IEOR 4111 Project Report: Imperative Fund

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1 Introduction

1.1 Imperative

Imperative is an investment fund company that focuses on helping communities out of poverty by providing necessary goods and services, while achieving competitive returns to impact investors. Imperative has successfully achieved a net 9% annual return and received all capital back within 5 years of deployment. Imperative empower individuals, families, and communities to alleviate poverty by building most foundational needs: housing, and giving financial literacy including access to microfinances services.

Imperative financing structure is gathering capital investment from lender with average returns on 8-9% APR, and lending the capital into borrower with averagely 11% - 16% APR, and finally borrower lending the capital into the final ultimate beneficiary (individual and families) with averagely 23% - 30% APR (compared to market as usual at 45-50%). Using these mechanics, Imperative has successfully managed fund investment. As a result communities in Tabasco, Mexico, zero percent of communities/families whose lended capital have defaulted and more than 40% annualized return was acquired on the debt after 3 years. Imperative mitigates the risk of default carefully by offering four layers of mitigation: mortgage (first priority claim on land and home), borrower assets (first priority claim on the entirety of all borrower loans), equity conversion (the right to convert any remain equity), and currency (USD usage of loan payment, to avoid currency risk).

Imperative has successfully given impact for communities in Mexico for the past years. Currently, Imperative is looking to expand the impact for greater communities in other challenging countries, such as Colombia and Ghana. Our team has worked to analyze the investment in Colombia by collecting the data, modifying social impact, and refining the robust optimization model to carefully find targeted communities to be invested in.

1.2 Colombia: Facts about Target Country

Colombia is a country in South America with a population of 50 million people in 2020. Colombia has improved their economy, and the poverty level has decreased in the recent years, but millions of people in Colombia are still desperately poor. Based on (The National Administrative Department of Statistics) in 2018, 27% of the population lives in poverty, and rising to **36% of the population lives in rural areas**. Furthermore, 7% of Colombia's population live in extreme poverty, lacking even the essentials of life. Not

only poverty, Colombia also suffers from a very high level of inequality. Although poverty levels have reduced in recent years, inequality has not.
Investments and infrastructure have unequally distributed among rural and urban areas. Municipalities in Colombia have experienced violent internal conflicts for more than 50 years, that causes people to migrate to urban areas and create informal settlements or illegal housing on the cities' borders. This informal settlement results in many challenges, including lack of access to basic services, poor structural quality and low accessibility to resources for progressive infrastructure, limited access to social and health services, education and employment possibilities. [1]

In 2018, the Ministry of Housing estimated there are about **3.8 millions households** that do not have adequate housing, and nearly 30 percent of all families in Colombia, even worse 5% of the population are homeless. To worsen the problem, according to Opportunity Colombia, only 2.5% of Colombians are using microfinance services. This urgency has made the Imperative Fund willing to invest in Colombia on social development for targeted municipalities.

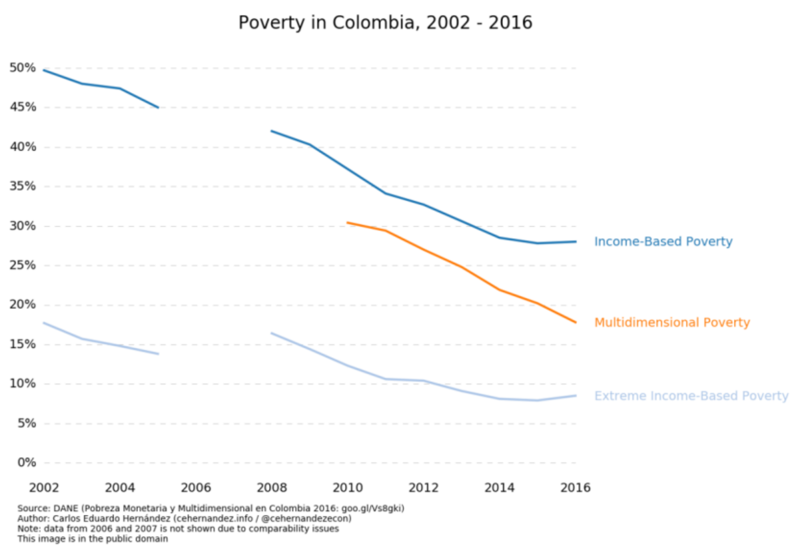

Figure 1 Poverty in Colombia

[1] See 10 Facts about Poverty in Colombia by Julia Lee (https://borgenproject.org/10-facts-about-poverty-in-colombia/)

2 Problem Description, Goals & Data

2.1 Problem Description

The core problem of this project is to get selected municipalities of Colombia out of poverty by bringing them indispensable materials. Poverty is defined as deprivation in well-being, and it is comprised of many dimensions, including low income and the inability to acquire the basic goods and services necessary for survival with dignity. Poverty also encompasses low levels of health and education, limited access to clean water and sanitation, inadequate physical security, lack of voice, and insufficient capacity and opportunity to better one's life.

2.2 Project Goals

This project has two goals. It strives to lift municipalities out of poverty by bringing them the necessary goods and commodities, to **accomplish their social and economic development as well as achieving market competitive return on investment**. Imperative Fund realizes this goal by lending capital to experienced social enterprises among this field and depending on them for successful and fair distribution of the resources. To allocate sufficient funds to the municipalities in need, we use a robust optimization model to locate the municipalities that fit the requirements such as that they possess the ability to pay back and the potential to generate high social impact. The model captures the trade-off between investment return and social impact and aims to find top optimal municipalities to invest under time and resource constraints.

2.3 Project Timeline

We follow the following steps to embark on this project, we (i) initialize the project (ii) data collecting, research and implement the code (iii) finalize the results and display results by Tableau (iv) wrap up results in a report and present investment recommendations based on quantitative results.

2.4 Data

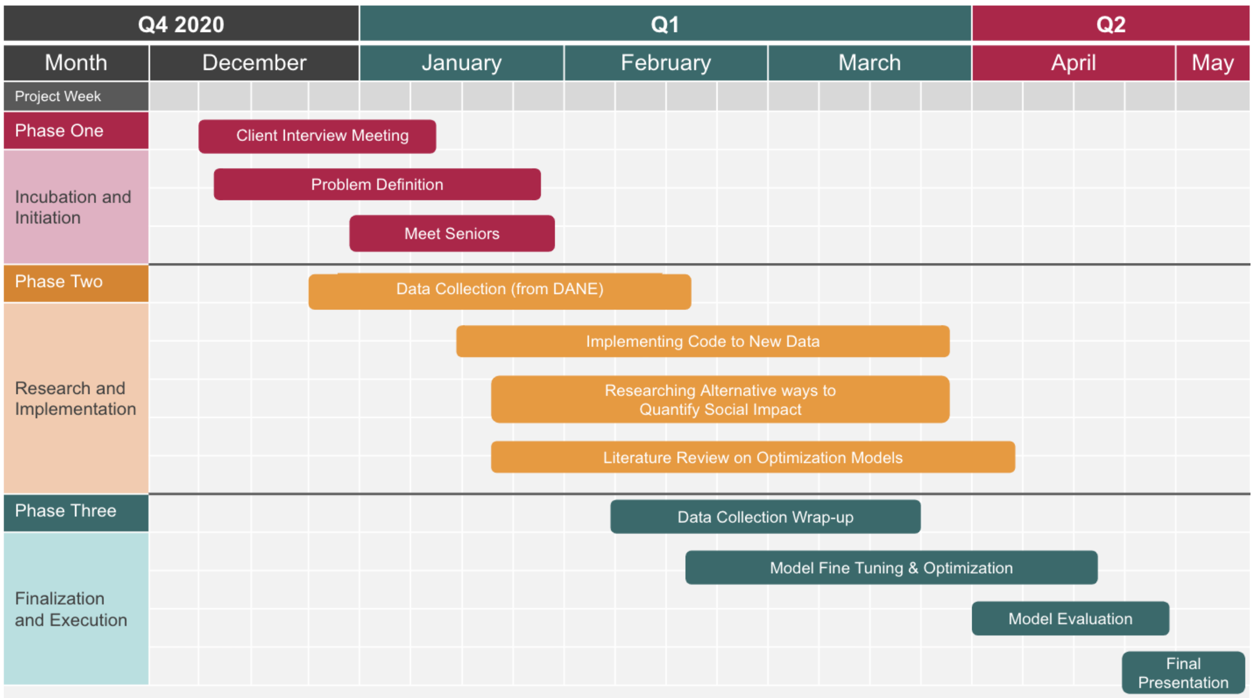

Figure 2 Project Timeline

The data we collect for the Imperative Fund is the **1,125 municipalities**, was obtained from national data sources such as DANE (The National Administrative Department of Statistics), regarding a multitude of quantitative data. Data is broken down on a state, municipality level, to be able to drill down to the exact municipalities where investment is the most sensible. The following quantitative data is provided for each municipality:

- Data for social impact:
    - Default rate (*)
    - Income (*)
    - Population
    - Number of Households

- Financial data:
    - Construction cost
    - Service cost
    - Interest rates
    - Exchange rates

- Data for living needs:
    - % of population without each of the 5 needs including housing, water, electricity, Internet, health insurance

  * These data are estimated from other columns

This data was used to calculate other metrics that are useful to feed into the optimization model, in order to better analyze maximum total social impact, reduction of expected default loss and achievement of max return on investment, that can be had by investing in a certain municipality.

3 Social Impact

3.1 Definition of Poverty Needs

Previously, we have outlined the goals of Imperative Fund – which are to maximize return on investment and social impact. Social impact, an important part of our objective, is derived from the criterions of poverty defined by the United Nations. The definition of poverty by the United Nations states that: "It (Poverty) means lack of basic capacity to participate effectively in society. It means not having enough to feed and clothe a family, not having a school or clinic to go to, not having the land on which to grow one's food or a job to earn one's living, not having access to credit. It means insecurity, powerlessness and exclusion of individuals, households and communities. It means susceptibility to violence, and it often implies living in marginal or fragile environments, without access to clean water or sanitation." Based on the definition, we narrowed down the criterions for poverty and came up with 5 needs to quantify them into the Social Impact metric. They are: Housing, Water, Electricity, Health Service, and Internet needs. We collect % of people that lack these needs from various sources such as DANE (National Administrative Department of Statistics) for all communities in Colombia.

3.2 Defining Weights for Needs through AHP

To better access the relative importance of each need, AHP (Analytic Hierarchy Process) was used. AHP is a mathematical technique used in the field of social sciences to organize and structuralize complex decision making.

The steps of AHP are:

1. Create a 5x5 matrix with assigned relative importance factor for each need. The factor ranges from 1-9. 1 being the same importance as other needs, and 9 for a much more important need.

2. Normalize the factors to make sure they are summed to 1.

3. Calculate individual weight by averaging normalized weights.

The result of AHP needs is gathered from a questionnaire made by previous year's seniors. Due to lack of data, originally, we decided to use 5 out of the 7 needs originally used from last year. As a result, we have modified the weights.

The new AHP weights are the following:

Needs	Weights
Housing	0.51
Water	0.21
Internet	0.05
Electricity	0.14
Health Services	0.09

Table 1 AHP Weights

3.3 Financial Data and Other Basic Data

Besides data for living needs, financial data and other basic data concerning information of each municipality are also necessary.

Financial data consists of interest rates, exchange rates and construction cost. For interest rates, the maximum yield is 23.37% per year (i.e., 1.77% per month) while the minimum yield is 20.06% per year (i.e., 1.54% per month). The exchange rate of COP/USD is 3600. For construction cost, we obtained the cost of building a house, accessing water, electricity and Internet for each family from the historical experience. The costs are shown as the following:

Needs	Costs	
	COP	**USD**
Housing	37,800,000	10,500
Internet	324,000	90
Electricity	1,980,000	550
Water	540,000	150
Health Services	0	0
Total	**40,644,000**	**11,290**

Table 2 Cost of Needs

The above data illustrates that the total cost per household in Colombia is $11,290. Since 60% of total cost should be paid back by each household while the other 40% is afforded by Colombia government, total payment per household is $6,774. The payback period is 60 months (i.e., 5 years) and payment by household per month is $183.94.

Other basic data includes default rate, average monthly income, population and number of households on municipal level. Average monthly income, population and number of households could be accessed from various official websites on municipal level while default rate is on country level.

3.4 Default Rates

We want to introduce the personalized default rate for each municipality to better simulate the actual situation. However, we only have access to the default rate on country level. So we need assumptions and inferences based on this data because each municipality has different average monthly income per household.

We have the following assumptions & facts:

1. Each municipality now has a common default rate ρ_r, we want to generate a personalized default rate ρ_j for every municipality.

2. We assume the default rate has an inverse relationship with average income. Municipalities with higher income have lower default rates, communities with lower income have lower default rates.

3. We assume the default rate and average income have the same coefficient of variation and follow the same distribution.

4. We assume the default rate and average income for a municipality have the same percentile.

5. If I_j is less than 0, then we assume I_j equals to 0.

We included the following set of variables:

- ρ_r : country level average default rate
- ρ_j : default rate for municipality j
- I_r : country level average monthly income per household
- I_j : average monthly income per household for municipality j

The formula for default rate is defined as:

$$\rho_j = \rho_r - \rho_r * (I_j - I_r) / I_r$$

3.5 Ability to Payback

The ability to payback is calculated by introducing the income/payment ratio. For a specific municipality, if the ratio is less than 3, then we assume this municipality does not have the ability to pay back and won't invest in this municipality. If the ratio is greater than 3, then we assume this municipality has the ability to pay back and will consider investing in this municipality. The income to payment ratio lower bound of 3 was set by the Imperative Fund with the idea being that any more than 33% of income dedicated to monthly payments would be difficult for people. According to the assumption above, 622 out of 1,122 municipalities have the ability to pay back. In the following social impact calculation and investment consideration, we only consider 622 municipalities who can afford the installment.

3.6 Social Impact Formulation

The original formula for Social Impact is defined as:

$$\underbrace{SI_j}_{\text{Social Impact of investing in community } j} = \underbrace{H_j}_{\text{Number of households}} * \left(1 - \underbrace{\rho_j}_{\text{Default Rate}}\right) * \sum_i \underbrace{w_i}_{\text{Weight of need } i} * \underbrace{p_{ij}}_{\text{Proportion of households lacking need } i}$$

Figure 3 2020 Social Impact Formula (ALMA Consulting, 2020)

Where H_j denotes the number of households in a municipality, ρ_j denotes default rate defined in section 2.4, w_i as weights for each of the 5 needs from section 2.2 and finally $p_{i,j}$ for the % of households lacking a specific need i.

4 Reformulating Social Impact

The above Social Impact formulation has been used by the previous year's model and has produced good results; however, after careful inspection, a series of flaws were found.

1. Weights are constant for all communities.
2. All needs are simply added together without taking account of any grouped effect.
3. There are no levels of precedence in our consideration. Although we can see from the needs that some are definitely more important than others and need to be prioritized.
4. Since we take into account the number of households, which causes our final selection to be biased toward large municipalities.

With the above issues in mind, we have come up with the following improvements to the weights w_i parts of our Social Impact formulation to take into account of these problems. New approach customizes weights for each municipality based on the condition of whether a municipality's proportion of people lacking the certain needs passes a threshold for a range of scenarios.

4.1 Using Average Social Impact per Household

As described in bullet point number 4 in the above section, we found that the model is biased toward larger communities with higher population, thus we decided to remove H in our SI formula and instead use average Social Impact per household.

4.2 Assigning Tiers to Needs

After examining the 5 needs, 3 needs are considered to be Tier 1 needs (Water, Housing and Electricity), the most important needs to be fulfilled in order to proceed. The remaining 2 needs are classified as Tier 2 needs (Access to Healthcare and Internet), which are less important.

4.3 Setting a 20% quantile Thresholds for Each Need

We select the top 20% quantile for the proportion of households lacking this need for all needs of the whole Colombia's data and use this as a benchmark to compare with a single municipality. If a municipality's proportion is greater or equal to the threshold, we will customize the weights according to scenarios.

4.4 Applying Amplifiers to Weights

In section 3.1, we have split our 5 needs into 2 categories, Tier 1 and Tier 2. The scenarios to which weights are amplified will be based on the categories. Tier 1 categories will be an important indicator for weight modification.

Scenario 1 Proportion of household lacking the needs is above the threshold for all 5 needs in a given municipality:

All 5 weights will be multiplied by 1.8.

Scenario 2 All 3 Tier 1 needs' proportion of households lacking the needs in a municipality are above the thresholds.

<u>All Tier 1 weights</u> will be multiplied by 1.5.

Scenario 3 Any 2 out of 3 Tier 1 needs proportion of households lacking the needs in a municipality are above the thresholds.

<u>The 2 Tier 1 Needs above the threshold</u> will be multiplied by 1.2.

If a municipality doesn't meet all the above requirements, the weights will remain the same with no amplifiers applied.

To illustrate this process better, a diagram is attached to the appendix section of the report. [Appendix 1]

4.5 Evaluation and Alternatives

The new method introduces a penalty for a municipality with 1 or more important proportion missing the need by increasing the weights through amplifiers.

The new formulation for Social Impact is shown below:

$$SI = \textbf{number of houlseholds in the municipality} * (1 - \textbf{default rate}) * \sum_i \textbf{weight of need i} * \textbf{percentage in need of need}$$

$$SI = (1-\rho_j) * \sum_{i=1}^{5} (w_i * I\{P_{ij} \in R_s\} * a_s) * P_{ij}$$

$s \in \{1,2,3,4\}$

$T_1 = \{1,2,3\}$

$T_2 = \{4,5\}$

$R_1 = \{P_{ij} | P_{ij} \in U_i, \forall i \in T_1 \cup \ T_2\}$

$R_2 = \{P_{ij} | P_{ij} \in U_i, \forall i \in T_1\}$

$R_3 = \{P_{ij} | P_{ij} \in U_i, \exists i_1, i_2 \in T_1\}$

$R_4 = \{P_{ij} | \forall i \in T_1 \cup \ T_2\}$

$a_1, a_2, a_3, a_4 = 1.8, 1.5, 1.2, 1$

U_i : Top 20% communities lacking need $i, i \in \{1,2,3,4,5\}$

P_{ij} only need to fall into at most 1 R_1, level of precedence in decision rule: $R_1 > R_2 > R_3 > R_4$

Figure 4 Modified Social Impact Formulation

The reformulated Social Impact addresses the problems outlined in section 4 by:

- Allows each municipality's weights to vary by customizing weights according to scenarios.
- Takes into account the possible grouped effect of needs through introduction of amplifiers.
- Prioritize the important Tier 1 needs based on defined scenarios as level of precedence is considered.

As a result of the new method for calculating weights, municipalities that meet the requirements for the scenarios will be prioritized as they will achieve higher Social Impact values.

There are also possible concerns with the new methodology, notably, that it will cause our model to invest in more default-prone municipalities, as by assumption, a municipality with a higher proportion of households lacking a need is usually in a less desirable financial state.

To address this concern, a few points can be raised:

1. Although the new method puts more emphasis on communities with a higher proportion of needs missing, the communities we invest in will need to meet a prior requirement of possessing the ability to pay back. This ensures that we can achieve a lower-bound on the fund that we can recover even under the most unfavorable conditions.

2. Amplifiers can be adjusted to accommodate the trade-off between probability of default and SI. The new methodology's proposed set of amplifiers (1.8, 1.5, 1.2) can be reduced in favor of a lower probability of default by reducing the potential generated social impact.

Alternatively, all weights can be multiplied by the amplifier instead of only applying to relevant weights for higher Social Impact.

5 Model Setting

This year we follow the robust models with the Bertsimas & Sim method from last year's report. We slightly changed the code to make it function right and use average social impact for comparison rather than using total social impact. Thus, the results will not be biased to the municipalities with large numbers of inhabitants. We also researched in new directions to try and decide to test if a fuzzy model can be used to solve the problem. We derived some feasible solutions and will be summarized in 5.4 and one strategic investment plan will be further studied at chapter 6.

5.1 Problem Formulation

We collaborate with Imperative Fund to formalize a $50 M investment plan to help communities eliminate poverty in Colombia. As the municipalities are **ranked by average social impact and pre-selected of the top 100**, then we use a **cash flow optimization model** to formulate the pipeline of the investment plan based on the duration of the launched project, and the total budget amount (2 inputs).

Then we generate a timeline for the investment, which would include when and which municipalities we would invest, whether partially or fully. For example, we could potentially invest in municipality 1 at stage 5 (month) with 50% of the capital required for that municipality. And we would consider the reinvestment in our model. We lastly measure the performance by the return on investment, annualized return, households helped and social impact.

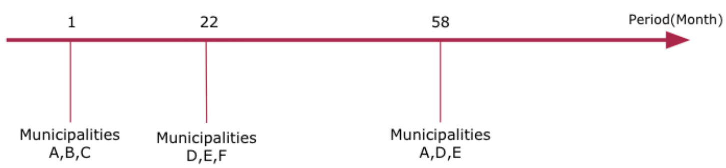

Figure 5 Sample Output, example timeline

Input:

- The social impact that each municipality would bring,
- The cash flows for launching the project, (assume consistent for all municipalities)
- The cash initially available,
- Duration expected for the whole project

Output:

The optimal capital allocation that maximizes the return on investment and the social impact *i.e.*
The optimal **percentage of investment in each community at each time** that maximizes the final cash available.

5.2 Robust Optimization

Because uncertainty in the data or in the cashflow, the solution should be robust to changes in the coefficients of the constraints. The intuition of **Robust optimization** is to enable controlling uncertainty in these coefficients – by sacrificing some objective value. It guarantees the feasibility and optimality of the solution for all values of the coefficients within certain **uncertainty sets**. Moreover, the level of robustness ($\Gamma^{(SI)}$ and $\Gamma^{(C)}$) are parameters, by which we could control the level of a compromise between robustness and optimality.

5.2.1 Variable Definition

We introduce the following set of variables (more details could be referred to Imperative report(ALMA Consulting, 2020)):

- K, *set of all municipalities*
- $J = |K|$, *number of municipalities*
- $T > 0$, *duration of project expected to recover interests*
- SI_j, *social impact brought when investing fully in municipality* j, $j \in K$
- $L(j)$, *length of cashflows of municipality* j, $j \in K$
- q_t, *cash at time* t, $t \in [\![0, T]\!]$
- $\left(C_{j,t}\right)_{t \in [\![1, L(j)]\!]}$, *sequence of cash flows for municipality* j, $j \in K$
- $y_{j,t}$, *percentage of capital invested in municipality* j *at time* t, $j \in K$ *and* $t \in [\![1, T]\!]$
- $\widehat{SI}_j$, *amount by which the social impact of municipality* j *can vary*, $j \in K$
- $\hat{C}_{j,t}$, *amount by which the cash flow of municipality* j *at time* t *can vary*, $j \in K$ *and* $t \in [\![1, L(j)]\!]$

5.2.2 Robust Formulation

The initial robust optimization is to establish. The robust model is thus:

$$\max_{(y_{i,j})_{(i,j)\epsilon\Omega}} \quad q_T$$

$$s.t \begin{cases} q_t - q_{t-1} - \sum_{(i,j)\epsilon\Omega_t} (y_{j,i} C_{j,t-i+1} - \pi_{i,j,t}) + \pi_t \Gamma_t^{(C)} \leq 0, & t \in [\![1,T]\!] \\ SI^* - \sum_{i=1}^{T} \sum_{j=1}^{J} \left(SI_j y_{j,i} - p_{i,j} \right) + p\Gamma^{(SI)} \leq 0, & \\ \pi_t + \pi_{i,j,t} \geq w_{j,i} \hat{C}_{j,t-i+1}, (i,j) \in \Omega_t, & t \in [\![1,T]\!] \\ p + p_{i,j} \geq w_{j,i} \widehat{SI}_j, & (i,j) \in \Omega \\ \sum_{i=1}^{T} y_{j,i} \leq 1, & j \in K \\ w_{j,i} \leq y_{j,i}, & (i,j) \in \Omega \\ w_{j,i} \geq -y_{j,i}, & (i,j) \in \Omega \\ y_{j,i} \geq 0, & (i,j) \in \Omega \\ q_t \geq 0, & t \in [\![1,T]\!] \\ \pi_t \geq 0, & t \in [\![1,T]\!] \\ \pi_{i,j,t} \geq 0, & (i,j) \in \Omega_t, t \in [\![1,T]\!] \\ p \geq 0, & \\ p_{i,j} \geq 0, & (i,j) \in \Omega \end{cases}$$

Figure 6 Imperative 2020 Robust Optimization Formulation

5.2.3 Degree of Robustness

We changed the number of cashflow that can vary ($\Gamma^{(C)}$) to examine the **tradeoff between robustness of the model and optimal values of return and social impact**. '$\Gamma^{(t)}$' is an array in which we store $\Gamma^{(C)}$ for all time periods. For each time t, after calculating the total number of coefficients of cashflow, we multiply it by a constant percentage pc which represents the degree of robustness and append it to $\Gamma^{(t)}$ so as to uniformly lower the upper bounds of the number of coefficients that are allowed to change. The results returned by the optimization model will be lower if we improve the $\Gamma^{(C)}$, which is in line with our expectation that Γ should be negatively correlated with optimal values – if we increase robustness, we would sacrifice the objective value. We further try several contraction coefficient (multiple of Γ to adjust the level of robustness) of [0.1, 0.01, 0.001], then we choose based on the probability of violating the constraints and sample size and choose the middle one 0.01. Then we solve for different pairs of returns and social impact by binary search on the social impact.

5.3 Fuzzy

The Fuzzy model is our new attempt to solve the problem. Fuzzy, in contrast to crisp, means things you cannot define the boundary clearly. Constraints like around x, good result, small loss fall into fuzzy. It is possible to define membership functions to capture those criteria. A membership function gives output from 0 to 1 to describe how well the criteria are met. For example, if you want to have a return of around 10% for an investment, the membership function can be built in the following way:

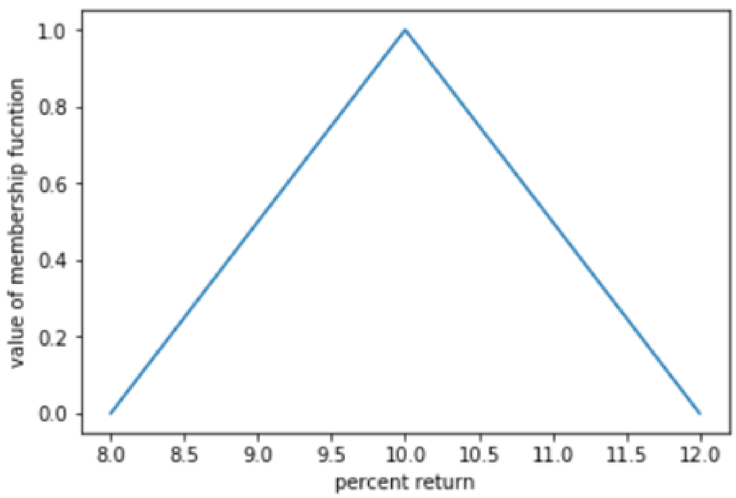

Figure 7 Sample Membership Function

The closer it is to 10% percent, the higher value. Membership functions are defined subjectively. Here, when the return is 2% away from the target value of 10%, the value of the membership function becomes 0. This 2% cent can be set as 1% or 3% based on one's judgement on what 'around' means.

This can be applied into optimization problems to get a solution that is suboptimal but captures a wider range of uncertainties based examples from the book of Eelco van Beek& Daniel P. Loucks(2005). If you can capture the objective with a membership function and change the constraint from crisp into fuzzy, you can get a solution with some level of robustness. For example, if you now the optimal value cannot exceed value X*, you can normalize the objective by X* to get the membership function for the objective. Then change the constraint of less than C1 into less than about less than C1, you can build a membership function for the constraint. Then instead of finding the optimal Value, change the goal to find the maximum of the minimum of those membership functions, you will get a solution that still holds if in reality the constraint is not strictly C1.

In our attempt we tried to use membership functions to describe the cashflow and social impact. To do that, we need to know around what value we expect the cashflow and social impact to be. Below is our framework for membership function for cashflow and social impact at time t. Vt represents the value of cashflow or social impact at time t, Gt represents the goal value at t and Tt is the maximum violation allowed at time t. The problem lies in finding proper values for goals at that specific time.

$$mc_t = \begin{cases} \frac{V_t}{G_t}, & \text{If } 0 \leq V_t \leq G_t \\ \frac{T_t - V_t}{T_t - G_t}, & \text{If } G_t \leq V_t \leq T_t \\ 0, & \text{otherwise} \end{cases}$$

Figure 8 Proposed Membership Function

We proposed we could use values from the solution of the original model without any robustness, because the solution of this model doesn't consider any uncertainty and will thus me the maximum value attainable. During our implementation, however, we realized there is a flaw in our logic. If we use the solution from crisp models to set membership functions for the fuzzy model, the fuzzy model can reproduce the invest decision of the crisp model to get the value of one to all membership functions. This way, no robustness is added. Due to the time constraint, we didn't come up with good enough membership functions to capture our problem, but we think fuzzy is a good direction to go.

5.4 Code

During our review of last year's code, we found some bugs in the code. The threshold is not introduced properly to the Social Impact, which leads to erroneous behavior of the model: even if the community is not fully invested, during the calculation of Social Impact, the model will use the total social impact. This way, the model tends to select communities with large populations instead of communities lacking many needs.

5.5 Result Display

The above optimization model was implemented to run simulations of Imperative Fund's returns for different scenarios. In addition to focusing on the two primary objectives of return on investment and social impact, we also aim to obtain a snapshot of the actual communities that are chosen for investment and the impact created in terms of the number of households and inhabitants helped.

Our model was applied to the communities in Mexico to get an idea of the outputs. For an investment of budget 50 Million USD for 100 Communities, 90-Month periods, and a Social Impact (SI) constraint of 10669, Imperative Fund could invest in 15 communities fully and 1 communities partially, as is shown below. Specifically, for period 1 (the first month), Imperative Fund could begin invest in the following 16 communities: **Pinillos, Tiquisio, San Jacinto Del Cauca, Paya, La Montanita, Milan, Riosucio, Alto Baudo, Carmen Del Darien, San Andres Sotavento, Monitos, Puerto Escondido, Los Córdobas, Canalete, Manaure, Sabanas De San Angel**. At the end of the project, would be partially invested with completion rate 97% and 66%, respectively. And other communities could be invested fully.

By setting of different compositions of a budget of [25, 50] million USD and a horizon of [90, 120] months, the results are displayed below:

Budget ($M)	25	50	25	50
Time (months)	90	90	120	120
Modified Social Impact	5609	10669	10845	20676
Return	33.0	67.1	66.9	133.8
Households included	8239	16497	15851	31466
Annualized Yield (%)	11.9	12.0	13.9	13.9

Table 3 Summarized Statistics for different sets of budget and timezone
(Note: This table takes only max social impact)

6 Visualize the Investment Plan

6.1 Process Flow

We collected the data for all 1,125 municipalities in Colombia that are divided into 33 departments. Initially, we chose 622 municipalities based on the ability to payback as mentioned in part 3.5. The ability to payback is determined by which municipality has 3x income per payment ratio.

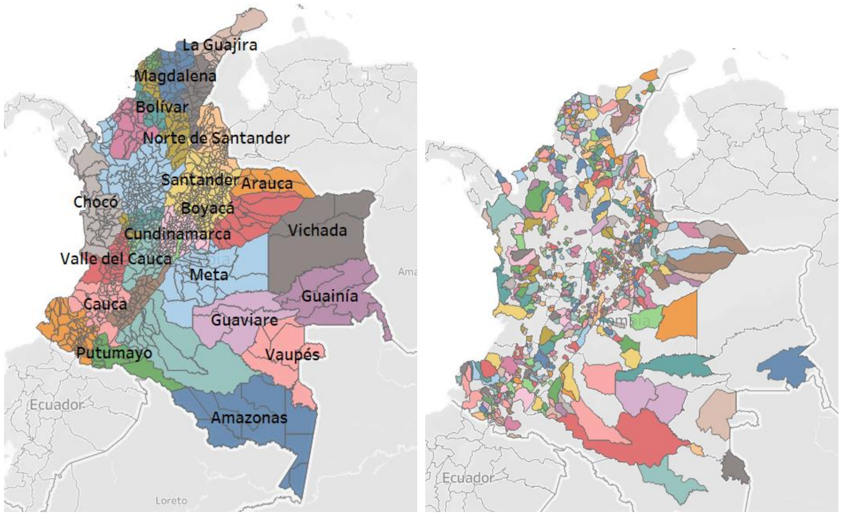

Figure 9 Municipalities selection based on ability to payback

After that, we pre-selected 100 municipalities based on social impact metric in order to speed up the model calculation . The picture on the left side is 100 municipalities based on original social impact, and the right side is based on modified social impact. The color of each municipality is based on the total social impact of each municipality.

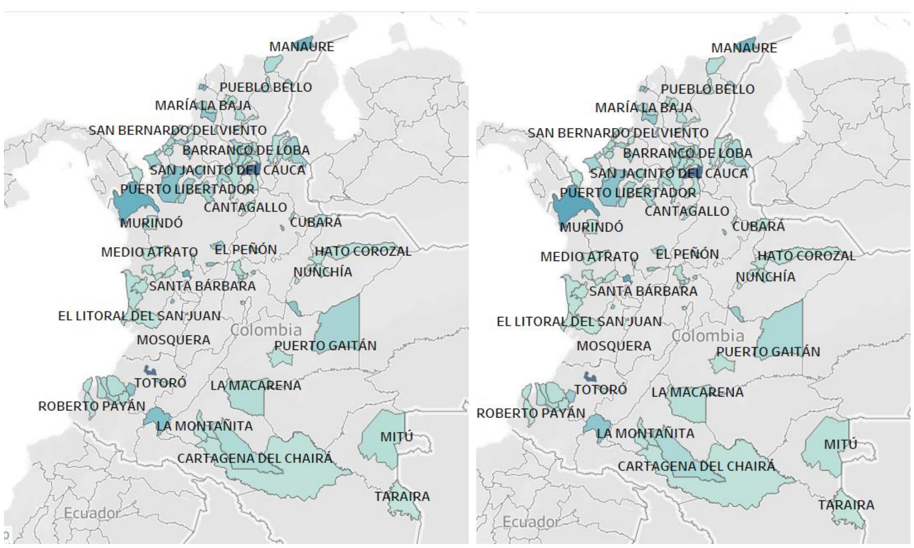

Figure 10 Municipalities selection based on social impact

6.2 Municipality List Comparison

We compare the results using different social impact methodology. The graph on the left shows the municipality list generated from the original social impact calculation; whereas the graph on the right shows the municipality list generated from the modified social impact calculation. The **red star signs indicate the non-overlapping municipality** and the number in the graph represents the social impact. As we can see from the graphs, the original social impact has a total of 19 municipalities and the modified social impact has a total of 16 municipalities. These municipalities are selected based on the prioritized needs mentioned in the social impact section.

State1	Municipality1	
ANTIOQUIA	SAN PEDRO DE URABA	4,041
	SAN JUAN DE URABÁ	2,668
BOLÍVAR	PINILLOS	2,926
	MORALES	2,713
	ACHÍ	2,614
	TIQUISIO	2,014
	SAN JACINTO DEL CAUCA	1,291
	NOROSÍ	1,221
BOYACÁ	CUBARÁ	1,386
	PAYA	281
CHOCÓ	RIOSUCIO	6,380
	ALTO BAUDO	2,420
CÓRDOBA	SAN ANDRÉS SOTAVENTO	5,804
	MOÑITOS	3,911
	PUERTO ESCONDIDO	2,998
	LOS CÓRDOBAS	2,816
	CANALETE	2,155
LA GUAJIRA	MANAURE	11,340
MAGDALENA	SABANAS DE SAN ANGEL	1,471

V.S.

State	Municipality	
BOLÍVAR	PINILLOS	4,183
	TIQUISIO	2,900
	SAN JACINTO DEL CAUCA	1,519
BOYACÁ	PAYA	403
CAQUETÁ	LA MONTAÑITA	2,549
	MILÁN	1,581
CHOCÓ	RIOSUCIO	11,483
	ALTO BAUDO	4,357
	CARMEN DEL DARIEN	2,844
CÓRDOBA	SAN ANDRÉS SOTAVENTO	8,386
	MOÑITOS	4,602
	PUERTO ESCONDIDO	3,537
	LOS CÓRDOBAS	3,323
	CANALETE	2,541
LA GUAJIRA	MANAURE	16,465
MAGDALENA	SABANAS DE SAN ANGEL	2,118

Table 4 Original Social Impact vs Modified Social Impact

6.3 Contribution of our team compared to previous Teams

This year we made several progress. First, we propose a different social impact methodology, which Use Average SI by removing #of Households and set thresholds for each need. We are grouping Needs into 2 tiers based on importance and applying amplifiers based on defined criterions. Second, we implement robust models on a new country, from collecting data, modeling, visualization, which facilitate the decision process for the Imperative fund.

7 Conclusion and Future Work

In short, our contribution to the Imperative fund this year is collecting a normalized dataset, proposing a new and more **reasonable social impact calculation** method, **implementing the robust optimization model on a new country** - Colombia and we further visualized the result by Tableau. The work could be further strengthened by more detailed study of Fuzzy model implementation and other robust techniques.

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Appendix

Scenario 1

<u>All 5 Needs</u> are above the thresholds for a municipality

Old Weights

	Weights
Need: Housing	0.51
Need: Water	0.21
Need: Internet	0.05
Need: Electricity	0.14
Need: Health Services	0.09

Applying Amplifier

All * 1.8

New Weights

	Weights
Need: Housing	0.92
Need: Water	0.38
Need: Internet	0.09
Need: Electricity	0.25
Need: Health Services	0.16

Scenario 2

<u>All 3 Tier 1 Needs</u> are above the thresholds for a municipality

Old Weights

	Weights
Need: Housing	0.51
Need: Water	0.21
Need: Internet	0.05
Need: Electricity	0.14
Need: Health Services	0.09

Applying Amplifier

All Tier 1 Weights * 1.5

New Weights

	Weights
Need: Housing	0.77
Need: Water	0.32
Need: Internet	0.05
Need: Electricity	0.21
Need: Health Services	0.09

Scenario 3

<u>2 out of 3 Tier 1 Needs</u> are above the thresholds for a municipality (Housing & Water for this example).

Old Weights

	Weights
Need: Housing	0.51
Need: Water	0.21
Need: Internet	0.05
Need: Electricity	0.14
Need: Health Services	0.09

Applying Amplifier

Relevant Tier 1 Weights * 1.2

New Weights

	Weights
Need: Housing	0.61
Need: Water	0.25
Need: Internet	0.05
Need: Electricity	0.14
Need: Health Services	0.09