For office use only	Team Control Number	For office use only
T1 ________________	**1902515**	F1 ________________
T2 ________________	Problem Chosen	F2 ________________
T3 ________________	**B**	F3 ________________
T4 ________________		F4 ________________

2019
MCM/ICM
Summary Sheet

(Your team's summary should be included as the first page of your electronic submission.)

Type a summary of your results on this page. Do not include the name of your school, advisor, or team members on this page.

In tackling the problem *Send in the Drones: Developing an Aerial Disaster Relief Response System,* we were tasked to solve four main problems by HELP Inc.

The first major challenge we encountered was to select a fleet of drones for deployment on Puerto Rico that offered both efficient deliveries of supplemental medical package payloads to medical centers and aerial reconnaissance capabilities for surveying storm damage. To complete these, we used real-world commercial drone specifications to model advanced flight range characteristics of the choice set of drones offered by HELP. Using these modeled specifications, we identified two drones (types B and C) which we distributed to serve the full gamut of medical package payloads.

The second task assigned was to place up to three ISO shipping containers, packed with drones and medical packages, optimally across the island. To begin locating each container, we used a raster map of the island, designing and applying image processing algorithms to break down the map into major components such as roads and urban areas. We then priority-weighted each of these component maps together and applied a range-biased filter to create a 'heatmap' of container placement interest. By combining this map with our modeled drone range specifications, we were able to place each container such that all hospitals can be reached with their required medical package payload while maximizing access to prioritized areas for aerial reconnaissance.

Our third obstacle to overcome was determining how many supplemental medical packages could be packed along with our specified drone fleet within the three ISO standard dry shipping containers. To do this, we designed a packing algorithm which uses both translation and rotation to place the drone containers and medical packages into a defined space. We validated this algorithm on a small control container size before scaling it to pack our specified drone fleet and medical packages in the correct ratio into each of the three shipping containers. Using this algorithm, we were able to pack each container to ca. 90% volumetric efficiency, limiting necessary padding materials.

Lastly, we were tasked to create a flight schedule of medical package deliveries and reconnaissance flights. Taking into consideration factors such as the costs of manually operating and staffing the drones and shipping containers, we elected to only place two drones in each shipping container. This allows one pilot to alternate flying delivery and reconnaissance flights, taking into consideration the time required to charge batteries, take off and land, etc. Our flight schedule completes all medical package deliveries daily while allowing ample time for aerial surveying.

Using all these metrics, we believe we have found the optimal solution for aiding the Puerto Rican recovery effort.

It's a Bird! It's a Plane!
It's the DroneGo Disaster Response System!

Team # 1902515

January 28, 2019

Contents

Memo

To the CEO of HELP Inc.,
Our group has spent several days identifying the requirements of the DroneGo disaster response system, and we have produced detailed solutions for you to recommend to the HELP, Inc. Board of Directors. We present a computerized model for determining a drone fleet and set of medical packages, where to position cargo containers to conduct both medical supply delivery and video reconnaissance of road networks, and provide drone payload packing configurations. In addition to this, we have produced a flight plan to asses major roadways, and delivery routes for the drones to meet the identified daily emergency medical package requirements. We propose the following:

- Each individual ISO cargo container will contain two drones, and the remaining volume of the cargo container will be filled with medical package supply kits for the purpose of aiding regional hospitals.
- ISO cargo containers will be placed on three different locations on Puerto Rico. One cargo container will be placed to the southwest of Arecibo which services Hospital Pavia Arecibo, another will be placed in close proximity to San Juan to support Hospital HIMA, Puerto Rico Childrend's Hospital, and Hospital Pavia Santurce, and a third container to the west of Fajardo, with the goal of aiding the Caribbean Medical Center.
- Every ISO cargo container deployment will be accompanied by one pilot and the minimal necessary support crew. Flight routes are between hospitals and cargo containers, and the flight schedule is based on drone charging and medical package loading time cycles. The focus of each pilot will initially be on delivering medical packages to hospitals, and the remaining time will be utilized on video reconnaissance.

While we developed our model, we kept the following factors in mind:

- **Cost:** Our model uses low resources with relatively high efficiency in order to conserve on costs of the project. For instance, the use of one pilot and two drones saves significantly on upfront costs, but still provides the necessary level of medical deliveries.
- **The Mission:** A specific goal of HELP Inc. is to more quickly evaluate and aid in the restoration of infrastructure. Therefore, each container is well placed to survey Puerto Rico's major interstates and urban centers.
- **Efficiency:** To prevent HELP from wasting time, we designed our model to combine each hospitals needs into purely one delivery, thereof saving time and operating costs.
- **Longevity:** Since the time frame for the recovery of Puerto Rico's recovery is unclear, we packed enough supplies into each crate to sustain each medical center's needs for at least 310 days.

We hope you consider our recommendations, as we believe they are in the best interests of all parties involved.

Regards, Team 1902515

1 Introduction

In this paper we present a computerized model for determining a drone fleet and set of medical aid packages for the HELP, Inc. DroneGo aerial disaster response system. Our model determines the best locations on Puerto Rico to position ISO cargo containers for medical supply delivery and video reconnaissance of road networks, provides drone payload configurations, and defines a flight plan. We take into account major roadways, urban areas, land mass, reconnaissance drone range, and drone delivery range for the five provided medical centers to construct our model. Our results will provide health-care clinics, hospital emergency rooms, an non-governmental organizations lifesaving insight on how to most effectively implement the DroneGo aerial disaster relief response system.

1.1 Background

On September 20, 2017 Puerto Rico suffered through Category 4 Hurricane Maria: Puerto Rico's worst natural disaster in over 80 years. According to the problem statement, Hurricane Maria caused more than 2900 fatalities, destroyed 80 percent of Puerto Rico's utility poles and all transmission lines, cut electricity across the island, and limited residents' clean water and food access. Widespread flooding blocked access to many roads across Puerto Rico causing emergency services and ground vehicles difficulty to navigate and supply aid. "Some Puerto Ricans were forced to cross swollen rivers after bridges collapsed to reach businesses where they could buy water and gas." [1] The combined destructive power of Hurricane Maria caused extensive damage to buildings, homes, roads, and the storm damaged the majority of the island's cellular communication networks.

1.2 Outline of Our Approach

In the aftermath of disasters like Hurricane Maria in Puerto Rico, it is critical that life-or-death institutions like hospitals are sustained with the necessary supplies and that damaged infrastructure — roads — can be repaired. Per the requests of HELP, our approach begins with prioritizing designing a model which, if applied, would aid in achieving these goals. Our objectives are to create a model that accurately recommends a drone fleet and set of medical aid packages, identifies locations on Puerto Rico to position ISO cargo containers conveying the DroneGo disaster response system, provide packaging configurations for such containers, and schedule flights which will enable the DroneGo fleet to deliver medical aid packages and use on board video cameras to survey major highways and roads. Here, we outline the construction and implementation of our model:

- **Modeling Drone Range** - In order to compare and decide on a drone fleet, we needed to assess how each drone would perform with a payload. The 2019_MCM_Problem_B pdf contains the flight time of each drone without cargo. We have developed a model for the flight time of each possible drone and cargo combination.

- **Selecting Drones and Generalized Container Locales** - The provided scenario in this problem identifies five medical centers, each with different daily medical package requirements. Our model takes into account the needs of each medical center, the absolute and relative location medical center, and the volume of each drone's cargo bay to determine which drones and define general container locations to select.

- **Locating ISO Containers Using a Raster Map** - Beginning with a raster map image, we designed and implemented image processing algorithms to create a priority-weighted map, used in conjunction with the general container locations determined earlier to pinpoint optimal positions for the cargo containers to serve all medical centers while maximizing access to prioritized features (e.g. roads/highways).

- **Packing the Containers** - To pack each ISO shipping container as efficiently as possible, we developed a spacial evaluation algorithm that automatically placed drones and medical packages inside each location's specific container.

- **Flight Scheduling** - To schedule flights, we calculated the time needed for each delivery leg and modeled a structure which allows a single operator at each container to alternate between flying two drones for medical package delivery and aerial reconnaissance.

2 Our Model

2.1 Assumptions

Creating an adaptable computer model to provide logistical details about implementing a drone relief system faces several complications: incomplete/insufficient information and statistics, unknown/unpredictable external factors (e.g. weather), etc. We made the following assumptions to construct our model:

- **Drones Will Fly with Constant Speed** - Regardless of payload weight, choice set drones fly at their stated speed. This vastly simplifies the calculation of drone ranges.
- **Choice Set Drones Are Similar to Existing Commercial Drones** - We model statistics of the choice set drones which aren't given using statistics of existing commercial drones. Therefore, all provided drone options are assumed to be similar to commercially available drones.
- **ISO Cargo Stations Have the Ability to Charge Drones** - We assume that all drone shipping containers contain the necessary equipment to repeatedly charge the drones when they return to the cargo containers. A more elaborate model could include power generation as a specification of the cargo container contents, however that is beyond the scope of this paper.
- **All Drone Flight Paths Avoid Obstacles** - Drones fly at high enough altitudes to avoid any man made or natural features which might impede the shortest path between two geographic points.
- **Medical Packages Can be Packed in Any Orientation** - We assume that medical packages and drones can be placed inside the ISO cargo containers in any orientation without damaging the contents in order to optimize volumetric efficiency.

2.2 Modeling Drone Range

In order to choose a drone package for HELP, we needed to understand how the drones would perform while carrying medical packages—in particular, how range would be affected by carrying a medical package. While each drone in the choice set has a specified flight time with no medical package, there is no specification of flight time with a medical package.

To understand how added weight would affect flight time of the provided drones options, we chose to create a model based on existing commercial drones whose statistics are publicly available. We found that drone manufacturers DJI Technology, CO., Ltd.[2] and Freefly Systems[3] produce commercial drones with performance similar to the choice set drones (and publish the necessary statistics and specifications). We selected eight drones manufactured by DJI Technology and Freefly Systems and recorded the characteristics which mirror those known about the provided drones (maximum payload capacity, speed, and flight time without cargo), as well as flight time with a full payload (Appendix A).

Using MATLAB's included tools for calculating linear regressions of multiple variables, we created a model of the form $Y \sim A + B + C$ — a linear model with three predictor and one response variable, with an intercept — for full payload flight time as a function of the given characteristics. This returns a modeled flight time for each provided drone option with a full payload.

With these data, we were able to model a continuous flight time function for each drone in terms of payload weight (Figure 1; note Drone H was not included because it is tethered and will not be considered for payload delivery or reconnaissance). To do so, we made the assumption that the inverse relationship between the weight of the package and the reduction in flight time is linear. We made this assumption because we have no intermediate data to inform a more detailed relationship.

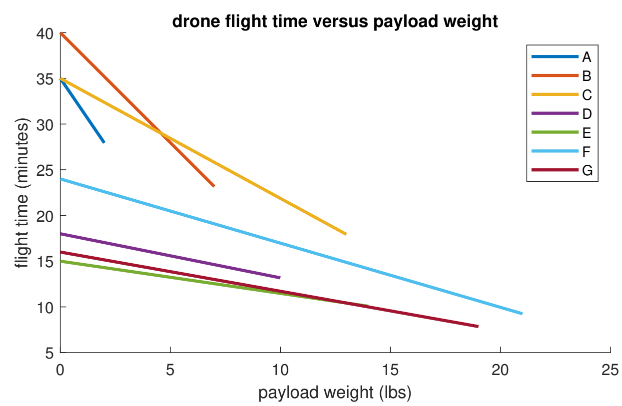

Figure 1: Choice set drones A-G

With a model of flight time as a function of payload weight, we then describe the maximum range of each drone as a function of payload weight under the assumptions that the drone makes its return flight without a payload and that only the drone's flight time, and not its maximum velocity, is inhibited by carrying a payload. See Appendix A.

2.3 Selecting Drones and Generalized Container Locales

2.3.1 Optimizing Cargo Drones for Each Medical Center

Prioritizing serving the five given medical centers, we considered which drones were capable of carrying each of the necessary medical package combinations (assuming one delivery made to one medical center everyday). By observation, we noted that the deliveries for Hospital HIMA and Puerto Rico Children's Hospital would only fit in cargo bay 2.

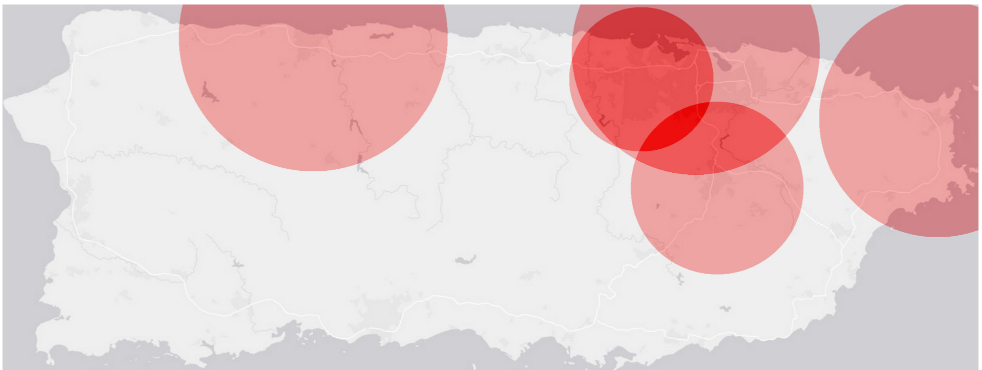

Figure 2: Map of maximum range to each hospital

For all drones which are capable of serving each medical center, we calculated a maximum flight range as a function of each hospital payloads' weight. From these flight ranges, we can see that Drone B offers the longest range for Hospital Pavia Aricebo, Hospital Pavia Santruce, and Caribbean Medical Center, while Drone C offers the longest range for Hospital HIMA and Puerto Rico Children's Hospital. We mapped these ranges as radii (Figure 2) and see that we must separate the ISO cargo containers in order to serve all five provided medical centers.

2.3.2 Validating Multiple Deliveries by a Single Drone

We consider whether a single drone can serve the three overlapping medical centers (Hospital Pavia Santruce, Hospital HIMA, and Puerto Rico Children's Hospital). To do so, we declare that the optimal drone would be Drone C, since it offers the longest flight range while meeting all three medical centers' delivery requirements. We re-map drone ranges with Hospital Pavia Santruce being served by Drone C (Figure 3) and confirm that Drone C can serve all three San Juan area medical centers. (We validate further that a single Drone C can make deliveries to all three within a day in section 2.6.)

Cargo Drone Distribution		
Container	Drone	Hospitals Served
1	B	Aricebo
2	C	Santruce, HIMA, Children's
3	B	Caribbean

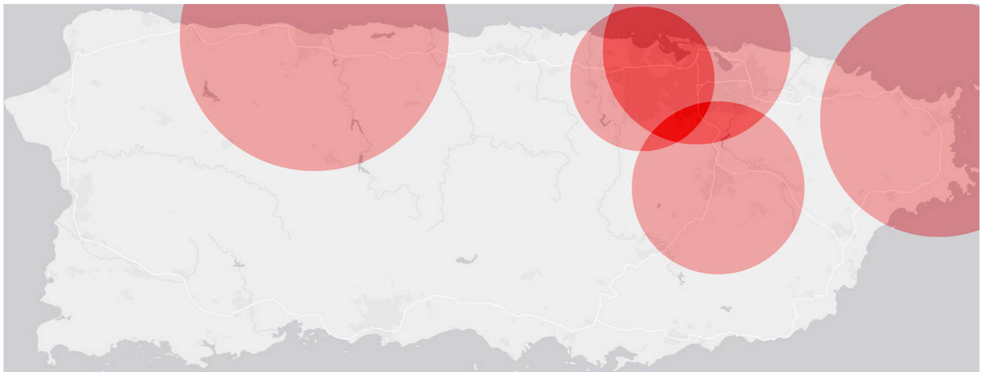

Figure 3: Map of maximum range, with Drone C for all overlapping medical centers

2.3.3 Choosing a Reconnaissance Drone

We turn to the task of aerial reconnaissance of road networks. We calculated the flight range of each provided drone option without a medical package payload and found that Drone B offers the longest range of the choice set. Next, we noted that the total volume of Drone B's shipping container represents only 1.0% of the total volume of one ISO cargo container. With this acknowledgement, we chose to forego any trade study of reconnaissance drone options and simply added one Drone B to all containers (elaboration on our two-drone arrangement in 2.6).

2.4 Locating ISO Containers Using a Raster Map

In order to optimize the placement of the International Standards Organization (ISO) standard dry cargo containers we modeled the utility that each container would provide, using metrics such as proximity to urban centers, access to major roadways, and access to medical centers to derive a map of discrete placement possibilities.

Figure 4: Original Map from MATLAB *webmap*[4], "Light Grey Canvas Map"

2.4.1 Peeling Data Layers Through Image Recognition

The first step in the process of creating the model described above was to generate a two-dimensional representation of Puerto Rico. This was achieved via iterating pixel by pixel though our original raster map, as shown in Figure 4, and then assessing which of our data sub-layers best fit each pixel, based on narrowly defined RGB color spectra correlated to different key features (i.e. roads, water, etc.). However, since the raster file we used for our map was compressed, image artifacts caused single-pixel values to be unreliable during sub-layer sorting. Therefore, we binned the image into 5x5 pixel squares that provided more consistent data as to the sub-layer belonging of certain areas of the map. This method allowed for us to effectively extract multiple layers of data to be used in optimization of our ISO container locations. The following figure, Figure 5, details examples of the data that was extracted from the map in Figure 4.

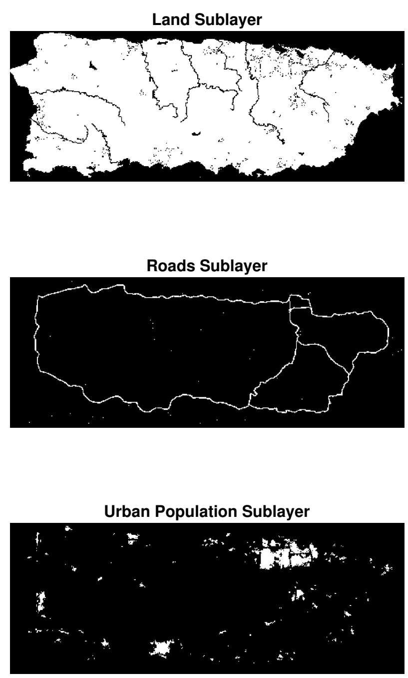

Figure 5: Examples of Map Sub-Layers

2.4.2 Relating a Raster Map to Geographic Coordinates

In order to use a raster map to identify areas of focus, we must be able to relate pixel coordinates of the map to geographic coordinates on Earth. We choose to define the relationship between the map and geographic coordinates in terms of a scalar coefficient to compare relative changes in pixel indices to degrees of latitude/longitude.

To begin validating our method, we ensure that our original raster map source, MATLAB's `webmap` function, is oriented to the cardinal directions, so that lines of latitude and longitude are aligned with our pixel grid.

We assume that Puerto Rico is a relatively small land mass at a relatively low latitude, so we do not expect to see significant impact from projection distortion. To confirm this assumption, we identify four spatially separated landmark points (Figure 6) with which we correlate pixel and geographic coordinate pairs visually, using the image display and `webmap` tools in MATLAB. We then calculate the mean degrees per pixel for both latitude and longitude for each of the six combinations of points. We calculate a coefficient of variation of 0.26% and 0.43% for the set of latitude and longitude values, respectively, indicating that there is not significant distortion in the projection over the scope of the island. We average the six pairs of degrees-per-pixel values to arrive at scalars which will be used to correlate any pixel to any geographic coordinate pair when used in conjunction with the absolute reference coordinates provided by the landmark points. .

Figure 6: Landmark reference points in red

2.4.3 Validating Our Raster Map to Binned Map Conversion

In order to verify the accuracy of the image recognition for the individual sub-layers, we evaluated the difference between a calculated land area of our map and Puerto Rico's actual land mass.

Using the pixel-geographic coordinate relationship validated above (Appendix B), we know that:

$$1 \text{ pixel} = 0.005272 \; km^2$$

From our data extraction of the "Land" and "Coast" layers, we have know that our digitized map has 1690025 pixels representing land mass. Therefore, our model's estimated land mass for Puerto Rico is:

$$A_{Land} = 8908\ km^2$$

Based on the figure for the land mass of Puerto Rico[8], 9104 km^2, we then can calculated the error in our sub-layer map to 2.142%. This relatively small margin of error, suggests that our model's individual sub-layers are accurate relative to our original raster map, despite our pixel binning.

Another way to display this seemingly small error, although not quantitative, is through the inspection of our model against that of an actual map. To do this we overlaid an image of our map on Google Earth and then used the major roadways to align our modeled image with the map. While we did not quantify the differences between Google Earth's map and that of our own, close inspection suggests that the two models are very similar, despite our binning. An example of this overlap can be seen in Figure 7.

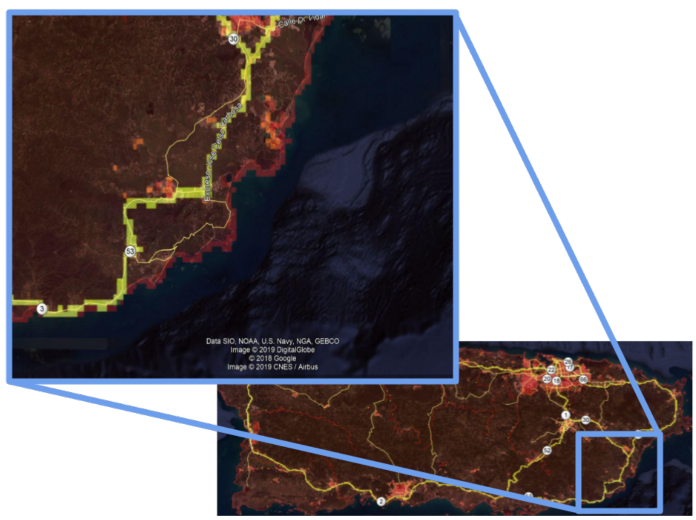

Figure 7: A map of combined sub-layers overlaid on Google Earth Pro [7]. Notice the similarity in feature recognition, such as coastlines and roadways.

2.4.4 Creating a Map of Interest

To determine the most beneficial locations for each of our three ISO cargo containers, our model assigns each pixel within range of a medical center a "Coefficient of Interest", Γ_I. This value was determined by taking the linear combination of certain data layers peeled from our original raster map, with each sub-layer's coefficient, γ, assigned a weighting based on that layer's importance to HELP's mission. This effectively pulled each shipping container's optimal location closer to the sub-layer features which will be more useful to HELP's recovery efforts. The linear combination was as follows:

$$\Gamma_{Interest} = (3 * \gamma_{land}) + (10 * \gamma_{urban}) + (50 * \gamma_{road})$$

Our reasoning for each sub-layers specific weighting was:

- **Land**: We weighted land pixels with a value of three so that land tiles would be weighted over any surrounding ocean tiles, since all of HELP's missions are conducted terrestrially. Additionally, most, if not all, land areas would have incurred some level of damage and should thus be surveyed in order to better understand the current physical state of the island. Despite this, though, land tiles were given a relatively smaller weighting in order to avoid overpowering other metrics due to their large quantity.

- **Urban Centers**: Due to their higher population densities and increased amounts of infrastructure, such as roads and power lines, we decided that urban centers should hold a relatively important weight when calculating the optimal location for each of our shipping containers. By placing shipping containers closer to these areas, HELP will be able perform more reconnaissance on the state of infrastructure. Similar to the reason for limiting the weight of land, we also decided to limit the weight of urban centers so that the density of urban tiles would not interfere with other metrics.

- **Roads**: Since Puerto Rico's major highways are the infrastructure that will be the backbone for the vast majority of the transportation of resources and recovery efforts, we decided that major roads should be heavily weighted in our calculations. This ensures that HELP will have the access to survey as many major roads as possible, so that any damaged freeways can be repaired, thereof benefiting other recovery efforts. Additionally, roads received a higher weight on account of the fact that they cover a smaller physical space than urban or land areas, but are still vital to HELP's mission to aid recovery efforts.

- **Medical Centers**: Although medical centers are not directly weighted in our linear combination above, the theoretical weight of hospitals is in fact infinite. This is a result of only scanning for the optimal placement of containers within the physical round-trip range of Drone B, ensuring that HELP's main mission, to aid in delivering supplies to medical centers, is accomplished.

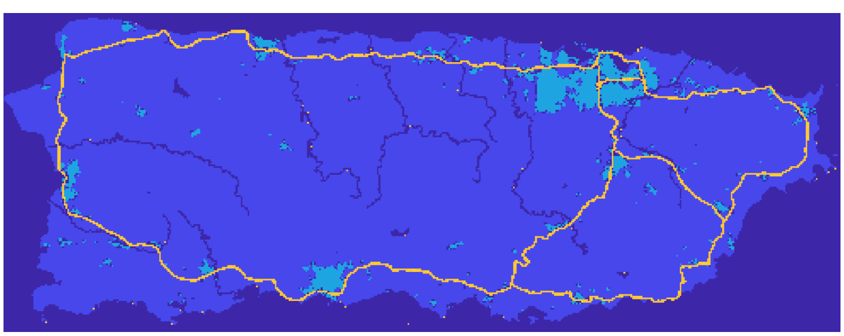

Figure 8: Weighted map of interest

2.4.5 Locating Containers

Our weighted Map of Interest represents our calculated coefficient of interest at a specific spatial point. In order to translate these values into ideal placement locations for our shipping containers, we first turned this point-map into a range-biased container placement map.

We began with the notion that each container would have one drone of type B specifically for reconnaissance (see section 2.3.3). Using our calculated empty range for this drone ($52.6km$, converted to pixel values — see section 2.4.2, Appendix B), we parsed through our map of interest. The value of any given pixel on our range-biased container placement map is given by:

$$I = \frac{\sum_{i=1}^{N} i_n}{N}$$

where N is the number of pixels within the range of the drone and $i_1 ... i_n ... i_N$ represents the intensity of each of these pixels on the map of interest. The resulting container placement map (Figure 9) gives weighted values of interest for placing a container in consideration of the reconnaissance range of Drone B.

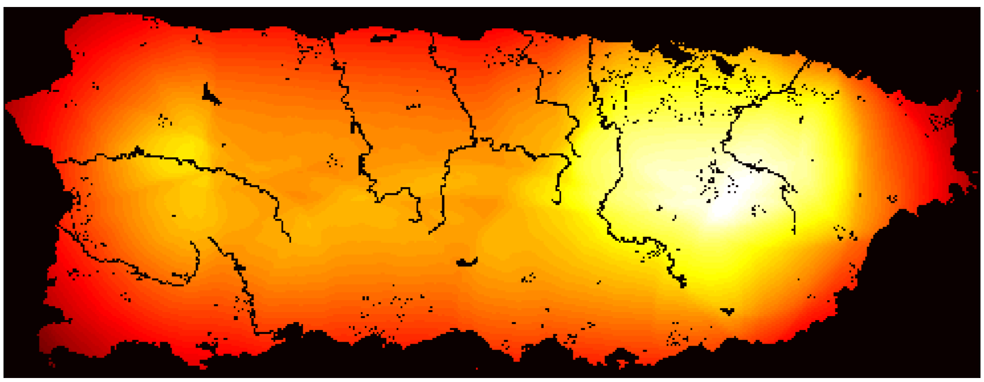

Figure 9: Range-biased container placement interest map

Next, we found the exact placement location for each container. This began by masking the container placement map three times, once for each container, to the locus of points within which the chosen cargo drone (see Section 2.3.1) can deliver the necessary packages to each medical center. For each masked map, we identified the locus of points whose intensities are the maximum value and calculated their centroids, converting these pixel indices back to geographic coordinates to find the optimal location to place each of the three shipping containers where drone deliveries to all medical centers are feasible. These coordinates are:

Container Locations		
Container	**Latitude**	**Longitude**
Arecibo	18.3398	-66.9205
San Juan	18.2947	-66.1010
Fajardo	18.2983	-65.8039

2.5 Packing the Containers

2.5.1 Our Algorithm

For the purpose of packing our ISO cargo containers we developed a spacial evaluation software in MATLAB. Our algorithm sought for open spaces within the bounds of the shipping container, then placed packages in those locations. Although initially not included, we eventualy altered out algorithm with the functionality to rotate individual packages when being packed. This not only allowed for more packages to be placed within any given container we chose, but resulted in a significant increase in packing efficiency.

For easier visualization and algorithm development, we initially started with a much smaller Control Container, a 50” x 50” x 50” cube, as shown in Figure 10.

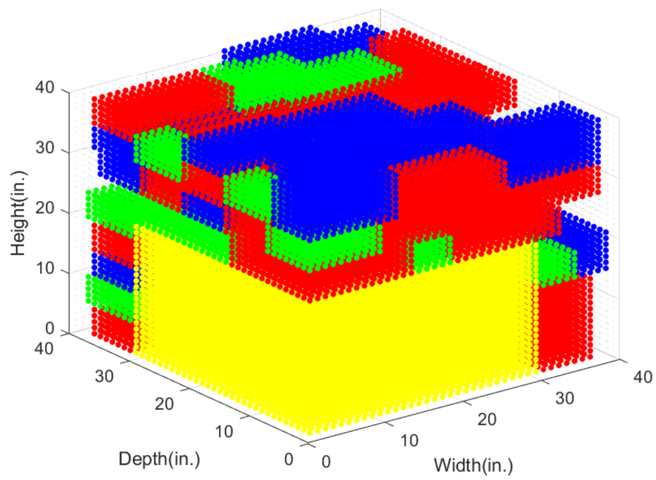

Figure 10: Sample packing of our Control Container.

For the scenario given in Figure 10, our algorithm was able to pack the container with an efficiency rating of 83% by volume. The packages inside the container were given by the algorithm as follows:

Control Container	
Package	Total Amount
Med 1	32
Med 2	33
Med 3	33
Drone B	1
Packing Efficiency = 83.08%	

2.5.2 Scaling the Algorithm to Full Size ISO Containers

Having validated our algorithm with the 50” x 50” x 50” container, we increased our scope to cover the full internal volume of the shipping container, 92” x 94” x 231”. We filled the three cargo containers as follows:

Arecibo Container	
Package	Total Amount
Med 1	3791
Drone B	2
Packing Efficiency = 94.97%	
Days of Supplies = 3791	

Fajardo Container	
Package	Total Amount
Med 1	2129
Med 3	2160
Drone B	2
Packing Efficiency = 90.53%	
Days of Supplies = 2129	

San Juan Container	
Package	Total Amount
Med 1	1554
Med 2	1654
Med 3	1571
Drone B	1
Drone C	1
Packing Efficiency = 86.60%	
Days of Supplies = 310	

2.6 Flight Scheduling

2.6.1 Flight Distances and Times

To construct a drone flight schedule for each container, we began by defining a basis: that schedules should be formatted in terms of all flights per day to deliver the necessary medical packages to medical centers. Using the haversine (Great Circle) distance formula [9], we calculated the straight-path distance of each flight, from container to hospital and back. Using these distances we then computed a total time for each flight using the given speed of the drone in use (see section 2.3.1).

2.6.2 Ground Logistics

Total daily flight time should be maximized in order to maximize utility given the limited drone availability — this is a basic principle with roots in economic theory, but it can be applied here as well. In pursuit of this goal, when drones are not *en route*, it should be for necessary activities: accessing payloads, safely taking off/landing, and charging batteries.

A reasonable charge time for the lithium-ion batteries used in modern drones is two hours [10]. With this number in mind, we chose to allocate two hours and thirty minutes in between flights as a reasonable amount of time to account for these logistical operations.

2.6.3 Allocating Drone Operator Time

We assume that cost minimization is likely a concern of HELP, Inc. As such, we offer a flight schedule which allows a single drone operator to perform both package delivery and reconnaissance flights.

This flight plan is built on offsetting the flight-charge cycle described above of two drones, i.e. alternating flights of two drones at each ISO cargo container. The operator alternates between delivery flights and reconnaissance flights until all delivery flights are complete, then uses both drones for reconnaissance for the remainder of the day.

The table below demonstrates this schedule applied to each ISO cargo container's necessary flights:

Arecibo			
Start time	**Duration**	**Activity**	**Distance**
00:00	00:37	Pavia Arecibo Delivery	49 km
00:37	-	Reconnaissance	-
San Juan			
Start time	**Duration**	**Activity**	**Distance**
0:00	0:20	Children's Delivery	26 km
0:20	2:30	Reconnaissance	-
2:50	0:17	HIMA Delivery	23 km
3:07	2:30	Reconnaissance	-
5:37	0:25	Pavia Santruce Delivery	33 km
6:00	-	Reconnaissance	-
Fajardo			
Start time	**Duration**	**Activity**	**Distance**
0:00	0:26	Caribbean M.C. Delivery	34 km
0:26	-	Reconnaissance	-

3 Model Analysis: Strengths and Weakness

Modeling Drone Range

Strengths:

- We modeled a *continuous* function for range in terms of payload weight which serves as a precise foundation for many other components of our solution.
- Our drone range model is based on real-world data, and therefore is likely an accurate representation of existing drone technologies.

Weaknesses:

- Our model relies heavily on assumptions of linear relationships due to a lack of more granular data for modeling.
- Our input data set of commercial drones is relatively small and heavily weighted towards a single manufacturer, DJI Technology, which could introduce systemic error in our approximations.

Selecting Drones and Generalized Container Locales

Strengths:

- Built on the base of our drone range model, our drone selection process considers real-world limitations (i.e. flight time reduction by payload) when identifying feasible delivery flights.

Weaknesses:

- Our choices of drones and container locations rely heavily on qualitative observation which would scale poorly when modeling larger disasters and/or more delivery destinations.
- We do not consider shipping package size when selecting drones because the drone packages are so small relative to the ISO shipping containers (Section 2.3.3). In a situation where a single container serves significantly more delivery destinations, these package sizes would have to be considered.

Locating ISO Containers using a Raster Map

Strengths:

- Our image processing algorithm runs with high accuracy and therefore can create a fairly accurate model of certain data from only one image. This makes our locating algorithm efficient and easily scalable to other scenarios and locations.
- Although our use of 'bins' (5x5 pixel clusters) to analyze sub-layer properties partially reduces the resolution of our map, the bins provide a consistent and accurate representation of the metrics we measure for (See 3.4.3 Validating our Raster Map to Binned Map Conversion).

Weaknesses:

- The weighting of each of our sub-layers is arbitrary. Therefore, how each individual personally values each sub-layer will influence the location of the final ISO Containers.
- Because the image is a raster map, the resolution, and thereof precision, of our model is limited by the image size. As a result all of our container locations can only be accurate within a maximum of a pixel (72.6m x 72.6m).
- On account of the fact that we pull all of our sub-layer data from RGB codes for individual pixels, it is very difficult, if not impossible, to overcome the compression of our image file. This results in some elements of the map displaying in data sub-layer to which they do not belong.
- The use of a single raster map to pull all of our limits the amount of information that can actually be incorporated into our final model.
- Some metrics, such as Urban Areas, are not precisely defined.
- We make the assumption that the distortion resulting from projecting the spherical earth onto a flat map is negligible. This results in an increasing distortion across the map as pixels distance themselves from our GPS anchor pixel, thereby distorting our Container Placement Map.

Packing the Containers

Strengths:

- The algorithm we developed tends to operate a high rate of packing efficiency, with the detailed location of every package incorporated into a storage container.
- We are able to pack an excess of supplies in every container, especially those located in Fajardo and Arecibo.

Weaknesses:

- When running potential packing configurations, our algorithm will always deliver the same output for a set number of packages to pack. Therefore, without further development the algorithm has a fixed packing efficiency which will never improve.
- The algorithm does not evaluate for the compactness of smaller sections of the container, nor does it evaluate the merits of rotating a package that can already be fit into the container in another configuration. Although our algorithm was generally efficient, this likely leaves out the possibility of the program obtaining a very high efficiency rating (95% +).

Flight Scheduling

Strengths:

- Our flight plan offers sufficient resources to complete the required tasks of MED package delivery and aerial reconnaissance with a minimized crew — just a single drone operator.
- Our schedule incorporates a large time-buffer to reduce the likelihood that an unforeseen issue delays or cancels critical medical package deliveries.

Weaknesses:

- The time in between flights is not particularly precise because we were unable to define an accurate model for short time-frame activities such as take-offs and landings.
- Only one drone can be in the air at a time, and therefore deliveries/reconnassaince must be made sequentially, rather than simultaineously.

4 Conclusions

After modeling drone flight characteristics, generating an optimal ISO container positioning map from raster graphics, calculating the correct packing configurations, and developing a flight plan, our team has concluded that HELP Inc. should roll out their DroneGo fleet in the following configuration:

Container 1: Arecibo	
Location	
Latitude:	18.3398
Longitude:	-66.9205
Container Contents	
Supplies for:	3971 days
Efficiency:	94.97%
Drones	
Cargo:	B
Recon:	B

Container 2: San Juan	
Location	
Latitude:	18.2947
Longitude:	-66.1010
Container Contents	
Supplies for:	310 days
Efficiency:	86.60%
Drones	
Cargo:	C
Recon:	B

Container 3: Fajardo	
Location	
Latitude:	18.2983
Longitude:	-65.8039
Container Contents	
Supplies for:	2129 days
Efficiency:	90.53%
Drones	
Cargo:	B
Recon:	B

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A Drone Range Modeling

Maximum flight time with a given payload:

$$t_p = \frac{(p_{max} - p)(t_e - t_{pmax})}{p_{max}} + t_{pmax}$$

where

$$\begin{aligned} t_p &= \text{Flight time with payload} \\ t_{pmax} &= \text{Flight time with full payload} \\ t_e &= \text{Flight time without payload} \\ p_{max} &= \text{Maximum payload weight} \\ p &= \text{Given payload weight} \end{aligned}$$

Maximum drone range with a given payload:

$$\text{Range} = \frac{(v_{max})(t_e)(t_p)}{t_e + t_p}$$

where

$$v_{max} = \text{Maximum speed}$$

B Conversion of Pixel to Area (km^2)

Using the approximation that the pixels of our raster map are square, we calculate the area of a single pixel of our original image as follows:

$$\text{side length} = r \cdot \Delta\theta$$

where

$$\begin{aligned} r &= \text{Earth's radius } (6.371 \times 10^6 m) \\ \Delta\theta &= \text{Incremental change in latitude across one pixel} \end{aligned}$$

Using $\Delta\theta = 6.530 \times 16^{-4}$ degrees from section **??**, convert to radians and find the side length of one pixel to be $72.6\,m$. The area of one pixel is $72.6^2 = 5272\,m^2 = 5.272 \times 10^{-3}\,km^2$.