sales_growth
        self.gross_profit_growth = gross_profit_growth
        self.std = std
        self.rsi = rsi
        self.ocf = ocf
        self.competitors = competitors #[[name, distance], [name,
        distance]]

    # Method that calculates the profit index for an EconomicFactor
    instance
    def profit_index(self):
        return self.ebitda_margin + 10 / self.pe_ratio

    # Method that calculates the growth index for an EconomicFactor
    instance
    def growth_index(self):
        return 0.01 * (0.3 * self.sales_growth + 0.7 *
        self.gross_profit_growth)

    # Method that calculates the risk index for an EconomicFactor
    instance
    def risk_index(self):
        return self.std / 100 + 1 / 80 * self.rsi - 1.1 / self.ocf

    # Method that calculates the competitor index for an
    EconomicFactor instance
    def competitor_index(self):
        total = 0
        for i in range(len(self.competitors)):
            total += 1 / np.sqrt(self.competitors[1])
        return total

```

```
    # Method that calculates the economic index for an EconomicFactor instance
    def economic_index(self):
        return self.profit_index() + self.growth_index() - self.risk_index() - self.competitor_index()

# Set the working directory to a specific location
os.chdir('C:\\Users\\charl\\MathModeling\\IM2C')

# Create an empty list called table to store EconomicFactor instances
table = []

# Open a CSV file called financialdata.csv in read mode
with open('financialdata.csv', 'r') as f:
    csvReader = csv.reader(f)
    # Read the header row of the CSV file
    fields = next(csvReader)

    # Iterate over each row in the CSV file
    for line in csvReader:
        # Extract the values from the row and convert them to floats
        temp = line[1:]
        temp[1:] = list(map(float, temp[1:]))
        # Create an EconomicFactor instance with the extracted values and append it to the table list
        table.append(EconomicFactor(*temp))

# Print the economic index for each EconomicFactor instance in the table list
for x in table:
    print(x.economic_index())
```

7.6 Appendix 6. Sliding Windows Implementation

./slidingwindows.py

```
# Package imports

import matplotlib.pyplot as plt
import numpy as np
import csv
import os
import random
import copy


# Plot Class for containing elevation data talbe

os.chdir('C:\\Users\\charl\\MathModeling\\IM2C')


class Plot:

    # Constructor for Plot
    def __init__(self, shape, elevations):
        self.shape = shape
        self.elevations = np.array(elevations)

    # Convert to string default method
    def __str__(self):
        print(f"Shape {self.shape} sized plot")

# Subclass SubPlot is a Plot, this is the window


dely = 0.174
delx = 0.174

# Sub plot subclass for getting sub window given x range and y range


class SubPlot(Plot):

    # Constructor for SubPlot

    def __init__(self, *args, x_range, y_range, **kwargs):
        super().__init__(*args, **kwargs)
        self.x_range = x_range
        self.y_range = y_range
        self.grads = None

```

```python
    # Returns pixel classification array with ranges and elevation array with ranges
    def get_plot_section(self):
        return self.elevations[self.y_range[0]:self.y_range[1], self.x_range[0]:self.x_range[1]]

    # Get gradients based on elevation array

    def get_grads(self):
        elev = self.get_plot_section()
        self.grads = copy.deepcopy(elev)
        for row in range(1, len(elev)-1):
            for col in range(1, len(elev[0])-1):

                # Gradient from the left coordinate
                left_grad = abs(elev[row][col-1] -
                                elev[row][col]) / (delx)

                # Gradient from the right coordinate
                right_grad = abs(elev[row][col+1] -
                                 elev[row][col]) / (delx)

                # Gradient from the top coordinate
                top_grad = abs(elev[row+1][col] -
                               elev[row][col]) / (dely)

                # Gradient from the below coordinate
                bot_grad = abs(elev[row-1][col] -
                               elev[row][col]) / (dely)

                # Sum gradients
                sum_grad = left_grad + right_grad + top_grad + bot_grad
                self.grads[row][col] = sum_grad / 4

        return self.grads[1:-1, 1:-1]

    # Return mean of the array of the gradients
    def avg_grad(self):
        return np.mean(self.get_grads())

    # Calculate total surface area
    def surface_area(self):
        total_area = 0

        # Loop over all gradients to calculate new side length
        for row in range(len(self.grads)):
            for col in range(len(self.grads[0])):
```

```
                # calculate side lengths

                # x_side length
                x_side = np.sqrt(delx ** 2 + self.grads[row][col] ** 2)

                # y_side length
                y_side = np.sqrt(dely ** 2 + self.grads[row][col] ** 2)
                total_area += x_side * y_side

        # return total area
        return total_area


# Find elevations from table
# elevations = [[random.random() / 100 for i in range(16)] for j in range(16)]

# # Initialize Subplot object
# plot = SubPlot((len(elevations), len(
#     elevations[0])), elevations=elevations,  x_range=[0, 16], y_range=[0, 16])

# # Get specific plot section and load variables
# plot2 = plot.get_plot_section()

# Testing print statements
# print(plot2)
# print(plot.get_grads())
# print(plot.avg_grad())
# print(plot.surface_area())

# Params: elevations=elevation table, x_partitions = num of x axis partitions, y_partitions = num y axis partitions

# Calculate all necessary components for the topological factors section
def calculate_all_topological_factors(elevations, x_partitions, y_partitions):

    #define some variables
    x_max = len(elevations[0])
    y_max = len(elevations[1])
    x_ranges = []
    y_ranges = []

    #if we do not partition along the x axis...
```

```
    if x_partitions == 0:
        x_len = 0
        x_ranges.append([0, x_max])
    else:
        assert x_max % x_partitions == 0
        x_len = int(x_max / x_partitions)

    #if we do not partition along the y axis...
    if y_partitions == 0:
        y_len = 0
        y_ranges.append([0, y_max])
    else:
        assert y_max % y_partitions == 0
        y_len = int(y_max / y_partitions)

    # create x_ranges variable
    for i in range(x_partitions):
        x_ranges.append([i*x_len, (i+1)*x_len])

    # create y_ranges variable
    for i in range(y_partitions):
        y_ranges.append([i*y_len, (i+1)*y_len])

    # loop over each x_range and y_range and create subplot and calculate values
    for x_range in x_ranges:
        for y_range in y_ranges:
            plot = SubPlot((len(elevations), len(
                elevations[0])), elevations=elevations, x_range=x_range, y_range=y_range)
            average_gradient = plot.avg_grad()
            surface_area = plot.surface_area()

            # print it out nicely
            print("___________________________________")
            print(f"X: {x_range[0]} --> {x_range[1]}")
            print(f"Y: {y_range[0]} --> {y_range[1]}")
            print(f"Surface Area: {surface_area}")
            print(f"Avg Elevation Change: {average_gradient}")


#elevations = [[random.random() / 100 for i in range(16)] for j in range(16)]
#calculate_all_topological_factors(elevations, 4, 2)

elevations = []

#data preprocessing step
```

```
with open('points_xyz.csv', 'r') as f:
    row = []
    counter = 0

    for line in f.readlines():
        row.append(float(line[-8:]) / 1000)
        counter += 1
        if len(row) % 16 == 0:
            elevations.append(row)
            row = []

with open('elevations.csv', 'w') as f:

    # using csv.writer method from CSV package
    write = csv.writer(f)

    write.writerows(elevations)

elevations = np.array(elevations)

x_partitions = 0 #INPUT VALUE HERE
y_partitions = 0 #INPUT VALUES HERE

calculate_all_topological_factors(elevations, x_partitions,
y_partitions)
```

7.7 Appendix 7. Importance Matrix Justification

Below we reason more specifically for why we decided to rank each factor for each company.

- Sports Complex

  Outdoor sports complexes maintain business by offering recreational fields for people to play sports. Thus, we decided that the economic factor is most important for outdoor sports complexes. Secondly, we decided that elevation and surface area were the following two most important factors because they affect the type and number of fields that can be built on the plot. Next, we determined that sunshine and rain levels are significant factors since outdoor sports usage is affected by weather conditions. Deforestation is a somewhat important but unnecessary factor since it can provide additional space for recreational fields but is not critical. Finally, we ranked proximity to a body of water as the least important factor, as it does not impact the creation or success of an outdoor sports complex.

- Skiing Facility

  The primary objective of a skiing facility is to offer skiing trails to appeal to snow sports enthusiasts. While economics is critical in sustaining the facility, having skiing trails is essential to attract and retain customers. The most critical factor that affects ski trails is elevation change, ranked first in importance. Economics is ranked second, as it plays a significant role in the facility's sustainability. Usable surface area is also an essential factor, as it determines the length and quantity of ski trails that can be built. We also recognized that deforestation is a crucial factor, as retaining trees on the land enables the creation of more challenging and diverse ski trails. Next, we prioritized proximity to water as the next significant factor, as it can be used for making artificial snow in the ski facility. We ranked sunshine and weather as least important because we are told to assume that there will be sufficient snow coverage. Additionally, skiers do not care about cloud coverage, and skiing is often done at night.

- Crop Farm

    Crop farms primarily grow and harvest crops for sale to food production, making economics the top priority. Usable surface area is the second most important factor, as it directly impacts the number of crops that can be grown. We ranked proximity to a body of water and sunshine levels next in importance because water aids in irrigation, and sunshine aids in crop growth. Deforestation was then ranked as the next important factor since it can clear up additional land for crop growth. However, since only a small fraction of the land is forest, there is already ample space for crop growth. We rated change in elevation as the sixth most important factor because it does not significantly affect the ability to grow crops (e.g., terrace farming can be used). Lastly, rain levels were ranked as a seven because it was previously assumed that there is sufficient irrigation. Being closer to a body of water would be more beneficial than rain because bodies of water also help fertilize crops.

- Grazing Farm

    The top priority to ensure the success of a grazing farm is to have enough land for raising animals and growing crops to feed them. Thus, the usable surface area is ranked as the most crucial factor. The following important factor is proximity to a body of water, which can serve as a source of water for the animals and provide irrigation to farmland (grass is food for animals). We then rated sunshine levels the next most important factor because they can significantly impact the growth of crops and grass, as well as the ability of animals to be outside and graze. We ranked deforestation as the next most crucial factor because deforestation can clear up additional land for grazing animals. Still, it is optional as sufficient land is already available. Because a grazing farm is designed for animals over economics, we ranked economics as the next important factor. The final two factors were rain and change in elevation. These factors were ranked lower because animals will continue to roam regardless of the weather.

- Regenerative Farm

    Regenerative farms, like crop farms, focus on growing crops, but their emphasis on sustainability and minimum water usage further impacts the factor rankings. We identified the most significant factor as the proximity to a body of water. Regenerative farming emphasizes sustainable practices and minimal water usage. It is located near a body of water and can provide additional irrigation and fertilization, which aligns to use the least possible amount of irrigation necessary. We ranked the usable surface area as the next important factor because having more surface area would allow for the growth of more crops. After that, we determined that sunshine was the third most important factor for crop growth, mainly because a regenerative farm aims to use minimal water. We ranked economics as the next crucial factor since regenerative farms aim to grow crops for the food industry. However, the previously rated factors are essential for achieving that goal. Additionally, we rated deforestation and rainfall as the fifth and sixth most essential factors, respectively, as a regenerative farm has ample land and water access to thrive, making these factors beneficial but not critical. Finally, we deemed a change in elevation the least important factor because different crops require varying elevations to grow. Additionally, we believed that the other factors were more important in determining a business's success than the change in elevation.

- Solar Array

  Solar arrays aim to convert sunlight into energy, making sunshine the most crucial factor for their success. We ranked the surface area as the second most important factor for solar arrays since it allows more solar panels to generate more energy. Next, we rated deforestation as the third most important factor since clearing land would create more usable surface area for additional solar panels and more energy production. Next, we considered economics the next most significant factor since the primary goal of a solar farm is to generate energy sustainably for profit. However, the factors rated higher than economics contribute to the business's success and profitability. We ranked the change in elevation and rain levels as the following factors of importance for solar farms, but their impact on the farm's success is relatively less significant. In contrast, a minor change in elevation and lower rain levels may be advantageous, but they are not crucial factors in determining the overall success of the solar farm. Finally, we ranked proximity to a body of water as the least essential factor because being near or far away from a body of water does not affect solar farms or the harvesting of energy in any way.

- Agrivoltaic Farm

  An agrivoltaic farm is the combination of both a crop farm and a solar array. Because both tasks require large land areas, we ranked the usable surface area as the most critical factor. We determined that economics was the second most crucial factor since, like both crop and solar farms, an agrivoltaic farm aims to generate revenue from the sale of crops and energy. We then assigned sunlight levels as the third most important factor, as it is crucial for the solar panels and beneficial for the crops' growth. We also rated deforestation as the next most crucial factor because an agrivoltaic farm requires solar panels and crop cultivation land, making additional usable land a higher priority. We ranked proximity to a body of water and rain levels as vital factors for agrivoltaic farms. They can play a role in crop growth but do not significantly impact the effectiveness of using solar panels. Lastly, we rated elevation change as the least important factor because, similar to crop and solar farms, the success of an agrivoltaic is least impacted by the change in elevation.

- Agritourist Center

  The primary focus of an agritourist center is to attract customers through the cultivation of crops and the production of animal products. Therefore, we ranked economics as the most crucial factor. We determined that usable surface area is the second most important factor for an agritourist center because the land will serve multiple purposes, such as crop cultivation, animal raising, visitor building facilities, and selling products. We also considered deforestation the third most important factor due to the benefits of having more usable surface area, as mentioned above. After that, we placed sunshine levels as the fourth most important factor, as it helps crop growth and provides favorable weather for increased tourism. We then considered proximity to a body of water and rain levels as important factors since they contribute to crop growth. However, they are optional, given adequate irrigation. We rated change in elevation as the least important factor because it has a relatively low impact on the success of an agritourist center compared to other factors. Moreover, crops can still be grown on hills, and large tourist buildings can also be built on hills.

7.8 Appendix 8. (Part 2 and 3) Score and Spearman's Coefficient Calculations

The following pages in this Appendix are broken up as follows.

1. The next 5 pages contain raw score calculations from the decision method for 2, 1, 1, and 0 partitions using the sliding window methodology.
2. The following 4 pages contain z-score calculations from the raw scores of the previous section.
3. The following 4 pages contain High-Low z-score calculations after applying the element-wise multiplication from the *High-Low Matrix*.
4. The next 16 pages of this Appendix contain the final calculations of the Spearman's Coefficients using ranked z-scores, the importance matrix, and the Spearman's Coefficient formula.
5. The final 15 pages of this Appendix contain the calculations of Spearman's Rank Correlation Coefficients after applying the revised competitor score. The final page of these contains the Rank Correlation Coefficient scores.

CONSTANTS USED THROUGHOUT							
	SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**	**Deforestation**	**Economic**
Sports	-	-	-	1345.32	66.90	-	-2.315
Grazing	-	-	-	1345.32	66.90	-	3.620
Ski	-	-	-	1345.32	66.90	-	1.127
Crop	-	-	-	1345.32	66.90	-	2.601
Regen	-	-	-	1345.32	66.90	-	1.284
Solar	-	-	-	1345.32	66.90	-	-119.991
Agrivoltaic	-	-	-	1345.32	66.90	-	-51.139
Agritourist	-	-	-	1345.32	66.90	-	-82.328

2X2 PARTITION							
Top Left							
	SA	delta E	W	Sunshine (hrs)	Rain	Deforestation	Economic
Sports	2.33	0.015	0.067	1345.32	66.90	0.727	-2.315
Grazing	2.33	0.015	0.067	1345.32	66.90	0.727	3.620
Ski	2.33	0.015	0.067	1345.32	66.90	0.727	1.127
Crop	2.33	0.015	0.067	1345.32	66.90	0.727	2.601
Regen	2.33	0.015	0.067	1345.32	66.90	0.727	1.284
Solar	2.33	0.015	0.067	1345.32	66.90	0.727	-119.991
Agrivoltaic	2.33	0.015	0.067	1345.32	66.90	0.727	-51.139
Agritourist	2.33	0.015	0.067	1345.32	66.90	0.727	-82.328
Top Right							
	SA	delta E	W	Sunshine (hrs)	Rain	Deforestation	Economic
Sports	2.34	0.009	0.077	1345.32	66.90	0.911	-2.315
Grazing	2.34	0.009	0.077	1345.32	66.90	0.911	3.620
Ski	2.34	0.009	0.077	1345.32	66.90	0.911	1.127
Crop	2.34	0.009	0.077	1345.32	66.90	0.911	2.601
Regen	2.34	0.009	0.077	1345.32	66.90	0.911	1.284
Solar	2.34	0.009	0.077	1345.32	66.90	0.911	-119.991
Agrivoltaic	2.34	0.009	0.077	1345.32	66.90	0.911	-51.139
Agritourist	2.34	0.009	0.077	1345.32	66.90	0.911	-82.328
Bot Left							
	SA	delta E	W	Sunshine (hrs)	Rain	Deforestation	Economic
Sports	2.37	0.029	0.040	1345.32	66.90	0.423	-2.315
Grazing	2.37	0.029	0.040	1345.32	66.90	0.423	3.620
Ski	2.37	0.029	0.040	1345.32	66.90	0.423	1.127
Crop	2.37	0.029	0.040	1345.32	66.90	0.423	2.601
Regen	2.37	0.029	0.040	1345.32	66.90	0.423	1.284
Solar	2.37	0.029	0.040	1345.32	66.90	0.423	-119.991
Agrivoltaic	2.37	0.029	0.040	1345.32	66.90	0.423	-51.139
Agritourist	2.37	0.029	0.040	1345.32	66.90	0.423	-82.328
Bot Right							
	SA	delta E	W	Sunshine (hrs)	Rain	Deforestation	Economic
Sports	2.38	0.011	0.032	1345.32	66.90	0.883	-2.315
Grazing	2.38	0.011	0.032	1345.32	66.90	0.883	3.620
Ski	2.38	0.011	0.032	1345.32	66.90	0.883	1.127
Crop	2.38	0.011	0.032	1345.32	66.90	0.883	2.601
Regen	2.38	0.011	0.032	1345.32	66.90	0.883	1.284
Solar	2.38	0.011	0.032	1345.32	66.90	0.883	-119.991
Agrivoltaic	2.38	0.011	0.032	1345.32	66.90	0.883	-51.139
Agritourist	2.38	0.011	0.032	1345.32	66.90	0.883	-82.328
	SA	delta E	W	Sunshine (hrs)	Rain	Deforestation	Economic
Mean	2.35	0.016	0.054	2721	37.14	0.736	-30.893
STD	0.020404934	0.009154230547	0.02174265461	356.8	14.78	0.2238183788	48.08350121

1 HORIZ PARTITION							
Top							
	SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**	**Deforestation**	**Economic**
Sports	4.49	0.012	0.095	1345.32	66.90	1.638	-2.315
Grazing	4.49	0.012	0.095	1345.32	66.90	1.638	3.620
Ski	4.49	0.012	0.095	1345.32	66.90	1.638	1.127
Crop	4.49	0.012	0.095	1345.32	66.90	1.638	2.601
Regen	4.49	0.012	0.095	1345.32	66.90	1.638	1.284
Solar	4.49	0.012	0.095	1345.32	66.90	1.638	-119.991
Agrivoltaic	4.49	0.012	0.095	1345.32	66.90	1.638	-51.139
Agritourist	4.49	0.012	0.095	1345.32	66.90	1.638	-82.328
Bot							
	SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**	**Deforestation**	**Economic**
Sports	4.578	0.019	0.040	1345.32	66.90	1.306	-2.315
Grazing	4.578	0.019	0.040	1345.32	66.90	1.306	3.620
Ski	4.578	0.019	0.040	1345.32	66.90	1.306	1.127
Crop	4.578	0.019	0.040	1345.32	66.90	1.306	2.601
Regen	4.578	0.019	0.040	1345.32	66.90	1.306	1.284
Solar	4.578	0.019	0.040	1345.32	66.90	1.306	-119.991
Agrivoltaic	4.578	0.019	0.040	1345.32	66.90	1.306	-51.139
Agritourist	4.578	0.019	0.040	1345.32	66.90	1.306	-82.328

1 VERT PARTITION							
Left							
	SA	delta E	W	Sunshine (hrs)	Rain	Deforestation	Economic
Sports	4.61	0.024	0.046	1345.32	66.90	1.15	-2.315
Grazing	4.61	0.024	0.046	1345.32	66.90	1.15	3.620
Ski	4.61	0.024	0.046	1345.32	66.90	1.15	1.127
Crop	4.61	0.024	0.046	1345.32	66.90	1.15	2.601
Regen	4.61	0.024	0.046	1345.32	66.90	1.15	1.284
Solar	4.61	0.024	0.046	1345.32	66.90	1.15	-119.991
Agrivoltaic	4.61	0.024	0.046	1345.32	66.90	1.15	-51.139
Agritourist	4.61	0.024	0.046	1345.32	66.90	1.15	-82.328
Right							
	SA	delta E	W	Sunshine (hrs)	Rain	Deforestation	Economic
Sports	4.564	0.010	0.057	1345.32	66.90	1.794	-2.315
Grazing	4.564	0.010	0.057	1345.32	66.90	1.794	3.620
Ski	4.564	0.010	0.057	1345.32	66.90	1.794	1.127
Crop	4.564	0.010	0.057	1345.32	66.90	1.794	2.601
Regen	4.564	0.010	0.057	1345.32	66.90	1.794	1.284
Solar	4.564	0.010	0.057	1345.32	66.90	1.794	-119.991
Agrivoltaic	4.564	0.010	0.057	1345.32	66.90	1.794	-51.139
Agritourist	4.564	0.010	0.057	1345.32	66.90	1.794	-82.328
	SA	delta E	W	Sunshine (hrs)	Rain	Deforestation	Economic
Mean	4.561	0.016	0.060	2721.000	37.140	1.472	-30.893
STD	0.052	0.007	0.025	356.800	14.780	0.296	48.084

NO PARTITION							
All							
	SA	delta E	W	Sunshine (hrs)	Rain	Deforestation	Economic
Sports	8.77	0.017	0.046	1345.32	66.90	2.944	-2.315
Grazing	8.77	0.017	0.046	1345.32	66.90	2.944	3.620
Ski	8.77	0.017	0.046	1345.32	66.90	2.944	1.127
Crop	8.77	0.017	0.046	1345.32	66.90	2.944	2.601
Regen	8.77	0.017	0.046	1345.32	66.90	2.944	1.284
Solar	8.77	0.017	0.046	1345.32	66.90	2.944	-119.991
Agrivoltaic	8.77	0.017	0.046	1345.32	66.90	2.944	-51.139
Agritourist	8.77	0.017	0.046	1345.32	66.90	2.944	-82.328
	8.53	0.01	0.03	2721.00	37.14	2.26	-30.89
	0.34	0.51	1.30	356.80	14.78	0.90	48.08

Z Scores Table

2x2 PARTITION							
Top Left							
	SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**	**Deforestation**	**Economic**
Sports	-1.202	-0.122	0.596	-3.855605381	2.01	-0.040	0.59433
Grazing	-1.202	-0.122	0.596	-3.855605381	2.01	-0.040	-0.92472
Ski	-1.202	-0.122	0.596	-3.855605381	2.01	-0.040	0.02344
Crop	-1.202	-0.122	0.596	-3.855605381	2.01	-0.040	0.05409
Regen	-1.202	-0.122	0.596	-3.855605381	2.01	-0.040	0.02670
Solar	-1.202	-0.122	0.596	-3.855605381	2.01	-0.040	-2.49547
Agrivoltaic	-1.202	-0.122	0.596	-3.855605381	2.01	-0.040	-1.06355
Agritourist	-1.202	-0.122	0.596	-3.855605381	2.01	-0.040	-1.71219
Top Right							
	SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**	**Deforestation**	**Economic**
Sports	-0.711	-0.778	1.056	-3.855605381	2.01	0.782	0.59433
Grazing	-0.711	-0.778	1.056	-3.855605381	2.01	0.782	-0.92472
Ski	-0.711	-0.778	1.056	-3.855605381	2.01	0.782	0.02344
Crop	-0.711	-0.778	1.056	-3.855605381	2.01	0.782	0.05409
Regen	-0.711	-0.778	1.056	-3.855605381	2.01	0.782	0.02670
Solar	-0.711	-0.778	1.056	-3.855605381	2.01	0.782	-2.49547
Agrivoltaic	-0.711	-0.778	1.056	-3.855605381	2.01	0.782	-1.06355
Agritourist	-0.711	-0.778	1.056	-3.855605381	2.01	0.782	-1.71219
Bot Left							
	SA	delta E	W	Sunshine (hrs)	Rain	Deforestation	Economic
Sports	0.759	1.407	-0.646	-3.855605381	2.01	-1.398	0.594
Grazing	0.759	1.407	-0.646	-3.855605381	2.01	-1.398	-0.925
Ski	0.759	1.407	-0.646	-3.855605381	2.01	-1.398	0.023
Crop	0.759	1.407	-0.646	-3.855605381	2.01	-1.398	0.054
Regen	0.759	1.407	-0.646	-3.855605381	2.01	-1.398	0.027
Solar	0.759	1.407	-0.646	-3.855605381	2.01	-1.398	-2.495
Agrivoltaic	0.759	1.407	-0.646	-3.855605381	2.01	-1.398	-1.064
Agritourist	0.759	1.407	-0.646	-3.855605381	2.01	-1.398	-1.712
Bot Right							
	SA	delta E	W	Sunshine (hrs)	Rain	Deforestation	Economic
Sports	1.249	-0.559	-1.014	-3.856	2.01	0.657	0.59433
Grazing	1.249	-0.559	-1.014	-3.856	2.01	0.657	-0.92472
Ski	1.249	-0.559	-1.014	-3.856	2.01	0.657	0.02344
Crop	1.249	-0.559	-1.014	-3.856	2.01	0.657	0.05409
Regen	1.249	-0.559	-1.014	-3.856	2.01	0.657	0.02670
Solar	1.249	-0.559	-1.014	-3.856	2.01	0.657	-2.49547
Agrivoltaic	1.249	-0.559	-1.014	-3.856	2.01	0.657	-1.06355
Agritourist	1.249	-0.559	-1.014	-3.856	2.01	0.657	-1.71219
	SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**	**Deforestation**	**Economic**
Mean	2.355	0.016	0.054	2721.0000	37.1400	0.736	-30.893
STD	0.020	0.009	0.022	356.8000	14.7800	0.224	48.08350121

Z Scores Table

ONE HORIZ PARTITION							
Top							
	SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**	**Deforestation**	**Economic**
Sports	-1.38	-0.670	1.441	-3.855605381	2.01	0.561	0.594
Grazing	-1.38	-0.670	1.441	-3.855605381	2.01	0.561	-0.925
Ski	-1.38	-0.670	1.441	-3.855605381	2.01	0.561	0.023
Crop	-1.38	-0.670	1.441	-3.855605381	2.01	0.561	0.054
Regen	-1.38	-0.670	1.441	-3.855605381	2.01	0.561	0.027
Solar	-1.38	-0.670	1.441	-3.855605381	2.01	0.561	-2.495
Agrivoltaic	-1.38	-0.670	1.441	-3.855605381	2.01	0.561	-1.064
Agritourist	-1.38	-0.670	1.441	-3.855605381	2.01	0.561	-1.712
Bot							
	SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**	**Deforestation**	**Economic**
Sports	0.33	0.395	-0.796	-3.855605381	2.01	-0.561	0.594
Grazing	0.33	0.395	-0.796	-3.855605381	2.01	-0.561	-0.925
Ski	0.33	0.395	-0.796	-3.855605381	2.01	-0.561	0.023
Crop	0.33	0.395	-0.796	-3.855605381	2.01	-0.561	0.054
Regen	0.33	0.395	-0.796	-3.855605381	2.01	-0.561	0.027
Solar	0.33	0.395	-0.796	-3.855605381	2.01	-0.561	-2.495
Agrivoltaic	0.33	0.395	-0.796	-3.855605381	2.01	-0.561	-1.064
Agritourist	0.33	0.395	-0.796	-3.855605381	2.01	-0.561	-1.712
	SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**	**Deforestation**	**Economic**
Mean	4.5611	0.016395	0.05956602667	2721.0000	37.1400	1.472	-30.893
STD	0.05157816075	0.006591314993	0.02458735767	356.8000	14.7800	0.2957927202	48.08350121

Z Scores Table

ONE HORIZ PARTITION							
Left							
	SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**	**Deforestation**	**Economic**
Sports	0.95	1.15	-0.55	-3.855605381	2.01	-1.09	0.453
Grazing	0.95	1.15	-0.55	-3.855605381	2.01	-1.09	0.580
Ski	0.95	1.15	-0.55	-3.855605381	2.01	-1.09	0.527
Crop	0.95	1.15	-0.55	-3.855605381	2.01	-1.09	0.558
Regen	0.95	1.15	-0.55	-3.855605381	2.01	-1.09	0.530
Solar	0.95	1.15	-0.55	-3.855605381	2.01	-1.09	-2.059
Agrivoltaic	0.95	1.15	-0.55	-3.855605381	2.01	-1.09	-0.589
Agritourist	0.95	1.15	-0.55	-3.855605381	2.01	-1.09	-1.712
Right							
	SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**	**Deforestation**	**Economic**
Sports	0.06	-0.97	-0.10	-3.855605381	2.01	1.09	0.453
Grazing	0.06	-0.97	-0.10	-3.855605381	2.01	1.09	0.580
Ski	0.06	-0.97	-0.10	-3.855605381	2.01	1.09	0.527
Crop	0.06	-0.97	-0.10	-3.855605381	2.01	1.09	0.558
Regen	0.06	-0.97	-0.10	-3.855605381	2.01	1.09	0.530
Solar	0.06	-0.97	-0.10	-3.855605381	2.01	1.09	-2.059
Agrivoltaic	0.06	-0.97	-0.10	-3.855605381	2.01	1.09	-0.589
Agritourist	0.06	-0.97	-0.10	-3.855605381	2.01	1.09	-1.712
	SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**	**Deforestation**	**Economic**
Mean	4.5611	0.016395	0.05956602667	2721.0000	37.1400	1.472	-30.893
STD	0.05157816075	0.006591314993	0.02458735767	356.8000	14.7800	0.2957927202	48.08350121

Z Scores Table

NO PARTITIONS							
All							
	SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**	**Deforestation**	**Economic**
Sports	0.70	0.01	0.01	-3.855605381	2.01	0.77	0.453
Grazing	0.70	0.01	0.01	-3.855605381	2.01	0.77	0.580
Ski	0.70	0.01	0.01	-3.855605381	2.01	0.77	0.527
Crop	0.70	0.01	0.01	-3.855605381	2.01	0.77	0.558
Regen	0.70	0.01	0.01	-3.855605381	2.01	0.77	0.530
Solar	0.70	0.01	0.01	-3.855605381	2.01	0.77	-2.059
Agrivoltaic	0.70	0.01	0.01	-3.855605381	2.01	0.77	-0.589
Agritourist	0.70	0.01	0.01	-3.855605381	2.01	0.77	-1.712
	8.53	0.012	0.03	2721.0000	37.1400	2.256	-30.893
	0.3405434	0.5069	1.2954	356.8000	14.7800	0.8993	48.08350121

High-Low Z Scores Table

2x2 PARTITION							
Top Left							
	SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**	**Deforestation**	**Economic**
Sports	-1.202	0.122	0.000	-3.856	0.00	0.000	0.59433
Grazing	-1.202	-0.122	0.596	0.000	-2.01	0.040	-0.92472
Ski	-1.202	0.122	0.596	-3.856	2.01	-0.040	0.02344
Crop	-1.202	0.000	0.596	-3.856	2.01	-0.040	0.05409
Regen	-1.202	0.000	0.000	-3.856	2.01	0.040	0.02670
Solar	-1.202	0.000	0.000	-3.856	0.00	-0.040	-2.49547
Agrivoltaic	-1.202	0.122	0.596	-3.856	2.01	-0.040	-1.06355
Agritourist	-1.202	0.122	0.596	-3.856	0.00	0.040	-1.71219
Top Right							
	SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**	**Deforestation**	**Economic**
Sports	-0.711	0.778	0.000	-3.856	0.00	0.000	0.59433
Grazing	-0.711	-0.778	1.056	0.000	-2.01	-0.782	-0.92472
Ski	-0.711	0.778	1.056	-3.856	2.01	0.782	0.02344
Crop	-0.711	0.000	1.056	-3.856	2.01	0.782	0.05409
Regen	-0.711	0.000	0.000	-3.856	2.01	-0.782	0.02670
Solar	-0.711	0.000	0.000	-3.856	0.00	0.782	-2.49547
Agrivoltaic	-0.711	0.778	1.056	-3.856	2.01	0.782	-1.06355
Agritourist	-0.711	0.778	1.056	-3.856	0.00	-0.782	-1.71219
Bot Left							
	SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**	**Deforestation**	**Economic**
Sports	0.759	-1.407	0.000	-3.856	0.00	0.000	0.594
Grazing	0.759	1.407	-0.646	0.000	-2.01	1.398	-0.925
Ski	0.759	-1.407	-0.646	-3.856	2.01	-1.398	0.023
Crop	0.759	0.000	-0.646	-3.856	2.01	-1.398	0.054
Regen	0.759	0.000	0.000	-3.856	2.01	1.398	0.027
Solar	0.759	0.000	0.000	-3.856	0.00	-1.398	-2.495
Agrivoltaic	0.759	-1.407	-0.646	-3.856	2.01	-1.398	-1.064
Agritourist	0.759	-1.407	-0.646	-3.856	0.00	1.398	-1.712
Bot Right							
	SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**	**Deforestation**	**Economic**
Sports	1.249	0.559	0.000	-3.856	0.00	0.000	0.59433
Grazing	1.249	-0.559	-1.014	0.000	-2.01	-0.657	-0.92472
Ski	1.249	0.559	-1.014	-3.856	2.01	0.657	0.02344
Crop	1.249	0.000	-1.014	-3.856	2.01	0.657	0.05409
Regen	1.249	0.000	0.000	-3.856	2.01	-0.657	0.02670
Solar	1.249	0.000	0.000	-3.856	0.00	0.657	-2.49547
Agrivoltaic	1.249	0.559	-1.014	-3.856	2.01	0.657	-1.06355
Agritourist	1.249	0.559	-1.014	-3.856	0.00	-0.657	-1.71219

High-Low Z Scores Table

1 HORIZ PARTITION							
Top							
	SA	delta E	W	Sunshine (hrs)	Rain	Deforestation	Economic
Sports	-1.38	0.670	0.000	-3.855605381	0.00	0.000	0.594
Grazing	-1.38	-0.670	1.441	0	-2.01	-0.561	-0.925
Ski	-1.38	0.670	1.441	-3.855605381	2.01	0.561	0.023
Crop	-1.38	0.000	1.441	-3.855605381	2.01	0.561	0.054
Regen	-1.38	0.000	0.000	-3.855605381	2.01	-0.561	0.027
Solar	-1.38	0.000	0.000	-3.855605381	0.00	0.561	-2.495
Agrivoltaic	-1.38	0.670	1.441	-3.855605381	2.01	0.561	-1.064
Agritourist	-1.38	0.670	1.441	-3.855605381	0.00	-0.561	-1.712
Bot							
	SA	delta E	W	Sunshine (hrs)	Rain	Deforestation	Economic
Sports	0.33	-0.395	0.000	-3.855605381	0.00	0.000	0.594
Grazing	0.33	0.395	-0.796	0	-2.01	0.561	-0.925
Ski	0.33	-0.395	-0.796	-3.855605381	2.01	-0.561	0.023
Crop	0.33	0.000	-0.796	-3.855605381	2.01	-0.561	0.054
Regen	0.33	0.000	0.000	-3.855605381	2.01	0.561	0.027
Solar	0.33	0.000	0.000	-3.855605381	0.00	-0.561	-2.495
Agrivoltaic	0.33	-0.395	-0.796	-3.855605381	2.01	-0.561	-1.064
Agritourist	0.33	-0.395	-0.796	-3.855605381	0.00	0.561	-1.712

High-Low Z Scores Table

1 VERT PARTITION							
Left							
	SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**	**Deforestation**	**Economic**
Sports	0.95	-1.15	0.00	-3.855605381	0.00	0.00	0.453
Grazing	0.95	1.15	-0.55	0	-2.01	1.09	0.580
Ski	0.95	-1.15	-0.55	-3.855605381	2.01	-1.09	0.527
Crop	0.95	0.00	-0.55	-3.855605381	2.01	-1.09	0.558
Regen	0.95	0.00	0.00	-3.855605381	2.01	1.09	0.530
Solar	0.95	0.00	0.00	-3.855605381	0.00	-1.09	-2.059
Agrivoltaic	0.95	-1.15	-0.55	-3.855605381	2.01	-1.09	-0.589
Agritourist	0.95	-1.15	-0.55	-3.855605381	0.00	1.09	-1.712
Right							
	SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**	**Deforestation**	**Economic**
Sports	0.06	0.97	0.00	-3.855605381	0.00	0.00	0.453
Grazing	0.06	-0.97	-0.10	0	-2.01	-1.09	0.580
Ski	0.06	0.97	-0.10	-3.855605381	2.01	1.09	0.527
Crop	0.06	0.00	-0.10	-3.855605381	2.01	1.09	0.558
Regen	0.06	0.00	0.00	-3.855605381	2.01	-1.09	0.530
Solar	0.06	0.00	0.00	-3.855605381	0.00	1.09	-2.059
Agrivoltaic	0.06	0.97	-0.10	-3.855605381	2.01	1.09	-0.589
Agritourist	0.06	0.97	-0.10	-3.855605381	0.00	-1.09	-1.712

High-Low Z Scores Table

NO PARTITION							
All							
	SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**	**Deforestation**	**Economic**
Sports	0.70	-0.01	0.00	-3.855605381	0.00	0.00	0.453
Grazing	0.70	0.01	0.01	0	-2.01	-0.77	0.580
Ski	0.70	-0.01	0.01	-3.855605381	2.01	0.77	0.527
Crop	0.70	0.00	0.01	-3.855605381	2.01	0.77	0.558
Regen	0.70	0.00	0.00	-3.855605381	2.01	-0.77	0.530
Solar	0.70	0.00	0.00	-3.855605381	0.00	0.77	-2.059
Agrivoltaic	0.70	-0.01	0.01	-3.855605381	2.01	0.77	-0.589
Agritourist	0.70	-0.01	0.01	-3.855605381	0.00	-0.77	-1.712
	8.53	0.012	0.03	2721.0000	37.1400	2.256	-30.893
	0.3405434	0.5069	1.2954	356.8000	14.7800	0.8993	48.08350121

Spearman's Coefficient

			Top Left			
	SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**	**Deforestation**
Sports	-1.202	0.122	0.000	-3.856	0.00	0.000
Grazing	-1.202	-0.122	0.596	0.000	-2.01	0.040
Ski	-1.202	0.122	0.596	-3.856	2.01	-0.040
Crop	-1.202	0.000	0.596	-3.856	2.01	-0.040
Regen	-1.202	0.000	0.000	-3.856	2.01	0.040
Solar	-1.202	0.000	0.000	-3.856	0.00	-0.040
Agrivoltaic	-1.202	0.122	0.596	-3.856	2.01	-0.040
Agritourist	-1.202	0.122	0.596	-3.856	0.00	0.040
			Top Right			
	SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**	**Deforestation**
Sports	-0.711	0.778	0.000	-3.856	0.00	0.000
Grazing	-0.711	-0.778	1.056	0.000	-2.01	-0.782
Ski	-0.711	0.778	1.056	-3.856	2.01	0.782
Crop	-0.711	0.000	1.056	-3.856	2.01	0.782
Regen	-0.711	0.000	0.000	-3.856	2.01	-0.782
Solar	-0.711	0.000	0.000	-3.856	0.00	0.782
Agrivoltaic	-0.711	0.778	1.056	-3.856	2.01	0.782
Agritourist	-0.711	0.778	1.056	-3.856	0.00	-0.782
			Bot Left			
	SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**	**Deforestation**
Sports	0.759	-1.407	0.000	-3.856	0.00	0.000
Grazing	0.759	1.407	-0.646	0.000	-2.01	1.398
Ski	0.759	-1.407	-0.646	-3.856	2.01	-1.398
Crop	0.759	0.000	-0.646	-3.856	2.01	-1.398
Regen	0.759	0.000	0.000	-3.856	2.01	1.398
Solar	0.759	0.000	0.000	-3.856	0.00	-1.398
Agrivoltaic	0.759	-1.407	-0.646	-3.856	2.01	-1.398
Agritourist	0.759	-1.407	-0.646	-3.856	0.00	1.398
			Bot Right			
	SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**	**Deforestation**
Sports	1.249	0.559	0.000	-3.856	0.00	0.000
Grazing	1.249	-0.559	-1.014	0.000	-2.01	-0.657
Ski	1.249	0.559	-1.014	-3.856	2.01	0.657
Crop	1.249	0.000	-1.014	-3.856	2.01	0.657
Regen	1.249	0.000	0.000	-3.856	2.01	-0.657
Solar	1.249	0.000	0.000	-3.856	0.00	0.657
Agrivoltaic	1.249	0.559	-1.014	-3.856	2.01	0.657
Agritourist	1.249	0.559	-1.014	-3.856	0.00	-0.657

Spearman's Coefficient

	2x2 PARTITION				
	Rankings				
Economic	**SA**	**delta E**	**W**	**Sunshine (hrs)**	**Rain**
0.59433	6.000	2.000	3.000	7.000	3.000
-0.92472	6.000	4.000	1.000	3.000	7.000
0.02344	6.000	3.000	2.000	7.000	1.000
0.05409	6.000	4.000	2.000	7.000	1.000
0.02670	6.000	4.000	4.000	7.000	1.000
-2.49547	5.000	1.000	1.000	7.000	1.000
-1.06355	6.000	3.000	2.000	7.000	1.000
-1.71219	5.000	2.000	1.000	7.000	4.000

Economic	**SA**	**delta E**	**W**	**Sunshine (hrs)**	**Rain**
0.59433	6.000	1.000	3.000	7.000	3.000
-0.92472	3.000	4.000	1.000	2.000	7.000
0.02344	6.000	4.000	2.000	7.000	1.000
0.05409	6.000	5.000	2.000	7.000	1.000
0.02670	5.000	3.000	3.000	7.000	1.000
-2.49547	5.000	2.000	2.000	7.000	2.000
-1.06355	5.000	4.000	2.000	7.000	1.000
-1.71219	4.000	2.000	1.000	7.000	3.000

Economic	**SA**	**delta E**	**W**	**Sunshine (hrs)**	**Rain**
0.594	1.000	6.000	3.000	7.000	3.000
-0.925	3.000	1.000	5.000	4.000	7.000
0.023	2.000	6.000	4.000	7.000	1.000
0.054	2.000	4.000	5.000	7.000	1.000
0.027	3.000	5.000	5.000	7.000	1.000
-2.495	1.000	2.000	2.000	7.000	2.000
-1.064	2.000	6.000	3.000	7.000	1.000
-1.712	2.000	5.000	4.000	7.000	3.000

Economic	**SA**	**delta E**	**W**	**Sunshine (hrs)**	**Rain**
0.59433	1.000	3.000	4.000	7.000	4.000
-0.92472	1.000	3.000	6.000	2.000	7.000
0.02344	2.000	4.000	6.000	7.000	1.000
0.05409	2.000	5.000	6.000	7.000	1.000
0.02670	2.000	4.000	4.000	7.000	1.000
-2.49547	1.000	3.000	3.000	7.000	3.000
-1.06355	2.000	4.000	5.000	7.000	1.000
-1.71219	1.000	2.000	5.000	7.000	3.000

Spearman's Coefficient

		Spearman Coefficient		Importance Matrix						
Deforestation	**Economic**									
3.000	1.000	**0.161**		3	2	7	4	5	6	1
2.000	5.000	**0.286**		1	7	2	3	6	4	5
5.000	4.000	**-0.143**		3	1	5	6	7	4	2
5.000	3.000	**-0.250**		2	6	3	4	7	5	1
2.000	3.000	**-0.518**		2	7	1	3	6	5	4
4.000	6.000	**-1.268**		2	5	7	1	6	3	4
4.000	5.000	**-0.786**		1	7	5	3	6	4	2
3.000	6.000	**-0.571**		2	7	5	4	6	3	1
Deforestation	**Economic**									
3.000	2.000	**0.125**		3	2	7	4	5	6	1
5.000	6.000	**0.679**		1	7	2	3	6	4	5
3.000	5.000	**-0.321**		3	1	5	6	7	4	2
3.000	4.000	**-0.357**		2	6	3	4	7	5	1
6.000	2.000	**-0.339**		2	7	1	3	6	5	4
1.000	6.000	**-0.839**		2	5	7	1	6	3	4
3.000	6.000	**-0.643**		1	7	5	3	6	4	2
5.000	6.000	**-0.643**		2	7	5	4	6	3	1
Deforestation	**Economic**									
3.000	2.000	**-0.054**		3	2	7	4	5	6	1
2.000	6.000	**0.000**		1	7	2	3	6	4	5
5.000	3.000	**-0.179**		3	1	5	6	7	4	2
6.000	3.000	**-0.036**		2	6	3	4	7	5	1
2.000	4.000	**-0.268**		2	7	1	3	6	5	4
5.000	6.000	**-0.696**		2	5	7	1	6	3	4
5.000	4.000	**0.071**		1	7	5	3	6	4	2
1.000	6.000	**0.071**		2	7	5	4	6	3	1
Deforestation	**Economic**									
4.000	2.000	**0.482**		3	2	7	4	5	6	1
4.000	5.000	**0.393**		1	7	2	3	6	4	5
3.000	5.000	**-0.036**		3	1	5	6	7	4	2
3.000	4.000	**-0.214**		2	6	3	4	7	5	1
6.000	3.000	**-0.089**		2	7	1	3	6	5	4
2.000	6.000	**-0.268**		2	5	7	1	6	3	4
3.000	6.000	**-0.214**		1	7	5	3	6	4	2
4.000	6.000	**-0.250**		2	7	5	4	6	3	1

Spearman's Coefficient

	Differences						
	9	0	16	9	4	9	0
	25	9	1	0	1	4	0
	9	4	9	1	36	1	4
	16	4	1	9	36	0	4
	16	9	9	16	25	9	1
	9	16	36	36	25	1	4
	25	16	9	16	25	0	9
	9	25	16	9	4	0	25
	9	1	16	9	4	9	1
	4	9	1	1	1	1	1
	9	9	9	1	36	1	9
	16	1	1	9	36	4	9
	9	16	4	16	25	1	4
	9	9	25	36	16	4	4
	16	9	9	16	25	1	16
	4	25	16	9	9	4	25
	4	16	16	9	4	9	1
	4	36	9	1	1	4	1
	1	25	1	1	36	1	1
	0	4	4	9	36	1	4
	1	4	16	16	25	9	0
	1	9	25	36	16	4	4
	1	1	4	16	25	1	4
	0	4	1	9	9	4	25
	4	1	9	9	1	4	1
	0	16	16	1	1	0	0
	1	9	1	1	36	1	9
	0	1	9	9	36	4	9
	0	9	9	16	25	1	1
	1	4	16	36	9	1	4
	1	9	0	16	25	1	16
	1	25	0	9	9	1	25

Spearman's Coefficient

			Top		
	SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**
Sports	-1.38	0.670	0.000	-3.855605381	0.00
Grazing	-1.38	-0.670	1.441	0	-2.01
Ski	-1.38	0.670	1.441	-3.855605381	2.01
Crop	-1.38	0.000	1.441	-3.855605381	2.01
Regen	-1.38	0.000	0.000	-3.855605381	2.01
Solar	-1.38	0.000	0.000	-3.855605381	0.00
Agrivoltaic	-1.38	0.670	1.441	-3.855605381	2.01
Agritourist	-1.38	0.670	1.441	-3.855605381	0.00
			Bot		
	SA	delta E	W	Sunshine (hrs)	Rain
Sports	0.33	-0.395	0.000	-3.855605381	0.00
Grazing	0.33	0.395	-0.796	0	-2.01
Ski	0.33	-0.395	-0.796	-3.855605381	2.01
Crop	0.33	0.000	-0.796	-3.855605381	2.01
Regen	0.33	0.000	0.000	-3.855605381	2.01
Solar	0.33	0.000	0.000	-3.855605381	0.00
Agrivoltaic	0.33	-0.395	-0.796	-3.855605381	2.01
Agritourist	0.33	-0.395	-0.796	-3.855605381	0.00

Spearman's Coefficient

				1 HORIZ PARTITION	
					Rankings
Deforestation	**Economic**	**SA**	**delta E**	**W**	**Sunshine (hrs)**
0.000	0.594	6.000	1.000	3.000	7.000
-0.561	-0.925	6.000	4.000	1.000	2.000
0.561	0.023	6.000	3.000	2.000	7.000
0.561	0.054	6.000	5.000	2.000	7.000
-0.561	0.027	6.000	3.000	3.000	7.000
0.561	-2.495	5.000	2.000	2.000	7.000
0.561	-1.064	6.000	3.000	2.000	7.000
-0.561	-1.712	5.000	2.000	1.000	7.000
Deforestation	Economic	SA	delta E	W	Sunshine (hrs)
0.000	0.594	2.000	6.000	3.000	7.000
0.561	-0.925	3.000	2.000	5.000	4.000
-0.561	0.023	2.000	4.000	6.000	7.000
-0.561	0.054	2.000	4.000	6.000	7.000
0.561	0.027	3.000	5.000	5.000	7.000
-0.561	-2.495	1.000	2.000	2.000	7.000
-0.561	-1.064	2.000	3.000	5.000	7.000
0.561	-1.712	2.000	4.000	5.000	7.000

Spearman's Coefficient

			Spearman Coefficient		Importance Matrix				
Rain	**Deforestation**	**Economic**							
3.000	3.000	2.000	**0.125**		3	2	7	4	5
7.000	3.000	5.000	**0.321**		1	7	2	3	6
1.000	4.000	5.000	**-0.214**		3	1	5	6	7
1.000	3.000	4.000	**-0.357**		2	6	3	4	7
1.000	5.000	2.000	**-0.446**		2	7	1	3	6
2.000	1.000	6.000	**-0.839**		2	5	7	1	6
1.000	4.000	5.000	**-0.786**		1	7	5	3	6
3.000	4.000	6.000	**-0.679**		2	7	5	4	6
Rain	Deforestation	Economic							
3.000	3.000	1.000	**0.018**		3	2	7	4	5
7.000	1.000	6.000	**0.107**		1	7	2	3	6
1.000	5.000	3.000	**0.107**		3	1	5	6	7
1.000	5.000	3.000	**-0.107**		2	6	3	4	7
1.000	2.000	4.000	**-0.268**		2	7	1	3	6
2.000	5.000	6.000	**-0.696**		2	5	7	1	6
1.000	4.000	6.000	**-0.321**		1	7	5	3	6
3.000	1.000	6.000	**0.000**		2	7	5	4	6

Spearman's Coefficient

			Differences						
6	1		9	1	16	9	4	9	1
4	5		25	9	1	1	1	1	0
4	2		9	4	9	1	36	0	9
5	1		16	1	1	9	36	4	9
5	4		16	16	4	16	25	0	4
3	4		9	9	25	36	16	4	4
4	2		25	16	9	16	25	0	9
3	1		9	25	16	9	9	1	25
6	1		1	16	16	9	4	9	0
4	5		4	25	9	1	1	9	1
4	2		1	9	1	1	36	1	1
5	1		0	4	9	9	36	0	4
5	4		1	4	16	16	25	9	0
3	4		1	9	25	36	16	4	4
4	2		1	16	0	16	25	0	16
3	1		0	9	0	9	9	4	25

Spearman's Coefficient

			Left		
	SA	delta E	W	Sunshine (hrs)	Rain
Sports	0.95	-1.15	0.00	-3.855605381	0.00
Grazing	0.95	1.15	-0.55	0	-2.01
Ski	0.95	-1.15	-0.55	-3.855605381	2.01
Crop	0.95	0.00	-0.55	-3.855605381	2.01
Regen	0.95	0.00	0.00	-3.855605381	2.01
Solar	0.95	0.00	0.00	-3.855605381	0.00
Agrivoltaic	0.95	-1.15	-0.55	-3.855605381	2.01
Agritourist	0.95	-1.15	-0.55	-3.855605381	0.00
			Right		
	SA	delta E	W	Sunshine (hrs)	Rain
Sports	0.06	0.97	0.00	-3.855605381	0.00
Grazing	0.06	-0.97	-0.10	0	-2.01
Ski	0.06	0.97	-0.10	-3.855605381	2.01
Crop	0.06	0.00	-0.10	-3.855605381	2.01
Regen	0.06	0.00	0.00	-3.855605381	2.01
Solar	0.06	0.00	0.00	-3.855605381	0.00
Agrivoltaic	0.06	0.97	-0.10	-3.855605381	2.01
Agritourist	0.06	0.97	-0.10	-3.855605381	0.00

Spearman's Coefficient

1 VERT PARTITION					
					Rankings
Deforestation	**Economic**	**SA**	**delta E**	**W**	**Sunshine (hrs)**
0.00	0.453	1.000	6.000	3.000	7.000
1.09	0.580	3.000	1.000	6.000	5.000
-1.09	0.527	2.000	6.000	4.000	7.000
-1.09	0.558	2.000	4.000	5.000	7.000
1.09	0.530	3.000	5.000	5.000	7.000
-1.09	-2.059	1.000	2.000	2.000	7.000
-1.09	-0.589	2.000	6.000	3.000	7.000
1.09	-1.712	2.000	5.000	4.000	7.000
Deforestation	**Economic**	**SA**	**delta E**	**W**	**Sunshine (hrs)**
0.00	0.453	3.000	1.000	4.000	7.000
-1.09	0.580	2.000	5.000	4.000	3.000
1.09	0.527	5.000	3.000	6.000	7.000
1.09	0.558	4.000	5.000	6.000	7.000
-1.09	0.530	3.000	4.000	4.000	7.000
1.09	-2.059	2.000	3.000	3.000	7.000
1.09	-0.589	4.000	3.000	5.000	7.000
-1.09	-1.712	2.000	1.000	4.000	7.000

Spearman's Coefficient

			Spearman Coefficient		**Importance Matrix**				
Rain	**Deforestation**	**Economic**							
3.000	3.000	2.000	**-0.054**		3	2	7	4	5
7.000	2.000	4.000	**-0.179**		1	7	2	3	6
1.000	5.000	3.000	**-0.179**		3	1	5	6	7
1.000	6.000	3.000	**-0.036**		2	6	3	4	7
1.000	2.000	4.000	**-0.268**		2	7	1	3	6
2.000	5.000	6.000	**-0.696**		2	5	7	1	6
1.000	5.000	4.000	**0.071**		1	7	5	3	6
3.000	1.000	6.000	**0.071**		2	7	5	4	6
Rain	**Deforestation**	**Economic**							
4.000	4.000	2.000	**0.554**		3	2	7	4	5
7.000	6.000	1.000	**0.464**		1	7	2	3	6
1.000	2.000	4.000	**0.036**		3	1	5	6	7
1.000	2.000	3.000	**-0.286**		2	6	3	4	7
1.000	6.000	2.000	**-0.161**		2	7	1	3	6
3.000	1.000	6.000	**-0.304**		2	5	7	1	6
1.000	2.000	6.000	**-0.536**		1	7	5	3	6
3.000	5.000	6.000	**-0.500**		2	7	5	4	6

Spearman's Coefficient

			Differences						
6	1		4	16	16	9	4	9	1
4	5		4	36	16	4	1	4	1
4	2		1	25	1	1	36	1	1
5	1		0	4	4	9	36	1	4
5	4		1	4	16	16	25	9	0
3	4		1	9	25	36	16	4	4
4	2		1	1	4	16	25	1	4
3	1		0	4	1	9	9	4	25
6	1		0	1	9	9	1	4	1
4	5		1	4	4	0	1	4	16
4	2		4	4	1	1	36	4	4
5	1		4	1	9	9	36	9	4
5	4		1	9	9	16	25	1	4
3	4		0	4	16	36	9	4	4
4	2		9	16	0	16	25	4	16
3	1		0	36	1	9	9	4	25

Spearman's Coefficient

	All				
	SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**
Sports	0.70	-0.01	0.00	-3.855605381	0.00
Grazing	0.70	0.01	0.01	0	-2.01
Ski	0.70	-0.01	0.01	-3.855605381	2.01
Crop	0.70	0.00	0.01	-3.855605381	2.01
Regen	0.70	0.00	0.00	-3.855605381	2.01
Solar	0.70	0.00	0.00	-3.855605381	0.00
Agrivoltaic	0.70	-0.01	0.01	-3.855605381	2.01
Agritourist	0.70	-0.01	0.01	-3.855605381	0.00

Spearman's Coefficient

					Rankings
Deforestation	**Economic**	**SA**	**delta E**	**W**	**Sunshine (hrs)**
0.00	0.453	1.000	6.000	3.000	7.000
-0.77	0.580	1.000	4.000	3.000	5.000
0.77	0.527	3.000	6.000	5.000	7.000
0.77	0.558	3.000	6.000	5.000	7.000
-0.77	0.530	2.000	4.000	4.000	7.000
0.77	-2.059	2.000	3.000	3.000	7.000
0.77	-0.589	3.000	5.000	4.000	7.000
-0.77	-1.712	1.000	4.000	2.000	7.000

Spearman's Coefficient

			Spearman Coefficient		Importance Matrix				
Rain	Deforestation	Economic							
3.000	3.000	2.000	**-0.054**		3	2	7	4	5
7.000	6.000	2.000	**0.500**		1	7	2	3	6
1.000	2.000	4.000	**-0.250**		3	1	5	6	7
1.000	2.000	4.000	**-0.214**		2	6	3	4	7
1.000	6.000	3.000	**-0.089**		2	7	1	3	6
3.000	1.000	6.000	**-0.304**		2	5	7	1	6
1.000	2.000	6.000	**-0.250**		1	7	5	3	6
3.000	5.000	6.000	**-0.179**		2	7	5	4	6

Spearman's Coefficient

			Differences						
6	1		4	16	16	9	4	9	1
4	5		0	9	1	4	1	4	9
4	2		0	25	0	1	36	4	4
5	1		1	0	4	9	36	9	9
5	4		0	9	9	16	25	1	1
3	4		0	4	16	36	9	4	4
4	2		4	4	1	16	25	4	16
3	1		1	9	9	9	9	4	25

Spearman's Coefficient After Competitor

Recalculated Raw Economic Scores						
	Economic	**Z-Scores**	**Competitor Value**			
Sports	-2.315	0.591928	Distance			
Grazing	3.620	0.716999	25			
Ski	1.127	0.664471	Internal			
Crop	2.601	0.695530	9000			
Regen	1.284	0.667778	External			
Solar	-118.036	-1.846719	40000		0.592	0.59433
Agrivoltaic	-49.184	-0.395763	-1.955		0.717	-0.92472
Agritourist	-82.328	-1.094224			0.664	0.02344
	-30.404				0.6955297407	0.05409
	47.453				0.6677782181	0.02670
					-1.846718639	-2.49547
					-0.3957629762	-1.06355
					-1.094223667	-1.71219

Spearman's Coefficient After Competitor

Top Left							
	SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**	**Deforestation**	**Economic**
Sports	-1.202	0.122	0.000	-3.856	0.00	0.000	0.592
Grazing	-1.202	-0.122	0.596	0.000	-2.01	0.040	0.717
Ski	-1.202	0.122	0.596	-3.856	2.01	-0.040	0.664
Crop	-1.202	0.000	0.596	-3.856	2.01	-0.040	0.6955297407
Regen	-1.202	0.000	0.000	-3.856	2.01	0.040	0.6677782181
Solar	-1.202	0.000	0.000	-3.856	0.00	-0.040	-1.846718639
Agrivoltaic	-1.202	0.122	0.596	-3.856	2.01	-0.040	-0.3957629762
Agritourist	-1.202	0.122	0.596	-3.856	0.00	0.040	-1.094223667
Top Right							
	SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**	**Deforestation**	**Economic**
Sports	-0.711	0.778	0.000	-3.856	0.00	0.000	0.592
Grazing	-0.711	-0.778	1.056	0.000	-2.01	-0.782	0.717
Ski	-0.711	0.778	1.056	-3.856	2.01	0.782	0.664
Crop	-0.711	0.000	1.056	-3.856	2.01	0.782	0.6955297407
Regen	-0.711	0.000	0.000	-3.856	2.01	-0.782	0.6677782181
Solar	-0.711	0.000	0.000	-3.856	0.00	0.782	-1.846718639
Agrivoltaic	-0.711	0.778	1.056	-3.856	2.01	0.782	-0.3957629762
Agritourist	-0.711	0.778	1.056	-3.856	0.00	-0.782	-1.094223667
Bot Left							
	SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**	**Deforestation**	**Economic**
Sports	0.759	-1.407	0.000	-3.856	0.00	0.000	0.592
Grazing	0.759	1.407	-0.646	0.000	-2.01	1.398	0.717
Ski	0.759	-1.407	-0.646	-3.856	2.01	-1.398	0.664
Crop	0.759	0.000	-0.646	-3.856	2.01	-1.398	0.6955297407
Regen	0.759	0.000	0.000	-3.856	2.01	1.398	0.6677782181
Solar	0.759	0.000	0.000	-3.856	0.00	-1.398	-1.846718639
Agrivoltaic	0.759	-1.407	-0.646	-3.856	2.01	-1.398	-0.3957629762
Agritourist	0.759	-1.407	-0.646	-3.856	0.00	1.398	-1.094223667
Bot Right							
	SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**	**Deforestation**	**Economic**
Sports	1.249	0.559	0.000	-3.856	0.00	0.000	0.592
Grazing	1.249	-0.559	-1.014	0.000	-2.01	-0.657	0.717
Ski	1.249	0.559	-1.014	-3.856	2.01	0.657	0.664
Crop	1.249	0.000	-1.014	-3.856	2.01	0.657	0.6955297407
Regen	1.249	0.000	0.000	-3.856	2.01	-0.657	0.6677782181
Solar	1.249	0.000	0.000	-3.856	0.00	0.657	-1.846718639
Agrivoltaic	1.249	0.559	-1.014	-3.856	2.01	0.657	-0.3957629762
Agritourist	1.249	0.559	-1.014	-3.856	0.00	-0.657	-1.094223667

Spearman's Coefficient After Competitor

2x2 PARTITION						
Rankings						
SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**	**Deforestation**	**Economic**
6.000	2.000	3.000	7.000	3.000	3.000	1.000
6.000	5.000	2.000	4.000	7.000	3.000	1.000
6.000	4.000	3.000	7.000	1.000	5.000	2.000
6.000	4.000	3.000	7.000	1.000	5.000	2.000
6.000	4.000	4.000	7.000	1.000	3.000	2.000
5.000	1.000	1.000	7.000	1.000	4.000	6.000
6.000	3.000	2.000	7.000	1.000	4.000	5.000
6.000	2.000	1.000	7.000	4.000	3.000	5.000
SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**	**Deforestation**	**Economic**
6.000	1.000	3.000	7.000	3.000	3.000	2.000
4.000	5.000	1.000	3.000	7.000	6.000	2.000
6.000	4.000	2.000	7.000	1.000	3.000	5.000
6.000	5.000	2.000	7.000	1.000	3.000	4.000
5.000	3.000	3.000	7.000	1.000	6.000	2.000
5.000	2.000	2.000	7.000	2.000	1.000	6.000
6.000	4.000	2.000	7.000	1.000	3.000	5.000
4.000	2.000	1.000	7.000	3.000	5.000	6.000
SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**	**Deforestation**	**Economic**
1.000	6.000	3.000	7.000	3.000	3.000	2.000
3.000	1.000	6.000	5.000	7.000	2.000	4.000
2.000	6.000	4.000	7.000	1.000	5.000	3.000
2.000	4.000	5.000	7.000	1.000	6.000	3.000
3.000	5.000	5.000	7.000	1.000	2.000	4.000
1.000	2.000	2.000	7.000	2.000	5.000	6.000
2.000	6.000	4.000	7.000	1.000	5.000	3.000
2.000	6.000	4.000	7.000	3.000	1.000	5.000
SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**	**Deforestation**	**Economic**
1.000	3.000	4.000	7.000	4.000	4.000	2.000
1.000	4.000	6.000	3.000	7.000	5.000	2.000
2.000	5.000	6.000	7.000	1.000	4.000	3.000
2.000	5.000	6.000	7.000	1.000	4.000	3.000
2.000	4.000	4.000	7.000	1.000	6.000	3.000
1.000	3.000	3.000	7.000	3.000	2.000	6.000
2.000	4.000	6.000	7.000	1.000	3.000	5.000
1.000	2.000	5.000	7.000	3.000	4.000	6.000

Spearman's Coefficient After Competitor

Spearman Coefficient		Importance Matrix										Differences				
0.161		3	2	7	4	5	6	1		9	0	16	9	4	9	0
0.143		1	7	2	3	6	4	5		25	4	0	1	1	1	16
-0.071		3	1	5	6	7	4	2		9	9	4	1	36	1	0
-0.179		2	6	3	4	7	5	1		16	4	0	9	36	0	1
-0.482		2	7	1	3	6	5	4		16	9	9	16	25	4	4
-1.268		2	5	7	1	6	3	4		9	16	36	36	25	1	4
-0.786		1	7	5	3	6	4	2		25	16	9	16	25	0	9
-0.536		2	7	5	4	6	3	1		16	25	16	9	4	0	16
0.125		3	2	7	4	5	6	1		9	1	16	9	4	9	1
0.500		1	7	2	3	6	4	5		9	4	1	0	1	4	9
-0.321		3	1	5	6	7	4	2		9	9	9	1	36	1	9
-0.357		2	6	3	4	7	5	1		16	1	1	9	36	4	9
-0.339		2	7	1	3	6	5	4		9	16	4	16	25	1	4
-0.839		2	5	7	1	6	3	4		9	9	25	36	16	4	4
-0.679		1	7	5	3	6	4	2		25	9	9	16	25	1	9
-0.643		2	7	5	4	6	3	1		4	25	16	9	9	4	25
-0.054		3	2	7	4	5	6	1		4	16	16	9	4	9	1
-0.179		1	7	2	3	6	4	5		4	36	16	4	1	4	1
-0.179		3	1	5	6	7	4	2		1	25	1	1	36	1	1
-0.036		2	6	3	4	7	5	1		0	4	4	9	36	1	4
-0.268		2	7	1	3	6	5	4		1	4	16	16	25	9	0
-0.696		2	5	7	1	6	3	4		1	9	25	36	16	4	4
0.179		1	7	5	3	6	4	2		1	1	1	16	25	1	1
0.286		2	7	5	4	6	3	1		0	1	1	9	9	4	16
0.482		3	2	7	4	5	6	1		4	1	9	9	1	4	1
0.357		1	7	2	3	6	4	5		0	9	16	0	1	1	9
0.000		3	1	5	6	7	4	2		1	16	1	1	36	0	1
-0.071		2	6	3	4	7	5	1		0	1	9	9	36	1	4
-0.089		2	7	1	3	6	5	4		0	9	9	16	25	1	1
-0.268		2	5	7	1	6	3	4		1	4	16	36	9	1	4
-0.107		1	7	5	3	6	4	2		1	9	1	16	25	1	9
-0.250		2	7	5	4	6	3	1		1	25	0	9	9	1	25

Spearman's Coefficient After Competitor

							1 VERT PARTITION
			Left				
	SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**	**Deforestation**	**Economic**
Sports	0.95	-1.15	0.00	-3.855605381	0.00	0.00	0.592
Grazing	0.95	1.15	-0.55	0	-2.01	1.09	0.717
Ski	0.95	-1.15	-0.55	-3.855605381	2.01	-1.09	0.664
Crop	0.95	0.00	-0.55	-3.855605381	2.01	-1.09	0.6955297407
Regen	0.95	0.00	0.00	-3.855605381	2.01	1.09	0.6677782181
Solar	0.95	0.00	0.00	-3.855605381	0.00	-1.09	-1.846718639
Agrivoltaic	0.95	-1.15	-0.55	-3.855605381	2.01	-1.09	-0.3957629762
Agritourist	0.95	-1.15	-0.55	-3.855605381	0.00	1.09	-1.094223667
			Right				
	SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**	**Deforestation**	**Economic**
Sports	0.06	0.97	0.00	-3.855605381	0.00	0.00	0.592
Grazing	0.06	-0.97	-0.10	0	-2.01	-1.09	0.717
Ski	0.06	0.97	-0.10	-3.855605381	2.01	1.09	0.664
Crop	0.06	0.00	-0.10	-3.855605381	2.01	1.09	0.6955297407
Regen	0.06	0.00	0.00	-3.855605381	2.01	-1.09	0.6677782181
Solar	0.06	0.00	0.00	-3.855605381	0.00	1.09	-1.846718639
Agrivoltaic	0.06	0.97	-0.10	-3.855605381	2.01	1.09	-0.3957629762
Agritourist	0.06	0.97	-0.10	-3.855605381	0.00	-1.09	-1.094223667

Spearman's Coefficient After Competitor

Rankings							Spearman Coeffi
SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**	**Deforestation**	**Economic**	
1.000	6.000	3.000	7.000	3.000	3.000	2.000	**-0.054**
3.000	1.000	6.000	5.000	7.000	2.000	4.000	**-0.179**
2.000	6.000	4.000	7.000	1.000	5.000	3.000	**-0.179**
2.000	4.000	5.000	7.000	1.000	6.000	3.000	**-0.036**
3.000	5.000	5.000	7.000	1.000	2.000	4.000	**-0.268**
1.000	2.000	2.000	7.000	2.000	5.000	6.000	**-0.696**
2.000	6.000	4.000	7.000	1.000	5.000	3.000	**0.179**
2.000	6.000	4.000	7.000	3.000	1.000	5.000	**0.286**
SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**	**Deforestation**	**Economic**	
3.000	1.000	4.000	7.000	4.000	4.000	2.000	**0.554**
2.000	5.000	4.000	3.000	7.000	6.000	1.000	**0.464**
5.000	3.000	6.000	7.000	1.000	2.000	4.000	**0.036**
4.000	5.000	6.000	7.000	1.000	2.000	3.000	**-0.286**
3.000	4.000	4.000	7.000	1.000	6.000	2.000	**-0.161**
2.000	3.000	3.000	7.000	3.000	1.000	6.000	**-0.304**
4.000	3.000	5.000	7.000	1.000	2.000	6.000	**-0.536**
2.000	1.000	4.000	7.000	3.000	5.000	6.000	**-0.500**

Spearman's Coefficient After Competitor

cient	Importance Matrix								Differences						
	3	2	7	4	5	6	1		4	16	16	9	4	9	1
	1	7	2	3	6	4	5		4	36	16	4	1	4	1
	3	1	5	6	7	4	2		1	25	1	1	36	1	1
	2	6	3	4	7	5	1		0	4	4	9	36	1	4
	2	7	1	3	6	5	4		1	4	16	16	25	9	0
	2	5	7	1	6	3	4		1	9	25	36	16	4	4
	1	7	5	3	6	4	2		1	1	1	16	25	1	1
	2	7	5	4	6	3	1		0	1	1	9	9	4	16
	3	2	7	4	5	6	1		0	1	9	9	1	4	1
	1	7	2	3	6	4	5		1	4	4	0	1	4	16
	3	1	5	6	7	4	2		4	4	1	1	36	4	4
	2	6	3	4	7	5	1		4	1	9	9	36	9	4
	2	7	1	3	6	5	4		1	9	9	16	25	1	4
	2	5	7	1	6	3	4		0	4	16	36	9	4	4
	1	7	5	3	6	4	2		9	16	0	16	25	4	16
	2	7	5	4	6	3	1		0	36	1	9	9	4	25

Spearman's Coefficient After Competitor

Top							
	SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**	**Deforestation**	**Economic**
Sports	-1.38	0.670	0.000	-3.855605381	0.00	0.000	0.592
Grazing	-1.38	-0.670	1.441	0	-2.01	-0.561	0.717
Ski	-1.38	0.670	1.441	-3.855605381	2.01	0.561	0.664
Crop	-1.38	0.000	1.441	-3.855605381	2.01	0.561	0.6955297407
Regen	-1.38	0.000	0.000	-3.855605381	2.01	-0.561	0.6677782181
Solar	-1.38	0.000	0.000	-3.855605381	0.00	0.561	-1.846718639
Agrivoltaic	-1.38	0.670	1.441	-3.855605381	2.01	0.561	-0.3957629762
Agritourist	-1.38	0.670	1.441	-3.855605381	0.00	-0.561	-1.094223667
Bot							
	SA	delta E	W	Sunshine (hrs)	Rain	Deforestation	Economic
Sports	0.33	-0.395	0.000	-3.855605381	0.00	0.000	0.592
Grazing	0.33	0.395	-0.796	0	-2.01	0.561	0.717
Ski	0.33	-0.395	-0.796	-3.855605381	2.01	-0.561	0.664
Crop	0.33	0.000	-0.796	-3.855605381	2.01	-0.561	0.6955297407
Regen	0.33	0.000	0.000	-3.855605381	2.01	0.561	0.6677782181
Solar	0.33	0.000	0.000	-3.855605381	0.00	-0.561	-1.846718639
Agrivoltaic	0.33	-0.395	-0.796	-3.855605381	2.01	-0.561	-0.3957629762
Agritourist	0.33	-0.395	-0.796	-3.855605381	0.00	0.561	-1.094223667

Spearman's Coefficient After Competitor

1 HORIZ PARTITION							
Rankings							**Spearman Coeffi**
SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**	**Deforestation**	**Economic**	
6.000	1.000	3.000	7.000	3.000	3.000	2.000	**0.125**
6.000	5.000	1.000	3.000	7.000	4.000	2.000	**0.286**
6.000	3.000	2.000	7.000	1.000	5.000	4.000	**-0.143**
6.000	5.000	2.000	7.000	1.000	4.000	3.000	**-0.214**
6.000	3.000	3.000	7.000	1.000	5.000	2.000	**-0.446**
5.000	2.000	2.000	7.000	2.000	1.000	6.000	**-0.839**
6.000	3.000	2.000	7.000	1.000	4.000	5.000	**-0.786**
6.000	2.000	1.000	7.000	3.000	4.000	5.000	**-0.643**
SA	delta E	W	Sunshine (hrs)	Rain	Deforestation	Economic	
2.000	6.000	3.000	7.000	3.000	3.000	1.000	**0.018**
4.000	3.000	6.000	5.000	7.000	2.000	1.000	**-0.179**
3.000	4.000	6.000	7.000	1.000	5.000	2.000	**0.143**
3.000	4.000	6.000	7.000	1.000	5.000	2.000	**-0.071**
4.000	5.000	5.000	7.000	1.000	3.000	2.000	**-0.304**
1.000	2.000	2.000	7.000	2.000	5.000	6.000	**-0.696**
2.000	3.000	6.000	7.000	1.000	5.000	4.000	**-0.143**
2.000	4.000	5.000	7.000	3.000	1.000	6.000	**0.000**

Spearman's Coefficient After Competitor

cient	Importance Matrix								Differences						
	3	2	7	4	5	6	1		9	1	16	9	4	9	1
	1	7	2	3	6	4	5		25	4	1	0	1	0	9
	3	1	5	6	7	4	2		9	4	9	1	36	1	4
	2	6	3	4	7	5	1		16	1	1	9	36	1	4
	2	7	1	3	6	5	4		16	16	4	16	25	0	4
	2	5	7	1	6	3	4		9	9	25	36	16	4	4
	1	7	5	3	6	4	2		25	16	9	16	25	0	9
	2	7	5	4	6	3	1		16	25	16	9	9	1	16
	3	2	7	4	5	6	1		1	16	16	9	4	9	0
	1	7	2	3	6	4	5		9	16	16	4	1	4	16
	3	1	5	6	7	4	2		0	9	1	1	36	1	0
	2	6	3	4	7	5	1		1	4	9	9	36	0	1
	2	7	1	3	6	5	4		4	4	16	16	25	4	4
	2	5	7	1	6	3	4		1	9	25	36	16	4	4
	1	7	5	3	6	4	2		1	16	1	16	25	1	4
	2	7	5	4	6	3	1		0	9	0	9	9	4	25

Spearman's Coefficient After Competitor

All							
	SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**	**Deforestation**	**Economic**
Sports	0.70	-0.01	0.00	-3.855605381	0.00	0.00	0.592
Grazing	0.70	0.01	0.01	0	-2.01	-0.77	0.717
Ski	0.70	-0.01	0.01	-3.855605381	2.01	0.77	0.664
Crop	0.70	0.00	0.01	-3.855605381	2.01	0.77	0.6955297407
Regen	0.70	0.00	0.00	-3.855605381	2.01	-0.77	0.6677782181
Solar	0.70	0.00	0.00	-3.855605381	0.00	0.77	-1.846718639
Agrivoltaic	0.70	-0.01	0.01	-3.855605381	2.01	0.77	-0.3957629762
Agritourist	0.70	-0.01	0.01	-3.855605381	0.00	-0.77	-1.094223667

Spearman's Coefficient After Competitor

Rankings							Spearman Coeffi
SA	**delta E**	**W**	**Sunshine (hrs)**	**Rain**	**Deforestation**	**Economic**	
1.000	6.000	3.000	7.000	3.000	3.000	2.000	**-0.054**
2.000	4.000	3.000	5.000	7.000	6.000	1.000	**0.357**
3.000	6.000	5.000	7.000	1.000	2.000	4.000	**-0.250**
3.000	6.000	5.000	7.000	1.000	2.000	4.000	**-0.214**
2.000	4.000	4.000	7.000	1.000	6.000	3.000	**-0.089**
2.000	3.000	3.000	7.000	3.000	1.000	6.000	**-0.304**
3.000	5.000	4.000	7.000	1.000	2.000	6.000	**-0.250**
1.000	4.000	2.000	7.000	3.000	5.000	6.000	**-0.179**

Spearman's Coefficient After Competitor

cient	Importance Matrix								Differences						
	3	2	7	4	5	6	1		4	16	16	9	4	9	1
	1	7	2	3	6	4	5		1	9	1	4	1	4	16
	3	1	5	6	7	4	2		0	25	0	1	36	4	4
	2	6	3	4	7	5	1		1	0	4	9	36	9	9
	2	7	1	3	6	5	4		0	9	9	16	25	1	1
	2	5	7	1	6	3	4		0	4	16	36	9	4	4
	1	7	5	3	6	4	2		4	4	1	16	25	4	16
	2	7	5	4	6	3	1		1	9	9	9	9	4	25

Spearman's Coefficient After Competitor

	Spearman Coefficient Final Table						
	2x2				Vert		Ho
	Top Left	**Top Right**	**Bottom Left**	**Bottom Right**	**Left**	**Right**	**Top**
Sports	**0.161**	0.125	-0.054	**0.482**	-0.054	**0.554**	0.125
Grazing	0.143	**0.500**	-0.179	0.357	-0.179	0.464	**0.286**
Ski	-0.071	-0.321	-0.179	0.000	-0.179	0.036	-0.143
Crop	-0.179	-0.357	-0.036	-0.071	-0.036	-0.286	-0.214
Regen	-0.482	-0.339	-0.268	-0.089	-0.268	-0.161	-0.446
Solar	-1.268	-0.839	-0.696	-0.268	-0.696	-0.304	-0.839
Agrivoltaic	-0.786	-0.679	0.179	-0.107	0.179	-0.536	-0.786
Agritourist	-0.536	-0.643	**0.286**	-0.250	**0.286**	-0.500	-0.643

Spearman's Coefficient After Competitor

riz	1
Bottom	**Single**
0.018	-0.054
-0.179	**0.357**
0.143	-0.250
-0.071	-0.214
-0.304	-0.089
-0.696	-0.304
-0.143	-0.250
0.000	-0.179