



NAVAL POSTGRADUATE SCHOOL

MONTEREY, CALIFORNIA

THESIS

**A LOCATION-BASED INSPECTION OF DIVERSITY IN
MARINE CORPS OFFICER ACCESSIONS**

by

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March 2021

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**A LOCATION-BASED INSPECTION OF DIVERSITY IN MARINE CORPS
OFFICER ACCESSIONS**

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Submitted in partial fulfillment of the
requirements for the degree of

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from the

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ABSTRACT

With the policy goal of gaining access to a higher quality and quantity of diverse Marine officer candidates, this thesis examines the spatial distribution of Officer Selection Offices relative to the Qualified Candidate Population (QCP) through the census by the Center for Naval Analyses (CNA). For context, the structure of U.S. Marine Corps Recruiting Command (MCRC) and the officer selection process are examined before exploring the types and methodology of the QCP process, including the delineation between school and county-level QCPs and the metrics that are considered in their formulations. A literature review examines minority thoughts on service in the Marine Corps and looks at an overview of demographics throughout the officer ranks of the service. The impact of diversity on professional organizations is considered. Set cover optimization models are discussed and proposed as an optimization modeling framework for follow on studies. Using an application program interface and computer programming, latitude and longitude data is retrieved and associated for all candidate and Officer Selection Station (OSS) locations. Visualization is then applied to inspect the adequacy of OSS coverage for the top geographic locations and universities identified by the CNA. Finally, a summary of findings is provided.

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TABLE OF CONTENTS

I.	INTRODUCTION.....	1
A.	OVERVIEW.....	1
B.	BACKGROUND.....	2
C.	PROBLEM STATEMENT.....	3
D.	POLICY IMPLICATIONS.....	3
E.	SUMMARY.....	4
II.	BACKGROUND AND RELEVANT METHODS.....	5
A.	MARINE CORPS RECRUITING COMMAND.....	5
1.	Structure.....	5
2.	Marine Corps Officer Selection Process.....	9
B.	QUALIFIED CANDIDATE POPULATION.....	10
1.	Fundamentals.....	10
2.	Methodology.....	11
3.	School-Level Results and Findings.....	14
4.	County-Level Results and Findings.....	18
C.	MARINE CORPS RACIAL DIVERSITY HISTORY.....	20
D.	LATITUDE AND LONGITUDE.....	21
III.	LITERATURE REVIEW.....	25
A.	MINORITY (BLACK) THOUGHTS ON RECRUITING, RETENTION, AND MARINE CORPS CULTURE.....	25
B.	STATE OF DIVERSITY IN THE U.S. AND THE MARINE CORPS.....	27
C.	IMPROVING PRODUCTIVITY THROUGH DIVERSITY.....	34
D.	FUNDAMENTALS OF THE SET COVER PROBLEM.....	37
E.	REAL-WORLD SET COVER SETUP AND EXAMPLE.....	42
IV.	METHODOLOGY AND RESULTS.....	49
A.	APPLICATION PROGRAMMING INTERFACE.....	49
B.	PYTHON CODING.....	50
1.	Contact API Server.....	50
2.	Retrieve JSON Data.....	52
3.	Parse Out Geospatial Information.....	53
4.	Location with Latitude and Longitude.....	55
5.	Run Multiple Steps of the Process in a Single Function.....	56
6.	Import Data File with Locations.....	57

7.	Saving Locations with Latitudes and Longitudes	59
8.	Output Data File with Latitude and Longitudes.....	60
C.	MAPPING	62
D.	OFFICER ACCESSION DATA.....	64
E.	OFFICER ACCESSION CODING.....	66
F.	MAP RESULTS AND FINDINGS.....	69
1.	Female Breakdown	69
2.	Race Breakdown	76
3.	Finding #1: Current OSS Structure May Not be Best Suited to Exploit Concentration and Variation of Black Officers in Southeast U.S.....	81
4.	Finding #2: Top Universities and Counties Identified by QCP Receive Adequate Coverage and Officer Accessions	86
V.	CONCLUSION	89
A.	SET COVER MODELS PROVIDE USEFUL INSIGHTS ON THE SPATIAL DISTRIBUTION OF OFFICER ACCESSIONS RELATIVE TO OSS LOCATIONS	89
B.	FEMALES HAVE LOWER PERCENTAGES ON THE PROPENSITY TO SERVE METRIC	89
C.	THERE IS ROOM TO IMPROVE PROPENSITY TO SERVE	93
	LIST OF REFERENCES	95
	INITIAL DISTRIBUTION LIST	99

LIST OF FIGURES

Figure 1.	MCRC organizational structure. Adapted from Tulaney (2008).	5
Figure 2.	U.S. Marine Corps recruiting districts. Adapted from Marine Corps Recruiting Command (2012).	6
Figure 3.	Marine Corps recruiting station structure. Adapted from Tulaney (2008).	7
Figure 4.	1st MCD OSS locations. Source: Getman (2020).	7
Figure 5.	4th MCD OSS locations. Source: Getman (2020).	8
Figure 6.	6th MCD OSS locations. Source: Getman (2020).	8
Figure 7.	8th MCD OSS locations. Source: Getman (2020).	8
Figure 8.	9th MCD OSS locations. Source: Getman (2020).	9
Figure 9.	12th MCD OSS locations. Source: Getman (2020).	9
Figure 10.	Black female QCP estimation at Temple University. Source: Malone and Kelley (2015).	13
Figure 11.	QCP by MCD. Source: Malone and Kelley (2015).	14
Figure 12.	School-level QCP, adjusted for medical. Source: Malone and Kelley (2015).	15
Figure 13.	School-level QCP, final. Source: Malone and Kelley (2015).	16
Figure 14.	School-level QCP, race/ethnicity. Source: Malone and Kelley (2015).	17
Figure 15.	County-level distribution of female college graduates. Source: Malone and Kelley (2015).	18
Figure 16.	County-level distribution of male college graduates. Source: Malone and Kelley (2015).	19
Figure 17.	Percentage of potential qualified candidates by top counties. Source: Malone and Kelley (2015).	19
Figure 18.	Latitude and longitude lines. Source: Journey North (n.d.).	22

Figure 19.	Latitude and longitude example. Source: Encyclopedia Britannica (2021).....	23
Figure 20.	Longitude resolution. Adapted from Souliman (2021).....	24
Figure 21.	Latitude resolution. Adapted from Souliman (2021).....	24
Figure 22.	2019 population estimates. Source: U.S. Census Bureau (2019).	27
Figure 23.	Historical immigration rates. Source: Brookings Institute (2020).....	28
Figure 24.	Population change for race-ethnic groups. Source: Brookings Institute (2020).....	28
Figure 25.	2006-2016 total Marine officer demographics. Source: Marine Corps Office of Diversity Management and Equal Opportunity (2016).....	30
Figure 26.	2006-2016 company grade Marine officer demographics. Source: Marine Corps Office of Diversity Management and Equal Opportunity (2016).	31
Figure 27.	2006-2016 field grade Marine officer demographics. Source: Marine Corps Office of Diversity Management and Equal Opportunity (2016).....	32
Figure 28.	2006-2016 Marine general officer demographics. Source: Marine Corps Office of Diversity Management and Equal Opportunity (2016).....	33
Figure 29.	2006-2016 Marine Corps officers by gender. Source: Marine Corps Office of Diversity Management and Equal Opportunity (2016).....	34
Figure 30.	Workforce diversity defined. Source: Saxena (2014).....	35
Figure 31.	Example cost-effectiveness curve. Source: Church and ReVille (1974).....	39
Figure 32.	MCLP solution 1. Source: Church and ReVille (1974).....	40
Figure 33.	MCLP solution 2. Source: Church and ReVille (1974).....	41
Figure 34.	MCLP solution 3. Source: Church and ReVille (1974).....	42
Figure 35.	Istanbul station type and costs. Source: Atkas et al. (2013).	44
Figure 36.	Example of subdistrict matrix. Source: Atkas et al. (2013).....	45
Figure 37.	Scenario results. Source: Atkas et al. (2013).	46

Figure 38.	Station data table. Source: Atkas et al. (2013).....	46
Figure 39.	Computer program process flowchart.....	50
Figure 40.	Cell 1 of Python code in Jupyter Notebook.	51
Figure 41.	Cell 2 of Python code in Jupyter Notebook.	51
Figure 42.	Cell 3 of Python code in Jupyter Notebook.	52
Figure 43.	Test of Cell 3 of Python code in Firefox.....	53
Figure 44.	Cell 4 of Python code in Jupyter Notebook.	54
Figure 45.	API call from Cell 5 of Python code viewed in Firefox.	54
Figure 46.	Cell 5 of Python code in Jupyter Notebook.	55
Figure 47.	Cell 6 of Python code in Jupyter Notebook.	56
Figure 48.	Cell 7 of Python code in Jupyter Notebook.	56
Figure 49.	Cells 8 and 9 of Python code in Jupyter Notebook.....	57
Figure 50.	Test Plain Text File viewed in Atom.	58
Figure 51.	Cell 10 of Python code in Jupyter Notebook.	58
Figure 52.	Cell 11 of Python code in Jupyter Notebook.	59
Figure 53.	Cell 12 of Python code in Jupyter Notebook.	59
Figure 54.	Sample of OSS locations viewed in Excel. Source: MCRC (2020).	60
Figure 55.	Cell 13 of Python code in Jupyter Notebook.	61
Figure 56.	data.csv viewed in Atom text editor.	61
Figure 57.	data.csv viewed in Excel.....	62
Figure 58.	OSS map to six decimals	63
Figure 59.	Officer city/state/zip geospatial coordinates outputted from Python.....	67
Figure 60.	Initial results for officer geospatial locations.....	68
Figure 61.	Geospatial initial errors.....	69
Figure 62.	Male and female total map.....	71

Figure 63.	Female total map with OSS locations.	72
Figure 64.	Female map by race with OSS locations.	74
Figure 65.	Southeast U.S. by female and race.....	75
Figure 66.	Total map by race with OSS locations.....	77
Figure 67.	Concentrations in 9th and 4th MCDs.....	78
Figure 68.	Total male and female map by black category with OSS locations.	79
Figure 69.	Southeast U.S. for black males and females.	80
Figure 70.	HBCU locations.....	82
Figure 71.	HBCU and OSS locations.	83
Figure 72.	HBCUs, OSS locations, and black officer locations.....	84
Figure 73.	Black middle class as a percentage of population. Source: Perry & Romer (2020).	86
Figure 74.	OSS and male/female officer locations in Florida.	87
Figure 75.	Male QCP calculations. Adapted from Malone and Kelley (2015).....	90
Figure 76.	White Female QCP calculations. Adapted from Malone and Kelley (2015).....	91
Figure 77.	Black Female QCP calculations. Adapted from Malone and Kelley (2015).....	91
Figure 78.	QCP percentage averages. Adapted from Malone and Kelley (2015).....	92

LIST OF ACRONYMS AND ABBREVIATIONS

ACT	American College Test
AO	Area of Operations
API	Application Programming Interface
BRFSS	Behavioral Risk Factor Surveillance System
BYU	Brigham Young University
CAN	Center for Naval Analyses
CPG	Commandant's Planning Guidance
CSV	Comma Separated Values
DOD	Department of Defense
ERR	Eastern Recruiting Region
FAU	Florida Atlantic University
FSU	Florida State University
GSU	Georgia Southern University
HBCU	Historically Black Colleges and Universities
HOR	Home of Record
IPEDS	Integrated Advertising Market Research & Studies
JAMRS	Joint Advertising Market Research & Studies
MCD	Marine Corps District
MCLP	Maximal Covering Location Problem
MCRD	Marine Corps Recruit Depot
MOS	Military Occupational Specialty
NPS	Naval Postgraduate School
OCC	Officer Candidate Course
OCS	Officer Candidates School
OSO	Officer Selection Officer
OSS	Officer Selection Station
PLC	Platoon Leaders Course
PUMS	Public Use Microdata Sample
QCP	Qualified Candidate Population
ROTC	Reserve Officer Training Center

RS	Recruiting Station
SAT	Scholastic Aptitude Test
SIU	Southern Illinois University
UCF	University of Central Florida
UF	University of Florida
UG	University of Georgia
UNT	University of North Texas
USF	University of South Florida
UW	University of Wisconsin
WRR	Western Recruiting Region
WWII	World War II

I. INTRODUCTION

A. OVERVIEW

This study considers the brief modern history of diversity goals and initiatives of the Marine Corps, specifically the officer corps, and analyzes them against the current officer recruiting structure to determine recommended methodology for spatially optimizing this structure to coincide with the Marine Corps' goals of increasing the number of diverse officers. The Marine Corps has historically defined Marines between male and female genders, and overall race and ethnicity categories including white, black, Hispanic, Asian and Pacific Islander, and other (Marine Corps Recruiting Command [MCRC], 2016). The Department of the Navy and the Marine Corps have employed various initiatives and efforts to increase the numbers of female and black, Hispanic, Asian, and other (non-white) Marine officers since at least the 1990s and have repeatedly fallen short of these goals (Walker, 2011).

The study first explores the current organizational structure of U.S. Marine Corps Recruiting Command (MCRC) and the selection process for finding and recruiting Marine Officers. MCRC is organized into two recruiting regions consisting of three recruiting districts each. These Districts control Recruiting Stations (RS), which own Officer Selection Stations (OSS). The location and area of responsibility of each District, RS, and OSS have been partly informed by the Qualified Candidate Population (QCP). The QCP is an estimation of the number, location, and density of potentially qualified officer candidates which has been produced multiple times by the Center for Naval Analyses (CNA) at the request of the Marine Corps and is thoroughly analyzed in this study.

Application Programming Interfaces (API) and the concept and mathematics behind geometric location are also explored and form the primary methodology for this study. A previous Naval Postgraduate School thesis by Maj. George Getman (2020) researched this topic using officer accession data from 2010–2019 provided by MCRC and analyzed accession rates for diverse officers for Districts and OSSs against the latest QCP using several multivariate regression models. Among his findings is that the current MCRC

structure does not appear to be aligned with female and diverse officer accessions, and that these accessions by District and OSS do not align with QCP projections (Getman, 2020). This being the case, this study prepares this problem for a future study to apply a set cover model for spatial optimization of these MCRC resources. The preparation work includes using APIs and Python programming to locate and anonymize recruit location data against the existing OSS structure.

B. BACKGROUND

Recent data from the Marine Corps Personnel and Readiness Office shows total numbers and percentages of Marine officers by race of around 0.8% American Indian / Alaskan Native, 3.1% Asian, 5.0% black or African American, 1.5% multi-racial, 0.6% Pacific Islander, 8.0% Hispanic, 7.9% Unknown or other, and 81.1% white (USMC Personnel & Readiness, 2016). These percentages are not in line with the latest census data, as virtually all diverse categories are below national total rates. From 2006–2016, certain categories like Hispanic saw marginal percentage gains, but no diverse category is rising in line with Marine Corps expectations. Black officer percentages have even declined during this time period (USMC Personnel & Readiness, 2016). Overall female percentages in 2016 stood at 7.4% of the officer corps but have only seen marginal percentage increases. Multiple Secretaries of the Navy and Commandants have echoed calls for increased numbers of female and diverse officers, but these plans have fallen short (Walker, 2011).

The Marine Corps has seen consistent success in the accession of white officers. While the overall percentage of white officers declined slightly from 2006–2016, it still stands at an overrepresented 81.1% of the officer corps and total numbers of white officers had increased by around 1,101 (USMC Personnel & Readiness, 2016). Recent census data and population estimates by Pew Research have concluded that the national of percentage of this white (and predominately male) pool the Marine Corps succeeds with is declining and will continue to do so at an exponential rate. In the 1960s whites made up over 80% of the population and are at or around 60% today (Cohn & Caumont, 2016). Projections through this century bring this percentage lower still to around 50% of the U.S. population (Cohn & Caumont, 2016).

C. PROBLEM STATEMENT

Maj Getman's research concluded that female and diverse combinations of candidates are not evenly spread geographically, and that there are many dense and non-dense population areas. He found that the QCP is a worthwhile tool for predicting where eligible officer candidates are located. Regardless, there remains a large percentage gap between the amount of female and diverse accessions versus the expectations and predictions of the QCP. While the Marine Corps is able to fill its ranks with predominately white male officers now, that population pool has and will continue to diminish over the coming decades.

These facts in mind combined with the desires to increase female and diverse officer numbers, the Marine Corps should consider the locations and responsibilities of each of its Districts and OSSs, and set cover model designed to maximize these accessions while minimizing costs and resources can assist in decision making.

D. POLICY IMPLICATIONS

While the Marine Corps makes effort in increasing officer accessions for diverse and female candidates, they also have mandated goals and end strength requirements assigned to them each year by the U.S. Congress. The service can explore the idea of redistributing resources to increase female and diverse numbers but cannot overly do so at the cost of meeting end strength. Possible scenarios to consider that would impact any redistribution decision can include

- shifting the current location of Officer Selection Offices (OSO) while maintaining the current level of recruiting resources
- maintaining the current location of OSOs, while reallocating coverage areas
- modifying the level of recruiting resources allocated

E. SUMMARY

Using APIs and programming, a list of over 48,000 data points are routed through the MapQuest server and latitude and longitude geospatial information is obtained. The precise geospatial information for each of the Marine Corps' OSS locations is also obtained. These points are plotted on a map of the continental U.S., separated by all officers, by gender, and by race.

These plots correlate well with the QCP data produced by the CNA. If there are any deficiencies in structure or strategy, I posit the Southeast as a potential strategy to obtain a higher number of black officers. However, I conclude that any strategy in this region should be limited to a task force or more informational in nature instead of structural, as the Marine Corps is struggling with a propensity to serve problem with low metrics for females of all racial categories, and possible minority males.

II. BACKGROUND AND RELEVANT METHODS

A. MARINE CORPS RECRUITING COMMAND

1. Structure

MCRC's mission is to recruit civilians into the Marine Corps and then prepare recruits (enlisted) and officer candidates (officer) for training at Marine Corps Recruit Training Depots – Marine Corps Recruit Depot (MCRD) San Diego, CA and MCRD Parris Island, SC – or at Officer Candidate School aboard Marine Corps Base Quantico, VA. It is commanded by a Marine Major General and its organizational structure is depicted in Figure 1 (Tulaney, 2008).

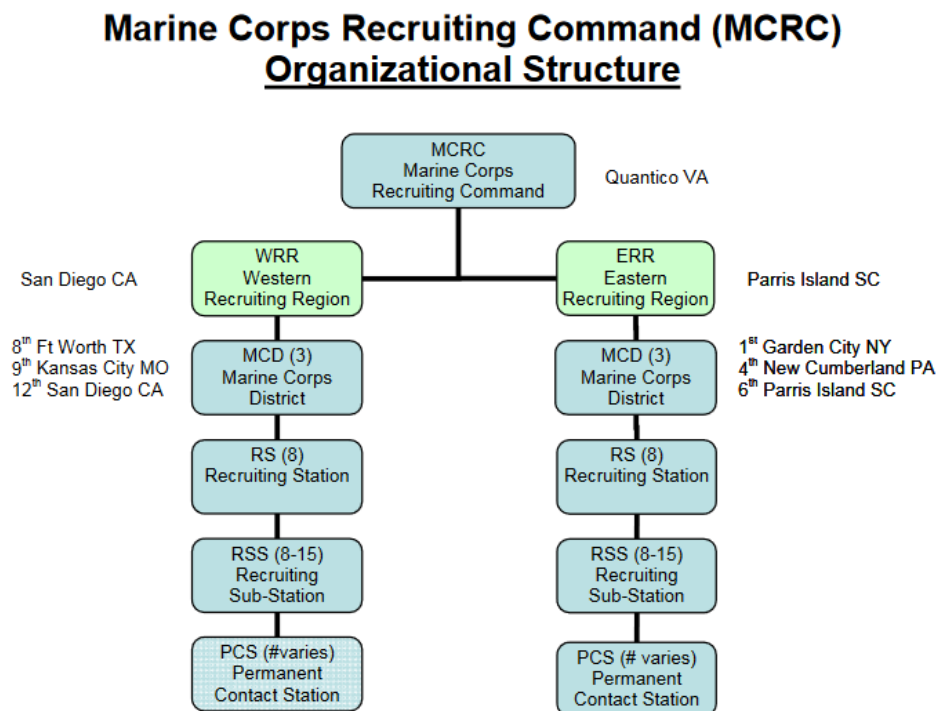


Figure 1. MCRC organizational structure.
Adapted from Tulaney (2008).

MCRC is separated into two main recruiting regions, Western Recruiting Region (WRR) and Eastern Recruiting Region (ERR) (Tulaney, 2008). These Regions are further

separated in to six total Marine Corps Districts (MCD), with the Eighth, Ninth, and Twelfth MCDs belonging to WRR, and the First, Fourth, and Sixth MCDs belonging to ERR. This structure is depicted in Figure 2 (p. 7).

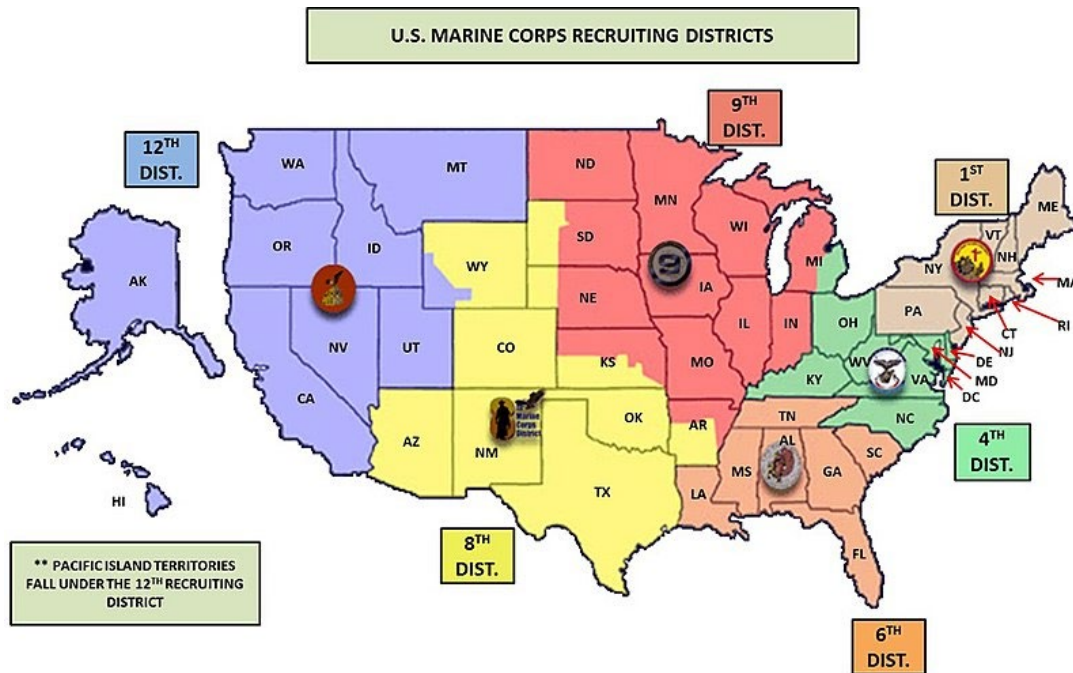


Figure 2. U.S. Marine Corps recruiting districts. Adapted from Marine Corps Recruiting Command (2012).

Each RS and MCD is further broken down into Recruiting Stations (RS), varying in number and location by the nature of each MCD (Tulaney, 2008). Each RS has several Recruiting Substations, responsible for seeking out enlisted recruits, but only one or two Officer Selection Stations (OSS), responsible for seeking out prospective officer candidates (only RS Pittsburgh has three OSSs) (Getman, 2020). The Marine Corps RS structure is depicted in Figure 3. Each OSS is headed by an Officer Selection Officer (OSO), billeted as a Captain, and also includes an Officer Selection Assistant and Human Resources Assistant (Archibeque, 2015).

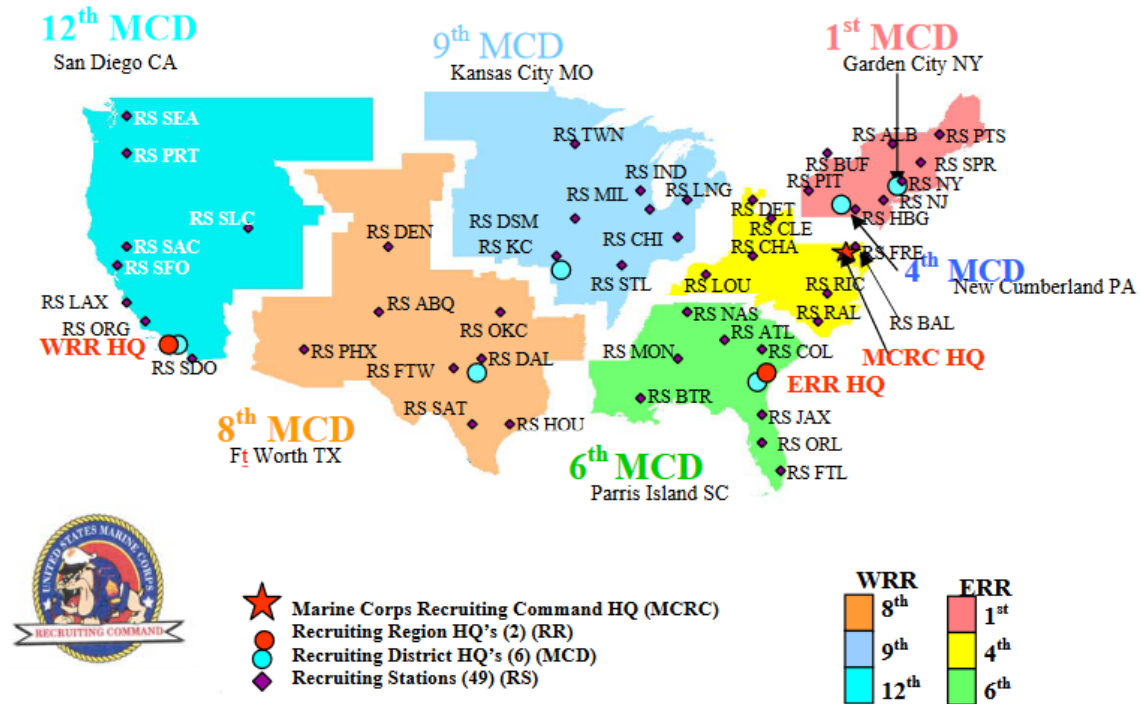


Figure 3. Marine Corps recruiting station structure.
Adapted from Tulaney (2008).

The ERR currently has a total of 40 OSSs, and the WRR has 34 for a total of 74. Broken down into each region: First MCD has 17 OSSs, Fourth MCD has 13, Sixth MCD has 10, Eighth MCD has 10, Ninth MCD has 13, Twelfth MCD has 11 (Getman, 2020). This breakdown and reporting relationship between RS and respective OSSs is depicted in Figures 4-9 (Getman, 2020).

1ST MCD		
RS ALBANY	OSS SYRACUSE	OSS ALBANY
RS PORTSMOUTH	OSS PORTSMOUTH	OSS BOSTON
RS HARRISBURG	OSS PHILADELPHIA	OSS READING
RS NEW JERSEY	OSS JERSEY CITY	OSS NEW BRUNSWICK
RS NEW YORK	OSS MANHATTAN	OSS GARDEN CITY
RS PITTSBURGH	OSS BUFFALO	OSS PITTSBURGH
RS BALTIMORE	OSS NEWARK	OSS HYATTSVILLE
RS SPRINGFIELD	OSS AMHERST	OSS PROVIDENCE

Figure 4. 1st MCD OSS locations. Source: Getman (2020).

4TH MCD	
RS CLEVELAND	OSS KENT
RS CHARLESTON	OSS COLUMBUS OSS ROANOKE
RS DETROIT	OSS ANN ARBOR
RS FREDERICK	OSS FAIRFAX
RS LANSING	OSS LANSING
RS LOUISVILLE	OSS LEXINGTON OSS CINCINNATI
RS NASHVILLE	OSS NASHVILLE
RS RALEIGH	OSS RALEIGH EAST OSS RALEIGH WEST
RS RICHMOND	OSS RICHMOND OSS NORFOLK

Figure 5. 4th MCD OSS locations. Source: Getman (2020).

6TH MCD	
RS ATLANTA	OSS KENNESAW OSS ATLANTA
RS BATON ROUGE	OSS BATON ROUGE
RS COLUMBIA	OSS COLUMBIA OSS CHARLOTTE
RS FORT LAUDERDALE	OSS MIAMI
RS JACKSONVILLE	OSS TALLAHASSEE OSS GAINESVILLE
RS MONTGOMERY	OSS TUSCALOOSA
RS ORLANDO	OSS ORLANDO

Figure 6. 6th MCD OSS locations. Source: Getman (2020).

8TH MCD	
RS ALBUQUERQUE	OSS LUBBOCK
RS DALLAS	OSS DALLAS
RS DENVER	OSS DENVER OSS FORT COLLINS
RS FORTH WORTH	OSS FORT WORTH
RS HOUSTON	OSS HOUSTON OSS COLLEGE STATION
RS PHOENIX	OSS PHOENIX
RS SALT LAKE CITY	OSS SALT LAKE CITY
RS SAN ANTONIO	OSS AUSTIN

Figure 7. 8th MCD OSS locations. Source: Getman (2020).

9TH MCD	
RS CHICAGO	OSS CHICAGO
RS DES MOINES	OSS LINCOLN, OSS IOWA CITY
RS INDIANAPOLIS	OSS BLOOMINGTON OSS W. LAFAYETTE
RS KANSAS CITY	OSS KANSAS CITY OSS SRINGFIELD
RS MILWUAKEE	OSS MILWUAKEE
RS OKLAHOMA	OSS NORMAN
RS ST. LOUIS	OSS ST. LOUIS OSS CHAMPAIGN
RS TWIN CITIES	OSS TWIN CITIES OSS FARGO

Figure 8. 9th MCD OSS locations. Source: Getman (2020).

12TH MCD	
RS LOS ANGELES	OSS LOS ANGELES OSS S. BARBARA
RS ORANGE	OSS ORANGE
RS PORTLAND	OSS CORVALLIS
RS SACRAMENTO	OSS SACRAMENTO
RS SAN DIEGO	OSS SAN DIEGO OSS RIVERSIDE
RS SAN FRANCISCO	OSS BERKLEY OSS SAN JOSE
RS SEATTLE	OSS SEATTLE OSS SPOKANE

Figure 9. 12th MCD OSS locations. Source: Getman (2020).

2. Marine Corps Officer Selection Process

MCRC derives its annual “mission” of officer candidates each year from congressional end-strength requirements assigned to the Deputy Commandant, Manpower & Reserve Affairs. These are delegated to MCRC, who then determines a percentage of officers to be accessed through either the Officer Candidate Course (OCC) or Platoon Leaders Course (PLC). Before commissioning, Marine officers must have degrees from accredited four-year institutions which require certain testing standards. Among those standards, prospective candidate must have a minimum combined Reading and Math score of 1000 on the Scholastic Aptitude Test (SAT) , a minimum score of 22 on the American College Test (ACT), or a combined Math and English score of 45 on the ACT (Malone & Kelley 2015). OCC and PLC share the same functions of screening, training, and evaluating candidates for future service as Marine officers, the main difference being that PLC is offered to college students still completing their degrees in two six-week training

sessions in the Summer months while OCC combines this training into a ten-week course for candidates who have already obtained their degrees (MCRC, 2016). MCRC further assigns each Region with an OCC and PLC mission, based on the area's QCP. Regions refine and filter these assignments still further to their Districts, and eventually OSSs and specifically the individual OSOs (MCRC, 2015).

OSOs are responsible for analyzing their assigned mission and conducting a detailed market analysis of their Area of Operations (AO) to determine their focuses of efforts for the coming year (MCRC, 2015). They build Annual Plans based around aggressive college relations programs and multiple campus visits that tend to focus on historically difficult mission objectives, namely aviators, females, and diverse candidates. OSOs begin prospecting their AO to obtain a steady flow of applicants, and then screen applicants for any physically, medically, or morally disqualifying conditions. Qualified applicants are then meticulously interviewed and, if competitive, the applicant's package is processed for selection to attend OCS (p. 1–7).

B. QUALIFIED CANDIDATE POPULATION

1. Fundamentals

To best understand the Marine Corps officer recruitment structure and overall process, it is important to know about the development and history of the primary tool which informs the overall recruitment strategy. The Marine Corps' specific model for structuring its OSS locations is based on the Qualified Candidate Population (QCP). Broadly speaking, the QCP is a method for estimating the number (concentration) of qualified Marine officer candidates both per school and county, and is generated by the Center for Naval Analysis (CNA) (Malone & Kelley, 2015). First generated in 2001, also by CNA and broader in scope, the QCP was originally defined as “the test score qualified, male college graduate population” (p. 2). MCRC used the products of this first study to inform its OSS locations throughout the country (p. 2). Having expanded in scope and notably in category since, the CNA has been asked to update or revisit the QCP multiple times, more generically so in 2005 and with increased weight on colleges and universities attended by Marine officers in 2006 (p. 3). In 2001, the Marine Corps asked CNA to

estimate the population and location data of all test and score qualified college attendees and appropriate graduates (namely adding women) (p. 1).

The latest CNA update, and that which is referred to in this study, was completed in 2015. At the time, the Marine Corps began initiatives to explore the integration of female Marines in ground combat units in various military occupational specialties (MOS), as well as specific service in ground combat MOSs, and asked CNA for the completion of the study in anticipation of higher numbers of females serving in the officer corps (Malone & Kelley, 2015). This prospective but likely policy change foreshadowed an estimated shock to the structure which would inject more females into the system as a whole and better spread them throughout the Corps. As such, the primary focus of the 2015 study was on females as a whole, but the authors also saw an opportunity (or future ‘ask’ from the Marine Corps) and also developed a QCP for different ethnic groups (Hispanic, Black, and ‘Other’) (p. 2). They then arranged their findings into combinations of ethnic groups and genders; an example being ‘black female.’

Just as notable, the 2015 study also adjusted QCP rates for schools and counties based on the likelihood of medical qualification and the propensity to serve. For the medical portion, the authors overlaid contemporary obesity and diabetes rates over the school and graduation rates to give an estimation of unqualified students and graduates. Race and ethnic information were readily available in their data, so no new work or methods were required to build out those separate categories (Malone & Kelley, 2015).

2. Methodology

Given that the Marine Corps runs two separate programs for recruiting and training new officer candidates, OCC and PLC, the QCP is divided in to two separate estimations to focus on each exclusively. Their “school-level” QCP is designed for projecting qualified applicants for PLC, aiming to estimate the densities of those that are in American colleges and universities (all called “schools” for the study) (Malone & Kelley, 2015). The authors describe this as more “flow” in nature, meaning that this measure is allowed to and is more susceptible to change. It aims to indicate the number of qualified students as they enter, attend, and prepare to graduate schools in the country, and this ends up being crucial for

OSS teams throughout the country as they design their annual plans (p. 3). The second is the county-level QCP, designed to estimate the amount of test and age-qualified college graduates who now live where they are working. The authors consider this more as a “stock” measure, with a (generally) more stable population and stable numbers with more permanent living arrangements (p. 9).

The school-level QCP is formulated through the use of four separate data sources: the Integrated Postsecondary Education Database (IPEDS), Barron’s Profile of American Colleges, Joint Advertising Market Research & Studies (JAMRS) propensity data, and the Behavioral Risk Factor Surveillance System (BRFSS) (Malone & Kelley, 2015).

IPEDS is maintained by the U.S. Department of Education and is a database of all colleges and universities in which qualified students can be eligible for financial aid (Malone & Kelley, 2015). It contains enrollment numbers, test score data, enrollment rates and graduation rates, among others. CNA obtained this data and investigated the 25th and 75th percentile of test scores to estimate the number of qualified enrollees at all reporting schools [p. 4]). Barron’s Profile of American Colleges is independent and analyzes all accredited schools in the U.S. in test score data, comparing student bodies in the numbers and distributions of various ACT and SAT milestones (p. 5). JAMRS is a database of academically and age qualified students and graduates who were all surveyed with questions which included, “How likely is it that you will be serving in the next few years?” Responding options included “definitely,” “probably,” “probably not,” and “definitely not.” JAMRS then compares the actual service rates of those who have historically taken this survey, and percentage of those who served by each answering category (p. 6). BRFSS was built by a survey from the Centers for Disease Control, and CNA used reported obesity and diabetic responses to adjust their overall metric (p. 7). The final school-level data set from CNA includes estimates for those U.S. colleges and universities that:

- Have less than 50% part time student rate
- Are not specialty schools
- Are not distance-learning schools
- Have one or a combination of: test score distributions, median test score values, competitiveness rating for school
- Have current enrollment and estimated completion and graduation rates

- Grant degrees
- Are four-year, non-profit schools (either public or private) (Malone & Kelley, 2015, p.7)

Using this criteria, the authors are able to build a school-level QCP map of 1,489 schools. At each one, they multiply their estimates for test-qualified rates by the number of students by gender and racial/ethnic groups, and can then estimate subgroup specific QCPs for each institution, the results of which are depicted in Figure 10 for black females at Temple University (Malone & Kelley, 2015).

Black female graduates	Percentage scoring 500+ on SAT Critical Reading	Percentage scoring 500+ on SAT Math	Test score qualification rate	QCP estimate
544	77	83	77	418

Figure 10. Black female QCP estimation at Temple University.
Source: Malone and Kelley (2015).

Just like how PLC and OCC candidates are similar in many ways with a few important differences (most notably, when they are recruited), the county-level QCP is structured very similarly to school-level QCP but has important differences and qualifications. Because OCC recruits college graduates, virtually all of these prospective candidates cannot be found on the campuses measured by the school-level QCP (Malone & Kelley, 2015). As the authors note, unemployment rates trend higher around traditional U.S. colleges and universities, and many college graduates tend to relocate to large cities and surrounding suburban areas where their new degrees and skills are more likely in demand (p. 9). As such, county-level QCP disregards most school-specific metrics and instead intends to estimate the number of test and age-qualified graduates (from qualifying institutions) that exist at any particular area (county). To do this, the authors must use metrics to estimate only the size of the age-qualified population, with methods that can correlate this to test-qualified, as there are no test-score metrics for the population at large. In other words, test-score data for universities becomes moot as an indicator when the majority of the graduating students move locations to begin their careers (p. 10).

County-level QCP estimates use the same JAMRS (propensity to serve) and BRFSS (medical indicators) data as school-level, as well as Public Use Microdata Sample (PUMS) and county-level data regarding sex/gender and age by educational attainment from the American Community Survey (Malone & Kelley, 2015). These county-level estimates for the proportion of bachelor's degree and higher for the local population are combined with the PUMS data to create distributions for race/ethnicity, age, gender, and level of degree (p. 11). This gives the authors an example initial output, like the estimation of 18–24 year old black females who have graduate degrees. This data then interacts with JAMRS and BRFSS to generate the county-level QCP (p. 12).

3. School-Level Results and Findings

School-level QCP results are first presented by totaling each eligible school results by MCD in an effort to show whether certain districts have better or worse access to diverse recruits. The Marine Corps currently uses these metrics to inform the location and recruiting missions assigned to districts and eventually OSSs (Malone & Kelley, 2015). 2015 QCP estimations (unadjusted for medical disqualifications) are depicted in Figure 11. Of note, the authors explain that the total QCP rose sharply in this most recent study. This is explained by a roughly 14.4% increase in school completions and higher test score distributions in the eligible schools. More students are now graduating from colleges and universities, and entering students have higher average SAT and ACT scores (p. 13).

Recruiting region	District	Total QCP	Per-centage	Female QCP	Per-centage	Male QCP	Per-centage
ERR	E01	235,309	22.8%	131,337	22.7%	103,972	22.9%
	E04	163,554	15.9%	92,345	16.0%	71,209	15.7%
	E06	161,003	15.6%	93,166	16.1%	67,837	15.0%
	Subtotal	559,866	54.3%	316,848	54.8%	243,018	53.6%
WRR	W08	117,463	11.4%	65,038	11.3%	52,425	11.6%
	W09	195,229	18.9%	107,861	18.7%	87,368	19.3%
	W12	158,843	15.4%	88,264	15.3%	70,579	15.6%
	Subtotal	471,535	45.7%	261,163	45.3%	210,372	46.5%
Total		1,031,401		578,011		453,390	

Source: CNA tabulations of Barron's and IPEDS data.

^a The percentages may not add to 100 due to rounding errors.

Figure 11. QCP by MCD. Source: Malone and Kelley (2015).

The ERR initially has a higher access to potential candidates than the WRR, with 53.6% of the male QCP, 54.8% of the female QCP, and 54.3% of the total QCP. 1st MCD has easily the most access to potential candidates than any other region, roughly 40,080 more than the next closest region (9th MCD). The number of qualified females throughout the country dwarfs qualified males, as there are 124,621 more qualified females than males. Females make up around 56.04% of the total QCP, and this is relatively steady throughout all regions, with the lowest female advantage being at 10.50% in 9th MCD. These numbers reflect the fact that more women than men are attending and graduating from accredited colleges and universities (Malone & Kelley, 2015).

Figure 12 shows the school-level QCP on a purely test and age qualified level. The authors then adjust their output for medical, as shown in Figure 13. This qualifier removes 71,409 potential male and 82,686 potential female candidates for 154,095 in total, a decrease in the pool of about 15%. Medical disqualifications seem steady nationwide, as no region's percentage of the candidate pool sees significant change.

Recruiting region	District	Total QCP	Per-centage	Female QCP	Per-centage	Male QCP	Per-centage
ERR	E01	195,269	22.3%	109,806	22.2%	85,463	22.4%
	E04	139,194	15.9%	78,923	15.9%	60,271	15.8%
	E06	137,955	15.7%	80,181	16.2%	57,774	15.1%
	Subtotal	472,418	53.9%	268,910	54.3%	203,509	53.3%
WRR	W08	101,399	11.6%	56,824	11.5%	44,575	11.7%
	W09	168,872	19.2%	93,940	19.0%	74,932	19.6%
	W12	134,617	15.3%	75,651	15.3%	58,966	15.4%
	Subtotal	404,888	46.1%	226,415	45.8%	178,473	46.7%
Total		877,306		495,325		381,981	

Source: CNA estimations using Barron's, IPEDS, and BRFSS data.

^a The percentages may not add to 100 due to rounding errors.

Figure 12. School-level QCP, adjusted for medical. Source: Malone and Kelley (2015).

Recruiting region	District	Total QCP	Per-centage	Female QCP	Per-centage	Male QCP	Per-centage
ERR	E01	4,523	19.9%	715	17.7%	3,808	20.3%
	E04	3,918	17.2%	722	17.8%	3,196	17.1%
	E06	4,087	17.9%	797	19.7%	3,290	17.6%
	Subtotal	12,528	55.0%	2,234	55.2%	10,294	55.0%
WRR	W08	2,788	12.2%	485	12.0%	2,303	12.3%
	W09	4,029	17.7%	685	16.9%	3,343	17.9%
	W12	3,428	15.1%	644	15.9%	2,784	14.9%
	Subtotal	10,244	45.0%	1,814	44.8%	8,431	45.1%
Total		22,772		4,047		18,725	

Source: CNA estimations using Barron's, IPEDS, BRFSS, and JAMRS data.

^a The percentages may not add to 100 due to rounding errors.

Figure 13. School-level QCP, final.
Source: Malone and Kelley (2015).

School-level QCP is then adjusted by the propensity to serve qualifier from the JAMRS survey, the results of which are depicted in Figure 13. This measure significantly impacts the total candidate pool, reducing it nationwide by an additional 854,534 from the medically-adjusted QCP (Malone & Kelley, 2015). In all, this final school-level QCP is only 2.2% of the original pool identified by test and age qualifications (p. 17). For OSS structure and mission plans, the Regions and MCDs see a few significant adjustments. ERR has a full 10% more access to potential candidates. The overall female school-level QCP decreases dramatically, losing projected access to about 573,964, over 99% of the originally identified population. 1st MCD loses access to female candidates than any other MCD. The authors note that there were some changes to the overall school-level QCP from the last CNA estimate, but none are significant.

The authors then apply these criteria to the male and female figures while adjusting for the race and ethnic groups described in the Methodology section, as depicted in Figure 14.

Region	District	White female QCP	Per-centage	Black female QCP	Per-centage	Hispanic female QCP	Per-centage	Other female QCP	Per-centage
ERR	E01	507	18.3%	75	15.0%	70	17.3%	63	16.6%
	E04	528	19.1%	115	23.0%	30	7.5%	49	12.9%
	E06	489	17.7%	190	38.1%	78	19.3%	39	10.4%
	Subtotal	1,525	55.1%	380	76.1%	178	44.1%	151	39.9%
WRR	W08	295	10.7%	39	7.8%	93	23.1%	58	15.2%
	W09	553	20.0%	62	12.3%	36	9.0%	34	9.1%
	W12	393	14.2%	19	3.7%	96	23.9%	135	35.8%
	Subtotal	1,242	44.9%	119	23.9%	225	55.9%	227	60.1%
Total		2,767		499		403		378	

Source: CNA estimations from Barron's, IPEDS, BRFSS, and JAMRS data.

^a The percentages may not add to 100 due to rounding errors. In addition, the sum of all the female numbers will not equal the female QCP presented in Table 5, due to females with an "unknown" race/ethnicity.

Region	District	White male QCP	Per-centage	Black male QCP	Per-centage	Hispanic male QCP	Per-centage	Other male QCP	Per-centage
ERR	E01	2,870	20.0%	239	19.1%	279	19.6%	421	24.3%
	E04	2,613	18.3%	251	20.0%	114	8.0%	218	12.6%
	E06	2,462	17.2%	379	30.2%	282	19.8%	167	9.7%
	Subtotal	7,945	55.5%	869	69.3%	674	47.5%	806	46.5%
WRR	W08	1,649	11.5%	147	11.7%	301	21.2%	205	11.8%
	W09	2,919	20.4%	146	11.7%	113	7.9%	165	9.5%
	W12	1,805	12.6%	92	7.3%	332	23.4%	555	32.1%
	Subtotal	6,373	44.5%	386	30.7%	746	52.5%	925	53.5%
Total		14,319		1,255		1,421		1,731	

Source: CNA estimations from Barron's, IPEDS, BRFSS, and JAMRS data.

^a The percentages may not add to 100 due to rounding errors. In addition, the sum of all the male numbers will not equal the male QCP presented in Table 5, due to males with an "unknown" race/ethnicity.

Figure 14. School-level QCP, race/ethnicity.
Source: Malone and Kelley (2015).

For both male and females, ERR has 10%+ more access to white candidates. ERR has an overwhelming advantage in potential black candidates, with WRR having nearly as large an advantage in potential Hispanic candidates. Here the propensity to serve adjustment shows its significance as every racial category had more age and test qualified potential candidates, and this measure brings female numbers far below male counterparts, 4,047 total and only around 21.61% compared to potential males. This reflects historically lower propensity to serve metrics than males, but the authors note that this metric is the most likely to change over time, saying that those with lower propensities may have little to no knowledge of what service in the officer corps is at a base level and could then possibly be more open to service after interacting with an OSO (Malone & Kelley, 2015).

The authors did highlight schools in the top 1% for males as a whole, white females, black females, Hispanic females, and “other” females. These schools hold a relatively large amount of the QCP for each category compared to the rest in the pool, due in part to their large sizes and the higher test scores needed to attend them. The authors note that high performing QCP schools are large and competitive public universities (Malone & Kelley, 2015).

4. County-Level Results and Findings

As with the school-level QCP, CNA finds that the county-level QCP tends to be highly concentrated (Malone & Kelley, 2015). This is in line with the fact that recent college graduates often relocate to more population dense areas, like cities (p. 27). They first report maps for the county-level concentration of male and female college graduates, depicted in Figures 15 and 16, which show concentrations in line with high density urban areas.

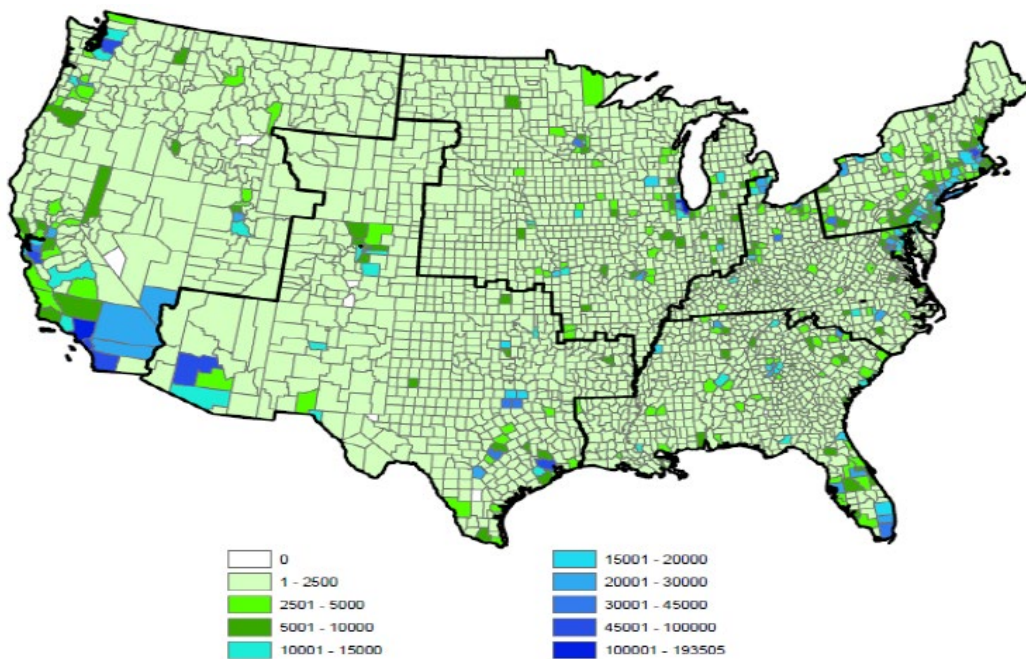


Figure 15. County-level distribution of female college graduates.
Source: Malone and Kelley (2015).

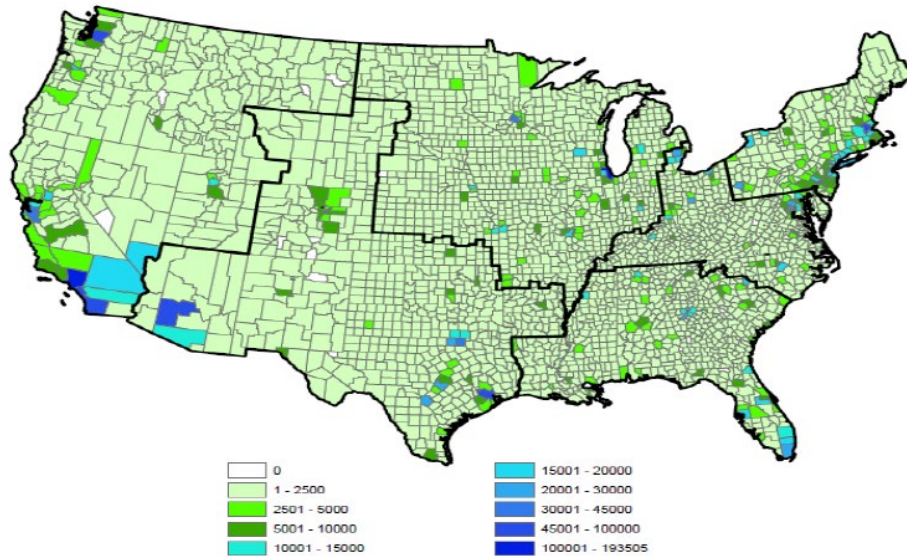


Figure 16. County-level distribution of male college graduates.
Source: Malone and Kelley (2015).

Findings are depicted in percentages; i.e., of all counties there is a top 1% of counties which hold the highest population of potential candidates, and so on. As depicted in Figure 17, these findings are so concentrated that the top 1% counties hold anywhere from 29% to 41% of the potential candidates for their respective genders and racial/ethnic groups. Extending that to the top 2% of counties shows that these hold 41% to 45% of the potential candidates.

	Top 1 percent	Top 2 percent
White women	29%	41%
White men	30%	43%
Black women	32%	45%
Black men	33%	47%
Hispanic women	50%	63%
Hispanic men	50%	63%
Other women	40%	52%
Other men	41%	54%

Source: CNA estimates based on ACS data.

Figure 17. Percentage of potential qualified candidates by top counties. Source: Malone and Kelley (2015).

As these top percentage of counties across groups strongly correlate and are easily accessible by the existing MCRC and OSS structure, CNA suggests that a large restructuring may not be necessary to meet current and future missions, and that increased emphasis on specific genders or groups by MCD may yield positive results (Malone & Kelley, 2015).

C. MARINE CORPS RACIAL DIVERSITY HISTORY

Black troops “officially” began serving during the War of 1812, when a shortage of manpower in the U.S. Navy led recruiters to accept “any able-bodied man” (Reidy, 2001). The U.S. Army remained segregated until the second year of the American Civil War. The United States Army Air Service, the precursor to the U.S. Air Force, was not integrated during its inception in 1918 despite being a part of the now-unsegregated Army (Morris, 1969). The first notable black Airmen included the Tuskegee Airmen, trained black aviators who served with distinction and were recruited during more manpower shortages early in World War II (WWII) (Reidy, 2001). Shortly after the onset of the same war, the Marine Corps first began accepting its first black recruits in 1942, and was the final branch of the military to open its doors (Morris, 1969). Recruitment began in June of that year but it could not accept any enlistees until August as they built a separate training center, Montford Point, in New River, NC (p. 58). As Ebony Magazine put it, “the thought of training black and white Marines together never crossed anyone’s mind.” Marines of other races (excluding Japanese Americans) were generally accepted and allowed to train and serve among white Marines (p. 58).

These first black Marines originally served in all black defense battalions but were later repurposed into ammunition and depot companies during hotly contested amphibious landings in the Pacific Campaign of WWII (Morris, 1969). After their heroic and round the clock performance during the D-Day invasion of Saipan in June of 1944, then Commandant Alexander Vandegrift stated, “The Negro Marines are no longer on trial. They are Marines, period” (p. 58). Despite this, black Marines remained in segregated units 1952, two years in to the Korean War . After integration, black Marines were not permitted to be Marine Embassy Guards, nor could they serve guard at the nation’s capital (p. 60). The next

decades saw the civil rights activism which eventually led to black Marines serving in all duties in MOSs.

In 1994, then Secretary of the Navy John H. Dalton issued new guidance specific to minority officer recruitment and retention for the Navy and Marine Corps (Jones, 1995). Informally called the “12-12-5 Plan,” this guidance sought recruitment and accession rates to more closely match census data for various races at the time, the intent being to reach these goals by the year 2000. Specifically, the plan called for accession and retention rates between 10% - 12% for both African American and Hispanic officers, and 5% for Asian or Pacific Islanders (p. 21). This plan saw little success in the Marine Corps officer ranks and was met with trepidation by interviewed minority Navy and Marine Corps officers around the time the guidance was issued (Jones 1995) (Wade, 1995).

Despite these and other efforts, the Marine Corps has historically lagged behind its sister services regarding diversity and still does today, according to their Office of Diversity Management and Equal Opportunity report of 2016 (USMC Personnel and Readiness, 2016). More recent efforts have been taken by multiple recent Commandants to increase the number of black Marines. In 2011 the then-new Commandant, General James Amos, announced a goal to increase the number of black officers. At the time, only around 1,326 of the 22,155 Marine officers were black, and he aimed to have it increased to around 2,860, or 13% and reflecting the census (Walker, 2011). He also directed the “enshrinement” of the legacy of the Montford Point Marines, with the intent that the history of these Marines be taught at all levels of Marine Corps professional military education (Walker, 2011).

D. LATITUDE AND LONGITUDE

Position calculations on Earth’s surface are oftentimes colloquially organized under the term Graphic Coordinate Systems. There are many types, but the Latitude/longitude system is widely used and understood at a base level and is useful for mathematical functions and models (Gade, 2010). It has mathematical limitations around the singularities North and South Poles, where longitude can be undefined and the latitude/longitude grid

becomes more “stretched” and non-linear (p. 397). These limitations are not necessarily relevant when doing position calculations away from the Poles (p. 398).

Latitude and longitude lines are organized in a grid map system, where latitude lines are displayed horizontally and longitude lines are displayed vertically, as depicted in Figure 18. Latitude lines are considered parallels, because they are parallel to the base latitude line at the Earth’s equator, all running east and west. They do not intersect, are larger and cover more area closer to the equator and smaller and cover less area near the Poles. Latitude lines serve to mathematically represent or measure how far a location is either north or south of the equator. The equator is measured as 0 degrees latitude, and each latitude line either north or south is denoted as positive (north) or negative (south), with a maximum of 90 degrees at each Pole. Longitude lines are called meridians, and all intersect at each Pole as they dissect the Earth running north and south. The base is the Prime Meridian, located closely to the British Royal Observatory in Greenwich, England. Longitude is measured from 0 to 180 degrees, with 0 being the prim meridian over Greenwich and 180 being this same meridian as it wraps the other side of Earth. Meridians are measured as positive going east from Greenwich, and negative going west (Journey North, n.d.).

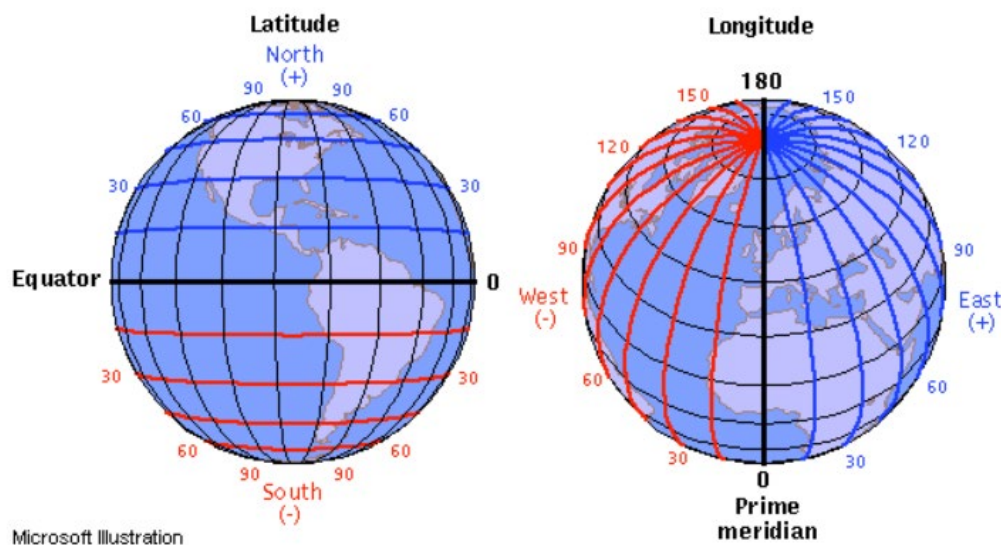


Figure 18. Latitude and longitude lines.

Source: Journey North (n.d.).

With the Equator and Prime Meridian as a base, combining latitude and longitude parallels and meridians creates the framework by which the location of positions on Earth can be referenced. For example, a point with a latitude of roughly 39 degrees and a longitude of roughly -77 degrees is located 30 degrees north of the Equator and 77 degrees west of the Prime Meridian, depicted in Figure 19.



Figure 19. Latitude and longitude example.
Source: Encyclopedia Britannica (2021).

For more clarity, decimal points are used with latitude and longitude measurements to provide a higher accuracy or finer resolution. Each whole line can be broken down into decimals to locate positions that fall in between the whole numbers. The increased accuracy of decimals between latitude and longitude varies, however, based mostly upon which relative latitude the measurement and decimals are taking place (Souliman, 2021). Because of the nature of longitude lines not being parallel and thus coming closer to each other before intersecting at the poles, longitude measurements become more precise for each decimal the closer to a pole (or the higher degree of latitude) (Souliman, 2021). While marginal in terms of overall relative distance, the percentage difference of measurements means that longitude accuracy becomes an important consideration while working further from the equator.

For example, as depicted in Figure 20, a longitude line to the third decimal is accurate to around 111.32 meters. That same unit of measurement around 30 degrees

latitude (containing parts of Florida and Texas) gives accuracy within 96.486 meters, and around 45 degrees (containing the Rust Belt and northern states) gives accuracy within 78.847 meters. These same degree measurements when only using two decimals gives accuracy around 1.1132 kilometers at the Equator, 0.96486 kilometers at 30 degrees latitude, and 0.78847 kilometers at 45 degrees latitude (a difference of over 320 meters or almost 30% worth of accuracy). As latitude lines run parallel, measurements remain largely consistent regardless of distance from the Equator or Prime Meridian, as depicted in Figure 21.

<i>Longitude Resolution</i>								
Dec Used	Number	Equator	15° LAT	30° LAT	45° LAT	60° LAT	75° LAT	Poles
0	1	111.32 km	107.551 km	96.486 km	78.847 km	55.8 km	28.902 km	0 km
1	0.1	11.132 km	10.7551 km	9.6486 km	7.8847 km	5.58 km	2.8902 km	0 km
2	0.01	1.1132 km	1.07551 km	0.96486 km	0.78847 km	0.558 km	0.28902 km	0 km
3	0.001	111.32 m	107.551 m	96.486 m	78.847 m	55.8 m	28.902 m	0 m
4	0.0001	11.132 m	10.7551 m	9.6486 m	7.8847 m	5.58 m	2.8902 m	0 m
5	0.00005	1.1132 m	1.07551 m	0.96486 m	0.78847 m	0.558 m	0.28902 m	0 m
6	0.000001	11.132 cm	10.7551 cm	9.6486 cm	7.8847 cm	5.58 cm	2.8902 cm	0 cm
7	0.0000001	1.1132 cm	1.07551 cm	0.96486 cm	0.78847 cm	0.558 cm	0.28902 cm	0 cm
8	0.00000001	1.1132 mm	1.07551 mm	0.96486 mm	0.78847 mm	0.558 mm	0.28902 mm	0 mm
9	0.000000001	0.11132 mm	0.107551 mm	0.096486 mm	0.078847 mm	0.0558 mm	0.028902 mm	0 mm

Figure 20. Longitude resolution. Adapted from Souliman (2021).

<i>Latitude Resolution</i>								
Dec Used	Number	Equator	15° LAT	30° LAT	45° LAT	60° LAT	75° LAT	Poles
0	1	110.574 km	110.649 km	110.852 km	111.132 km	111.412 km	111.618 km	111.694 km
1	0.1	11.0574 km	11.0649 km	11.0852 km	11.1132 km	11.1412 km	11.1618 km	11.1694 km
2	0.01	1.10574 km	1.10649 km	1.10852 km	1.11132 km	1.11412 km	1.11618 km	1.11694 km
3	0.001	110.574 m	110.649 m	110.852 m	111.132 m	111.412 m	111.618 m	111.694 m
4	0.0001	11.0574 m	11.0649 m	11.0852 m	11.1132 m	11.1412 m	11.1618 m	11.1694 m
5	0.00005	1.10574 m	1.10649 m	1.10852 m	1.11132 m	1.11412 m	1.11618 m	1.11694 m
6	0.000001	11.0574 cm	11.0649 cm	11.0852 cm	11.1132 cm	11.1412 cm	11.1618 cm	11.1694 cm
7	0.0000001	1.10574 cm	1.10649 cm	1.10852 cm	1.11132 cm	1.11412 cm	1.11618 cm	1.11694 cm
8	0.00000001	1.10574 mm	1.10649 mm	1.10852 mm	1.11132 mm	1.11412 mm	1.11618 mm	1.11694 mm
9	0.000000001	0.110574 mm	0.110649 mm	0.110852 mm	0.111132 mm	0.111412 mm	0.111618 mm	0.111694 mm

Figure 21. Latitude resolution. Adapted from Souliman (2021).

III. LITERATURE REVIEW

A. MINORITY (BLACK) THOUGHTS ON RECRUITING, RETENTION, AND MARINE CORPS CULTURE

A master's thesis at Naval Postgraduate School (NPS) was conducted in 1995 by Marine student named Joseph F. Wade. It remains relevant despite its age because the stated benefit of the study was focused on many of the same issues the Marine Corps and Department of Defense aim to grapple with today. The minority share of the general population has and will continue to increase, as will the number of minorities obtaining baccalaureate and other advanced degrees. Despite this (at the time of the original writing) the Marine Corps' goals and attempts at increasing the accession of minority officers had been met with limited success and was not accelerating at the rate of the qualified pool of potential minority candidates.

The methodology of the study included 15 extensive personal interviews with male and female black Marine officers between the ranks of Second Lieutenant to Colonel and including officers from various levels of experience, backgrounds, and military occupational specialties. A note and a cogent example of the significance of the study, the interviews were not conducted at NPS, but instead at the National Naval Officers Association Annual National Convention, held from July 18–24 in Virginia Beach, VA, as a relevant and large enough sample was not able to be gathered from NPS nor any nearby Marine Corps installation due to the relatively small number of black Marine officers co-located on said installations. Interviews were considered cordial, candid, and at times were both positive and negative. All interviews were confidential. This thesis was conducted simultaneously with another at NPS that was focused on the Navy exclusively.

Fifteen major themes came from the interviews, which were echoed in the Navy thesis. They vary in their relative importance (according to the author) and the "category" of the Marine Corps they apply to, but they are useful in identifying family, recruiting, and cultural trends.

Related to recruiting, virtually all of the interviewed officers came from two-parent homes. Thirteen of fifteen still had two-parent homes, and the other two had fathers with positive and active family roles which are deceased. All of the officers also reported having semi-significant experience with the military at a relatively young age, as eleven had fathers who were in a branch of service and two others had siblings currently serving. Only two had no prior service in their family. These two themes related to another, in that nearly all of the officers had expressed interest in joining the armed forces at a relatively young age and that all reported interest in joining when they came of age before speaking to a recruiter. That these fifteen officers joined the Marine Corps specifically was due to the direct conversation initiated by a Marine Corps recruiter. Eleven of the fifteen interviewed officers planned to remain in the Marine Corps until they are eligible for retirement – a considerable theme that is worthy of research as the Marine Corps focuses on minority recruitment.

Those themes largely family-oriented interest are valid and useful to the Marine Corps as it seeks to best align its recruiting resources, but their views on the culture at that time are just as useful. All fifteen officers reported instances of racial discrimination during their time in service. The experiences and their perceptions of them varied by their specific point in their career. Most of the reported discrimination came during Marine Corps entry-level training, be it at Officer Candidate School or Boot Camp, mostly considered “small” instances but some overt. The respondents notably indicated that not all discrimination came from whites, as some officers noted they felt clear discrimination from their black drill instructors, perhaps with the goal in mind of pushing them harder so that they would be “up to the challenge,” be that of service as an officer or to harden them up for overt discrimination they may face later in their careers. Also of note, female interviewees reported that most – if not all – of their perceived discrimination was based upon gender, and not race. All of the officers expressed that instances of discrimination were isolated to a few perpetrators and was not something they considered a large theme of their service. Each interviewee stated or agreed with the fact that they want to be treated the same as white officers (or any other race) – no better and no worse.

B. STATE OF DIVERSITY IN THE U.S. AND THE MARINE CORPS

The latest census population estimates for the United States shows a projected population increase of 6.3% over the last ten years. Estimates for 2010 show a total U.S. population of around 308,758,105, while estimates for 2019 show a total of around 328,239,523. In 2019, whites (alone) are the majority racial category and make up around 60.1% of the total population. Hispanic or Latino is the largest minority class, reporting at around 18.5%, followed by blacks at an estimated 13.4%. Asians make up and estimated 5.9%, and another 4.3% is comprised of American Indian and Alaska Native, Native Hawaiian and Other Pacific Islander, and Two or More Races (Quick Facts, United States 2019). Census Estimates are depicted in Figure 22.

Population estimates, July 1, 2019, (V2019)	328,239,523
PEOPLE	
Population	
Population estimates, July 1, 2019, (V2019)	328,239,523
Population estimates base, April 1, 2010, (V2019)	308,758,105
Population, percent change - April 1, 2010 (estimates base) to July 1, 2019, (V2019)	6.3%
Population, Census, April 1, 2010	308,745,538
Age and Sex	
Persons under 5 years, percent	6.0%
Persons under 18 years, percent	22.3%
Persons 65 years and over, percent	16.5%
Female persons, percent	50.8%
Race and Hispanic Origin	
White alone, percent	76.3%
Black or African American alone, percent (a)	13.4%
American Indian and Alaska Native alone, percent (a)	1.3%
Asian alone, percent (a)	5.9%
Native Hawaiian and Other Pacific Islander alone, percent (a)	0.2%
Two or More Races, percent	2.8%
Hispanic or Latino, percent (b)	18.5%
White alone, not Hispanic or Latino, percent	60.1%

Figure 22. 2019 population estimates.
Source: U.S. Census Bureau (2019).

As of 2018–2019, the U.S. is experiencing its slowest population growth by percentage in history. Despite this, virtually all estimates agree that this slowing growth pattern will not stop the steady increase of diversity. This is chiefly caused by the declining percentage increase of the white, non-Hispanic population. Models suggest that even with

zero percent immigration, diversity will increase as white (only) populations decline and virtually all other racial categories increase. Estimates on immigration rates are depicted in Figure 23. Projections for U.S. population change for race and ethnic groups is depicted in Figure 24. (Patton-Bullock, Dews 2020).

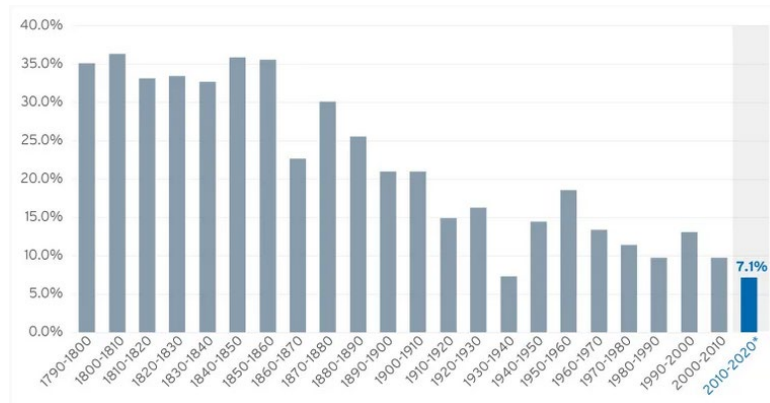


Figure 23. Historical immigration rates.
Source: Brookings Institute (2020).

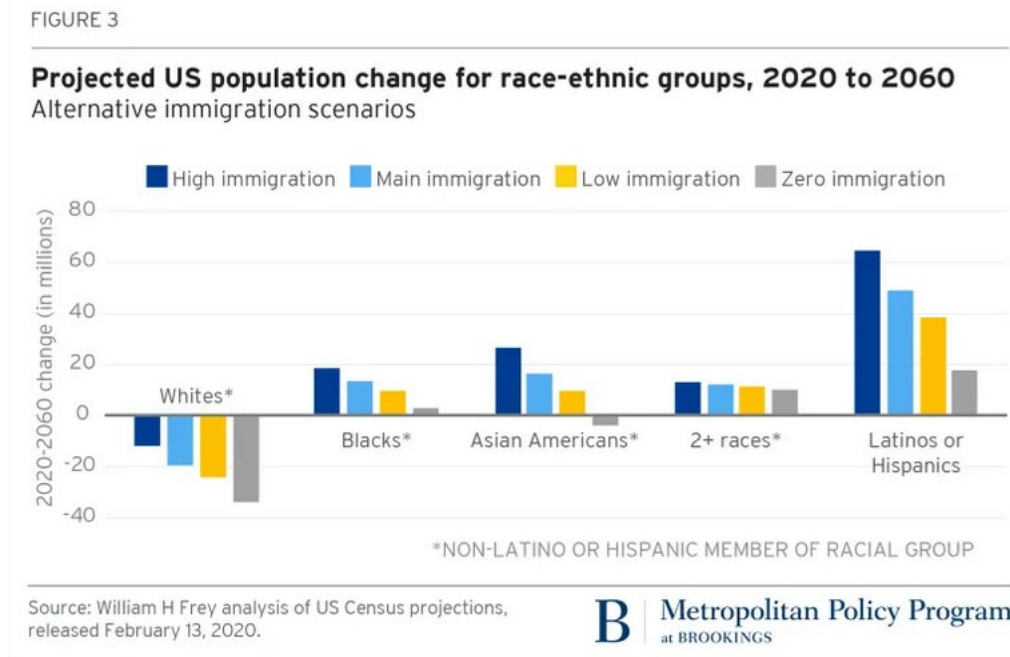


Figure 24. Population change for race-ethnic groups.
Source: Brookings Institute (2020).

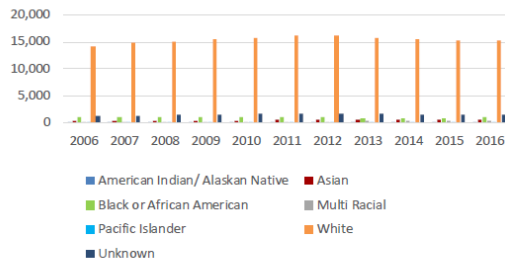
A recent 2016 report from the Marine Corps Office of Diversity Management and Equal Opportunity (depicted in Figures 25 - 28) shows Marine Corps populations which do not reflect the most recent census. A comparison of all white officers versus the 2019 census shows a particularly overrepresented population. While the overall count of white officers plateaued with the service's troop buildup for the War on Terror around 2010–2012, the percentage of white officers showed a slight overall decline from 2006–2016 of about 1.5%. The percentage of white company grade officers remained relatively steady during this timeframe, and the percentage of white field grade officers saw a relatively sharp decline of around 4.1%, with the total numbers of white field grade officers staying steady. The general officer ranks showed the greatest percentage of diversification, with white officer percentages dropping 5.5%, with the total numbers staying virtually the same. A telling statistic, however, still shows that 88% percent of general officers are white, a difference of about 28.4% when compared to the 2019 U.S. Census (USMC Personnel and Readiness, 2016).

The diversification progress of the Marine Corps' officer ranks varies by other categories. As a percentage of all officers, Asian counts and percentages have both increased, up 214 and 0.9% respectively from 2006–2016. Multi-Racial increased in both categories, up 119 and 0.5%. Hispanic rates have shown the most progress in the officer ranks, up 435 and 1.7%. The black officer population has shown a slow and steady decline for this period, down around 11 total officers, and losing 0.6%. However, interesting trends can be seen by grade. Despite the decrease in overall numbers and percentages, black percentages have increased by 0.2% for field grade, and 2.1% for general officers. The percentage increase for black general officers can be seen as a successful start at face-value, but it is only just that. A 50% increase from the old number to the new still only accounts for 6 total black general officers in 2016 (USMC Personnel and Readiness, 2016).

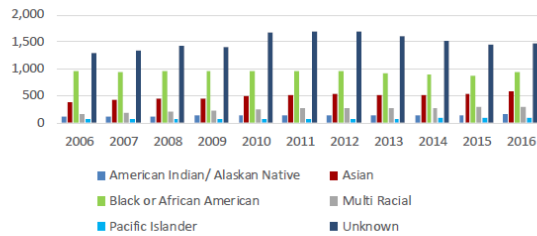


Marine Corps Officers O1-O10

USMC O1-O10 Population by Race



USMC O1-O10 Population by Race
Racial Populations of fewer than 2,000



USMC Officer Race Data - All Officers (Hispanic Ethnicity Included as Reference Only)																	
Year	American Indian/ Alaskan Native		Asian		Black or African American		Multi Racial		Pacific Islander		White		Unknown		Total Count	Hispanic Ethnicity	
	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%		Count	%
2006	112	0.7%	374	2.2%	954	5.6%	167	1.0%	63	0.4%	14,134	82.6%	1,298	7.6%	17,102	1,070	6.3%
2007	122	0.7%	419	2.4%	942	5.3%	184	1.0%	67	0.4%	14,733	82.8%	1,337	7.5%	17,804	1,121	6.3%
2008	122	0.7%	443	2.4%	954	5.2%	202	1.1%	66	0.4%	15,076	82.4%	1,434	7.8%	18,297	1,182	6.5%
2009	138	0.7%	458	2.4%	964	5.1%	222	1.2%	71	0.4%	15,468	82.6%	1,412	7.5%	18,733	1,226	6.5%
2010	147	0.8%	491	2.5%	964	5.0%	250	1.3%	67	0.3%	15,723	81.4%	1,681	8.7%	19,323	1,272	6.6%
2011	148	0.7%	517	2.6%	968	4.9%	268	1.4%	80	0.4%	16,113	81.4%	1,691	8.5%	19,783	1,324	6.7%
2012	141	0.7%	531	2.7%	954	4.8%	269	1.4%	80	0.4%	16,122	81.5%	1,692	8.6%	19,789	1,355	6.8%
2013	132	0.7%	523	2.7%	922	4.8%	281	1.5%	78	0.4%	15,647	81.5%	1,606	8.4%	19,188	1,387	7.2%
2014	142	0.8%	522	2.8%	895	4.8%	277	1.5%	89	0.5%	15,372	81.7%	1,508	8.0%	18,805	1,409	7.5%
2015	143	0.8%	547	2.9%	881	4.7%	287	1.5%	97	0.5%	15,172	81.7%	1,452	7.8%	18,579	1,449	7.8%
2016	155	0.8%	588	3.1%	943	5.0%	286	1.5%	105	0.6%	15,235	81.1%	1,481	7.9%	18,793	1,505	8.0%

Figure 25. 2006-2016 total Marine officer demographics. Source: Marine Corps Office of Diversity Management and Equal Opportunity (2016).



Marine Corps Officers O1-O3

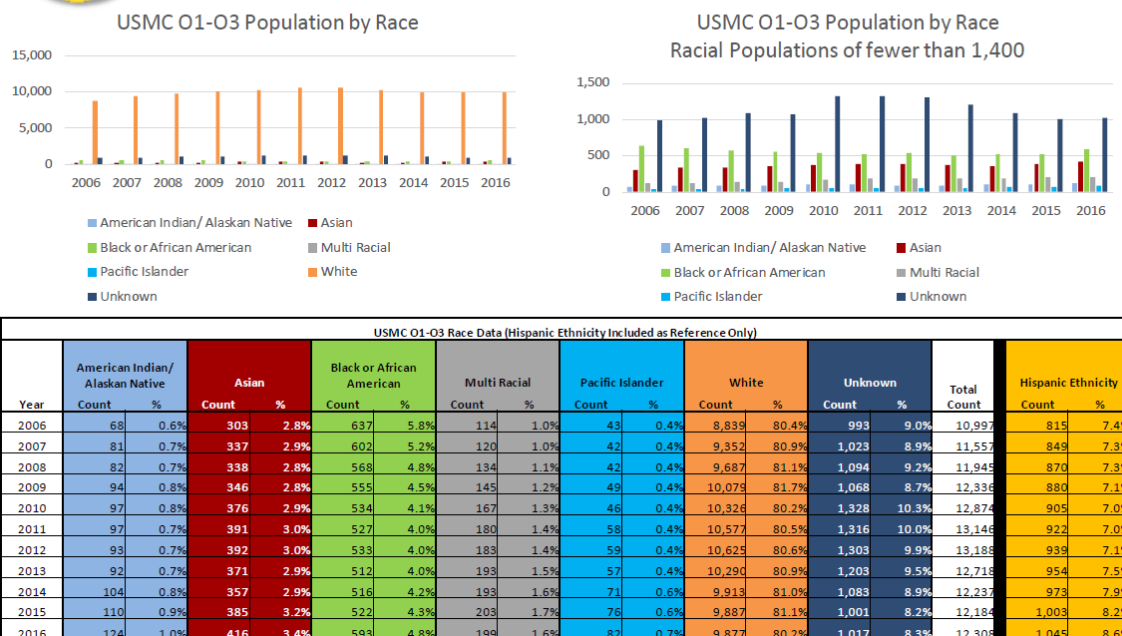
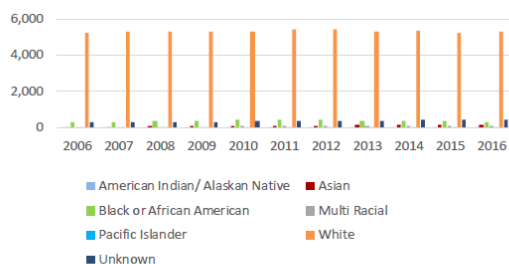


Figure 26. 2006-2016 company grade Marine officer demographics.
Source: Marine Corps Office of Diversity Management and Equal Opportunity (2016).

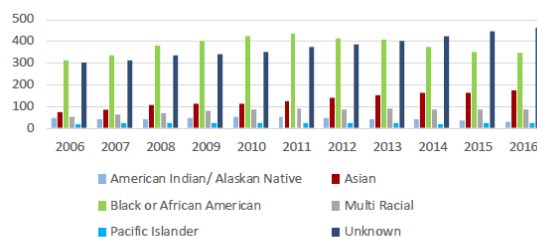


Marine Corps Officers O4-O6

USMC O4-O6 Population by Race



USMC O4-O6 Population by Race
Racial Populations of fewer than 500



Year	American Indian/ Alaskan Native		Asian		Black or African American		Multi Racial		Pacific Islander		White		Unknown		Total Count	Hispanic Ethnicity	
	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%	Count	%		Count	%
2006	44	0.7%	71	1.2%	313	5.2%	53	0.9%	20	0.3%	5,217	86.6%	304	5.0%	6,022	253	4.2%
2007	41	0.7%	82	1.3%	335	5.4%	64	1.0%	25	0.4%	5,305	86.1%	311	5.0%	6,163	269	4.4%
2008	40	0.6%	105	1.7%	381	6.1%	68	1.1%	24	0.4%	5,310	84.8%	337	5.4%	6,265	309	4.9%
2009	44	0.7%	112	1.8%	403	6.4%	77	1.2%	22	0.3%	5,313	84.2%	341	5.4%	6,312	344	5.4%
2010	50	0.8%	115	1.8%	424	6.7%	83	1.3%	21	0.3%	5,313	83.6%	350	5.5%	6,356	364	5.7%
2011	51	0.8%	126	1.9%	435	6.6%	88	1.3%	22	0.3%	5,456	83.3%	372	5.7%	6,550	399	6.1%
2012	48	0.7%	138	2.1%	415	6.4%	86	1.3%	21	0.3%	5,419	83.2%	385	5.9%	6,512	412	6.3%
2013	40	0.6%	151	2.4%	405	6.3%	88	1.4%	21	0.3%	5,282	82.7%	401	6.3%	6,388	430	6.7%
2014	38	0.6%	164	2.5%	374	5.8%	84	1.3%	18	0.3%	5,385	83.0%	422	6.5%	6,485	432	6.7%
2015	33	0.5%	161	2.5%	353	5.6%	84	1.3%	21	0.3%	5,214	82.6%	448	7.1%	6,314	442	7.0%
2016	31	0.5%	171	2.7%	344	5.4%	87	1.4%	23	0.4%	5,281	82.5%	461	7.2%	6,398	457	7.1%

Figure 27. 2006-2016 field grade Marine officer demographics.
Source: Marine Corps Office of Diversity Management and Equal
Opportunity (2016).

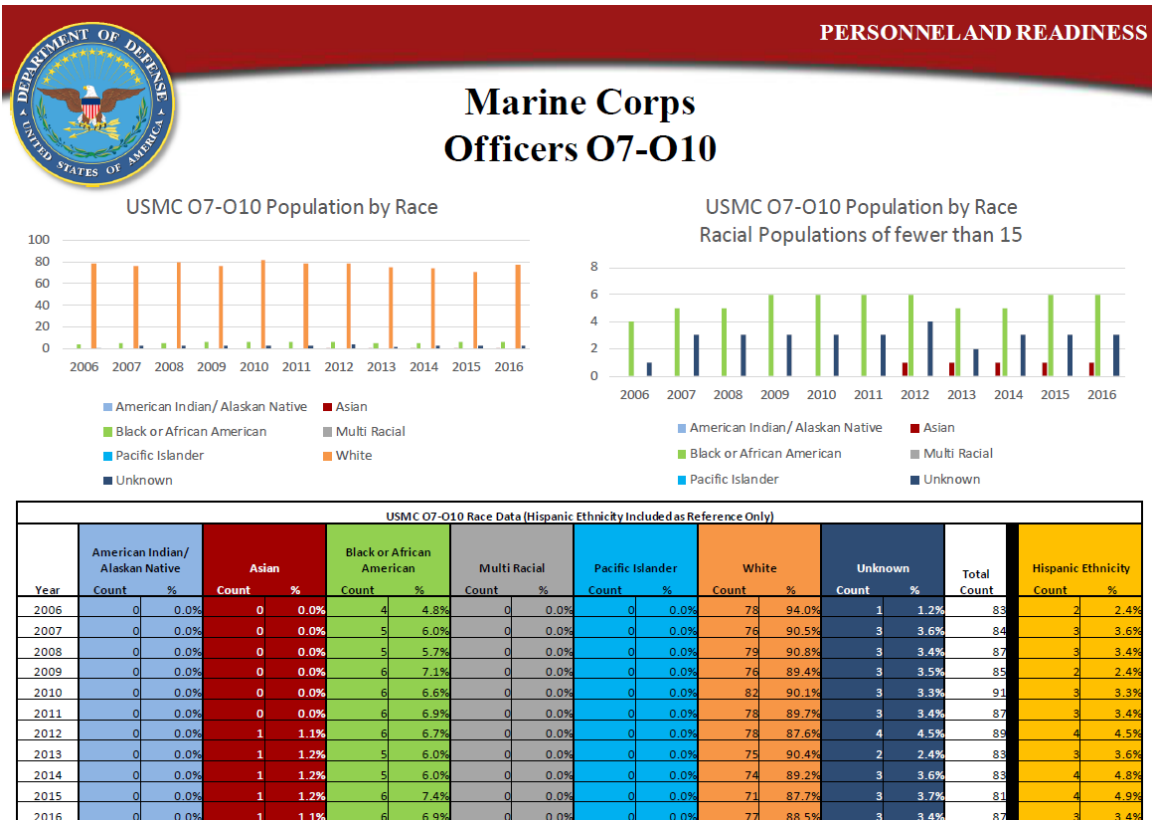


Figure 28. 2006-2016 Marine general officer demographics. Source: Marine Corps Office of Diversity Management and Equal Opportunity (2016).

The mixed results for race and ethnicity during this timeframe are notably outperformed by female metrics, when all races and ethnicities are combined. Females have seen gains in virtually all officer categories, raising total officer population counts by 1,205 (+1.6% representation), company grade numbers by 980 (+1.2% representation), and doubling the female field grade population by adding 156 officers (+2.3% representation). Despite these increases, there was only one female general officer in 2016, down from 3 in 2006 (USMC Personnel and Readiness, 2016). This is compared with 86 male general officers. Female officer numbers and percentages are depicted in Figure 29.



Marine Corps Officers by Gender

O1-O10				
Year	Count		%	
	Male	Female	Male	Female
2006	16,118	984	94.2%	5.8%
2007	16,775	1,029	94.2%	5.8%
2008	17,225	1,072	94.1%	5.9%
2009	17,632	1,101	94.1%	5.9%
2010	18,212	1,165	94.0%	6.0%
2011	18,562	1,222	93.8%	6.2%
2012	18,541	1,248	93.7%	6.3%
2013	17,930	1,259	93.4%	6.6%
2014	17,506	1,307	93.1%	6.9%
2015	17,243	1,336	92.8%	7.2%
2016	17,323	1,375	92.6%	7.4%

O1-O3				
Year	Count		%	
	Male	Female	Male	Female
2006	10,172	825	92.5%	7.5%
2007	10,697	860	92.6%	7.4%
2008	11,076	869	92.7%	7.3%
2009	11,440	896	92.7%	7.3%
2010	11,929	942	92.7%	7.3%
2011	12,175	971	92.6%	7.4%
2012	12,211	977	92.6%	7.4%
2013	11,734	984	92.3%	7.7%
2014	11,222	1,023	91.6%	8.4%
2015	11,148	1,036	91.5%	8.5%
2016	11,152	1,062	91.3%	8.7%

O4-O6				
Year	Count		%	
	Male	Female	Male	Female
2006	5,866	156	97.4%	2.6%
2007	5,997	166	97.3%	2.7%
2008	6,065	200	96.8%	3.2%
2009	6,109	203	96.8%	3.2%
2010	6,194	221	96.6%	3.4%
2011	6,300	250	96.2%	3.8%
2012	6,242	270	95.9%	4.1%
2013	6,114	274	95.7%	4.3%
2014	6,202	283	95.6%	4.4%
2015	6,015	299	95.3%	4.7%
2016	6,085	312	95.1%	4.9%

O7-O10				
Year	Count		%	
	Male	Female	Male	Female
2006	80	3	96.4%	3.6%
2007	81	3	96.4%	3.6%
2008	84	3	96.6%	3.4%
2009	83	2	97.6%	2.4%
2010	89	2	97.8%	2.2%
2011	87	1	98.9%	1.1%
2012	88	1	98.9%	1.1%
2013	82	1	98.8%	1.2%
2014	82	1	98.8%	1.2%
2015	80	1	98.8%	1.2%
2016	86	1	98.9%	1.1%

Figure 29. 2006-2016 Marine Corps officers by gender. Source: Marine Corps Office of Diversity Management and Equal Opportunity (2016).

C. IMPROVING PRODUCTIVITY THROUGH DIVERSITY

Analyzing workforce diversity in a macro-sense focuses on the differences among employees and how these various perspectives and prejudices can make an organization for flexible and thus more effective in tackling any given situation. The diversity of an organization will have an impact on the work employees accomplish, which itself has an impact on the overall organization (Saxena, 2014).

In his initial Commandant's Planning Guidance (CPG), General David G. Berger outlines five priority focus areas of Force Design, Warfighting, Education and Training, Core Values, and Command and Leadership. Tying these priorities together and, indeed his basis for selecting these focus areas, is the blurred and murky nature of the Marine

Corps' future conflicts, operating environments, and operational and strategic goals (Berger 2019). The Corps will only be successful with a flexible and adaptable force, made up of talented Marines bringing many different perspectives and talents to the table.

Ankita Saxena defines Workforce Diversity as the differences and similarities that employees have regarding age, caste, religion, gender, language, qualifications, geographical region, and perceptions and attitudes, depicted in Figure 30.

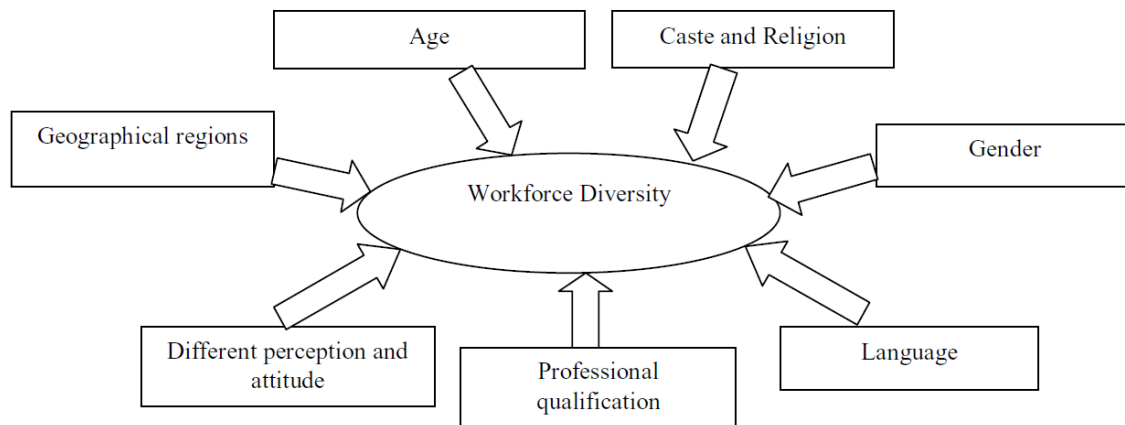


Figure 30. Workforce diversity defined. Source: Saxena (2014).

Having these differences means that employees will differ in terms of their thinking, perception, and ideas of defining situations or challenges. When mixed together, people of these varying qualifiers will oftentimes not agree on the details or even the basis of a problem (Saxena, 2014). As such, the organization must go to great lengths to clearly and transparently define and manage the proper interpersonal relationships between their employees. The Marine Corps recognizes this fact and defines it in Marine Corps Order 5354.1E, "The effectiveness of the Marine Corps relies on the trust and teamwork shared between individual Marines, regardless of grade or position. Inherent in this trust is the understanding that fair and equitable treatments in the Marine Corps leadership standard." As the Marine Corps seeks to expand its recruiting diversity, an understanding of the differences and qualities these Marines bring, as well as the ability to properly manage and integrate them, is paramount.

Various studies show that more and better implemented diversity in organizations, in this case the Marine Corps, can and will lead to a more adaptable and productive force. Saxena reports the following benefits of this implementation in her study (Saxena, 2014):

- Diversity stimulates innovation and productivity and creates a world class culture that can outperform the competition.
- A multicultural organization is better suited to serve a diverse clientele in a more increasingly global market. Such organizations have a better understanding of the requirements of the legal, political, social, economic, and cultural environments of foreign nations.
- In research-oriented and hi-tech industries, the broad base of talents generated by a gender-and ethnic-diverse organization becomes a priceless advantage.
- Multicultural organizations are found to be better at problem solving, possess better ability to extract expanded meanings, and are more likely to display multiple perspectives and interpretations in dealing with complex issues.
- Organizations employing a diverse workforce can supply a greater variety of solutions to problems in service, sourcing, and allocation of resources.
- Employees from diverse backgrounds bring individual talents and experiences in suggesting ideas that are flexible in adapting to fluctuating markets and customer demands.
- A diverse collection of skills and experiences (languages, cultural understanding) allows a company to provide service to customers on a global basis.
- A diverse workforce that feels comfortable communicating varying points of view provides a larger pool of ideas and experiences (Saxena, 2014).

These generic “organizational” or “customer oriented” points by Saxena are easily translated into a Marine Corps relevant language. Outperforming the competition is, according to the CPG, “maintaining our warfighting overmatch.” Displaying multiple perspectives and interpretations in dealing with complex issues means “Marines [being] comfortable with chaos, comfortable with mission tactics, and comfortable operating in a highly distributed manner across any potential battlefield.” Serving customers on a global basis of course means “a certain force for an uncertain world,” ready to “fight tonight.”

Continued and aggressive actions toward obtaining a more diverse officer corps and Marine Corps at large will allow the Marine Corps to continue to innovate, adapt, and win in rapidly changing and uncertain environments.

D. FUNDAMENTALS OF THE SET COVER PROBLEM

As Richard Church and Charles ReVelle define a version of a set cover problem, “the belief that mathematical location modeling can identify ‘optimal’ location patterns rests on the basis that some realistic objective can be identified and by some measures quantified.” Set covering problems can be used to attempt to optimally solve problems such as private or public facility locations, based upon a set of constraints that help define the problem. Constraints could be the maximum overall area to be “served” by said facilities, the minimum distance to facilities by those nodes they serve, or any other number of combinations along with additional constraints (Church & ReVelle, 1974). A simple example of a maximal covering location problem (MCLP) could be a given (set) number of distribution centers whose optimal objective is to be able to serve the maximum number of customers. A simple minimal version of this problem could be a given (set) number of police stations for a given county, optimally located to provide a given or most-efficient average response times to citizens in the covered area. Church and ReVelle explore the foundations of a MCLP in their 1974 essay “The Maximal Covering Location Problem.”

As Church & ReVelle note, public facility location analyses tend to be more difficult to quantify, as it is more difficult to define the direct measures of public objectives of these facilities, and trade-offs thusly arise. They explain that two common trade-offs, or surrogate measures, that are often weighed against each other include the weighted time or distance required to travel to the facilities and time or distance the furthest user would have to travel to the facilities. However, there is evidence that the number of facilities used to “cover the set” is the most significant cost in these problems, so it is reasonable to treat it as the “highest” or most important cost, as it often is in many examples (Church & ReVelle, 1974).

Set cover problems serve as decision-making tools, however, there may be multiple (but different) “optimal” solutions that solve a problem but in different ways. Alternatively,

there may not be only one optimal solution. Consider the issue of facilities, again, and the fact that you may have a certain distance that you eventually consider too far to be “served” by your distribution facility – called the maximal service distance. If there were no feasible solutions – i.e., that your set number of facilities you could afford would always leave some of nodes you wish to serve outside of that maximal service distance – you could then shift your focus to the total population that you *are* covering with your proposed set locations, and trying to maximize that (Church & ReVile, 1974).

And even still, you have even more tradeoffs to consider as you may have an optimal solution but before considering costs needed to get there. In Church and ReVile’s hypothetical problem, they determined that they could cover or serve the entire target population with 12 facilities, but perhaps some of these funds could be used better elsewhere? The cost-effectiveness curve from their example problem is depicted in Figure 31. In this example, “an important choice for the decision maker is deciding what level of expenditure (how many facilities can be used) can be justified by the resultant coverage. For example, even if there are enough funds to build twelve facilities and cover 100 percent, the eight-facility solution and 90 percent coverage may be very acceptable. Further, the reduced location cost may allow funds to be spent upgrading other levels of service not related to location... Such information would seem beneficial to the formulation of logical and sound location plans.” (Church & ReVile, 1974).

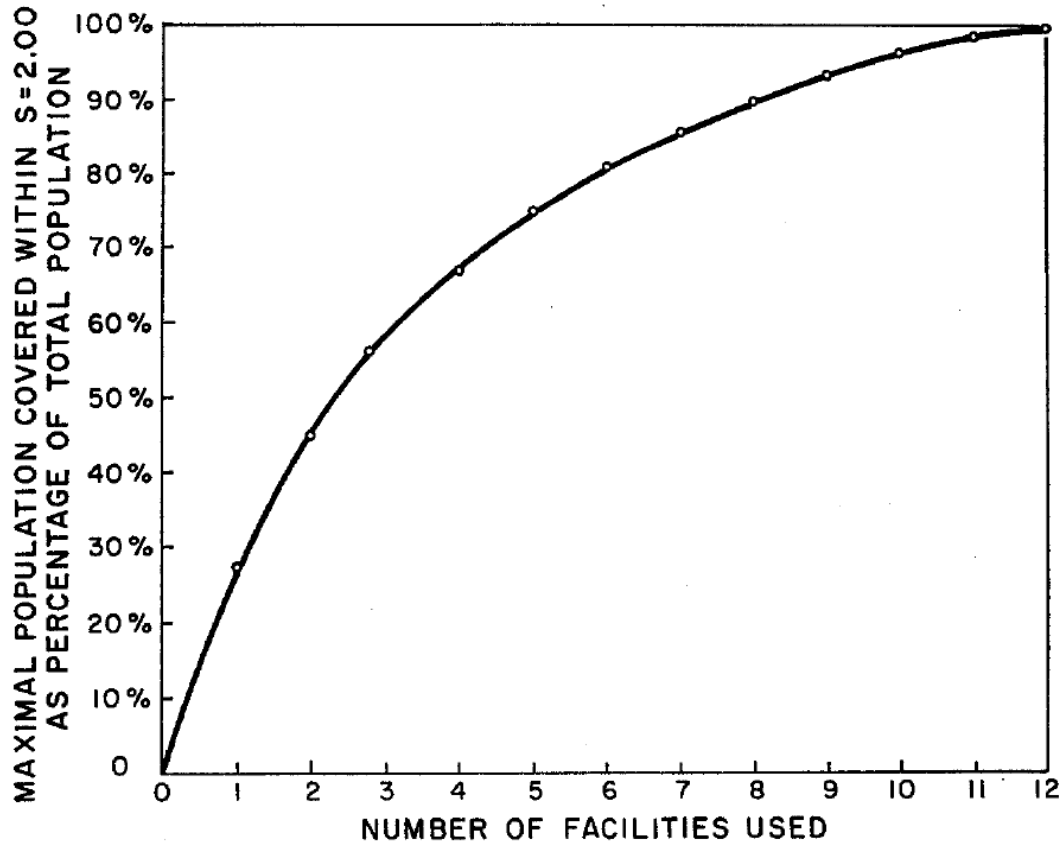


Figure 31. Example cost-effectiveness curve. Source: Church and ReVelle (1974).

Another basic example from Church and ReVelle is what they define as the maximal of covering with mandatory closeness constraints. If, as discussed earlier in this section, facility numbers and locations are one of the chief concerns in set covering problems (if not *the* chief concern) then the idea of a mandatory closeness constraint within a maximal covering problem will constrain your facility locations to capture and serve as many “nodes” as possible while covering the area. It is logical that you would prefer your locations to be centrally located to as many nodes as possible within this closeness constraint. They consider a network of 55 nodes needed to be covered, with a maximal service distance of 15 units of measurement – for example, miles. They find multiple optimal solutions, satisfying both constraints, the first of which is depicted in Figure 32. Every node is serviced, and all are within the maximal distance from the facilities. Note the dashed inner circle of mandatory closeness, 10 miles, that they are not yet considering.

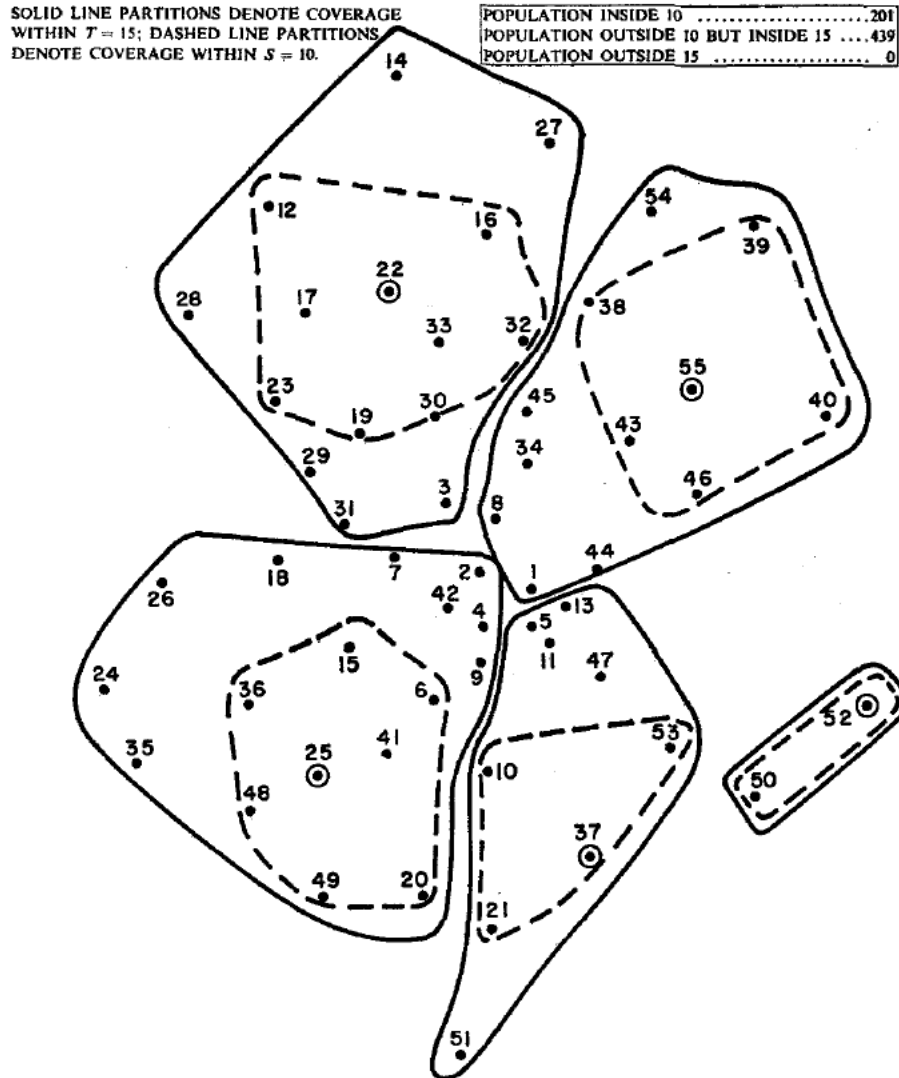


Figure 32. MCLP solution 1. Source: Church and ReVelle (1974).

While it turns out that many nodes, 29 of 55, are located within their hypothetical mandatory closeness constraint, there is a better and more efficient solution when aiming to maximize mandatory closeness and still satisfying the maximal coverage. Their second solution, depicted in Figure 33, rearranges the facility locations to more optimally satisfy mandatory closeness. 38 nodes are now within 10 miles, with only 15 within the maximal 15 miles, and all nodes are covered. Considering this additional constraint more optimally located their facilities according to the population density of the surrounding market.

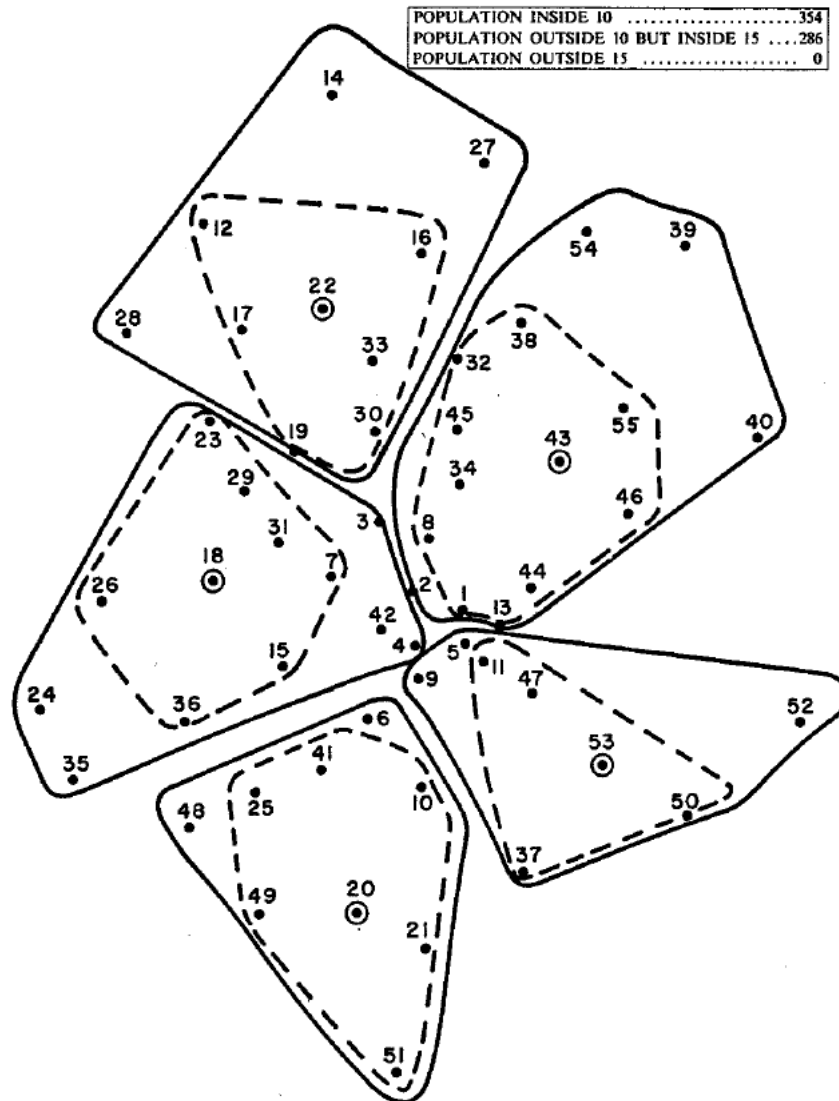


Figure 33. MCLP solution 2. Source: Church and ReVelle (1974).

The idea of trade-offs in MCLP problems persists even further, as Church and ReVelle lastly look at this final example through the lens of maximizing this mandatory closeness constraint while relaxing the maximum coverage. By doing so they capture 45 nodes within the mandatory closeness and six more within their maximal distance, while trading off 4 nodes that cannot be covered by this network, as depicted in Figure 34. If mandatory closeness was added as a constraint because these closer nodes can be serviced or exploited at a much more efficient rate, this may be the most optimal of solutions (Church & ReVelle, 1974).

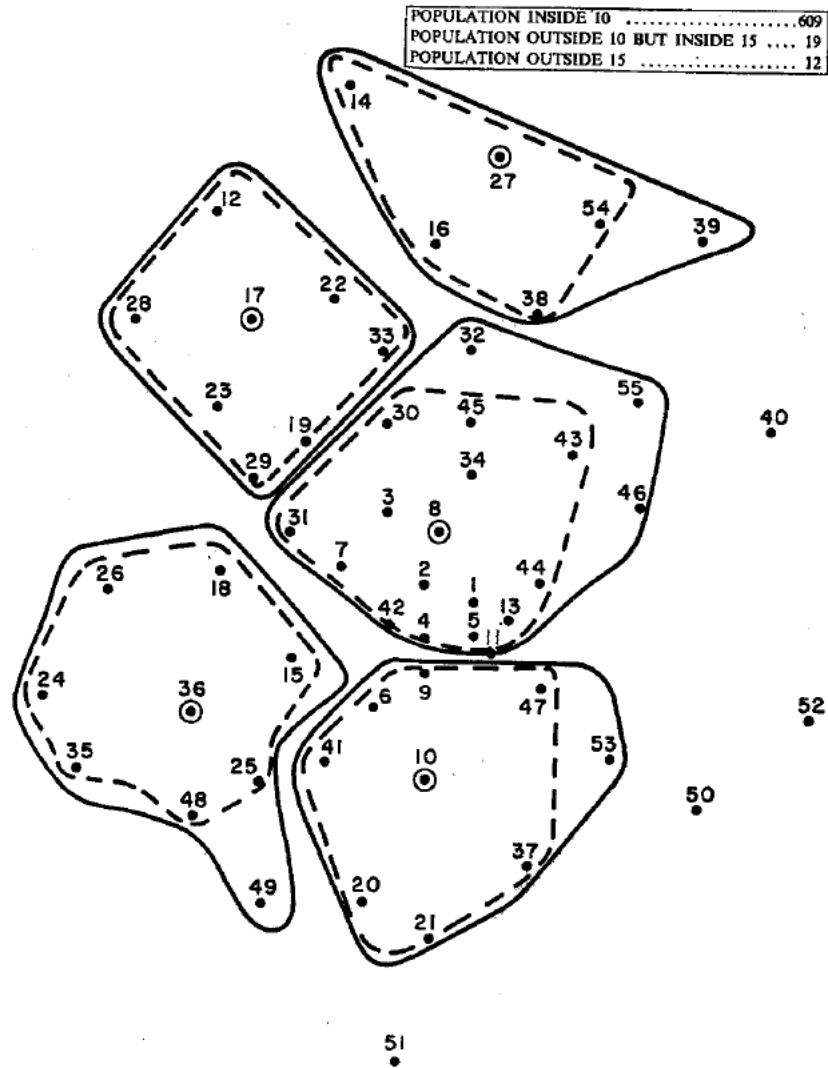


Figure 34. MCLP solution 3. Source: Church and ReVelle (1974).

E. REAL-WORLD SET COVER SETUP AND EXAMPLE

A real-world example of a set covering problem can be found examining the fire station locations in Istanbul, Turkey. As discussed earlier, the location of public facilities like fire stations is highly important and at times difficult to quantify, especially in large and growing cities like Istanbul which is itself one of the world's largest cities at around 13.5 million population. Response time is of course a chief consideration, but city planners also have to take traffic congestion, infrastructure deficiencies, and the population densities of the 790 Istanbul subdistricts into account while considering locations. Each of these

additional considerations has a cost associated with it. Fire stations being a public good with which no citizens can be realistically left without, the authors argue that this is a more pure set covering problem, without the luxury of building a network that does not serve the entire municipality and making it different from the last section's introductory example (Atkas et al., 2013). Even so, budgetary constraints are an inevitability and even 100% coverage within a given response time may not be possible (five minutes for this model).

Given these constraints, the authors of this study formulated their relevant scenarios as full set covering and maximal-covering models. As with most problems of this type, the authors designed it with potential sites (subdistricts) for the fire stations, as well as a set of communities (also subdistricts) which must be protected from fires. The focus is the subdistricts that can be reached in five minutes of wherever fire stations are located. With that, the authors arrange a minimum-cost set covering problem so that all subdistricts are covered with the minimum amount of fire station locations and reporting those districts that are covered by which specific stations. They do this as a forecast including already built fire stations, and then a from-scratch model assuming no pre-built fire stations. Lastly for our purposes, they do consider a maximal-coverage model, taking Istanbul's budget into consideration with the costs of a certain amount and type of fire station (Atkas et al., 2013).

The main goal of their models is to minimize the number of new fire stations to serve all subdistricts within 5 minutes. They implement binary decision variables (1 if a fire station is opened in the designated subdistrict, 0 otherwise), with their constraints designed that all subdistricts can be reached by at least one station. They consider a subdistrict reached or "covered" if the "centroid" of the district can be reached in 5 minutes – the centroid being defined as the center of mass of a district regarding population density. Fire stations themselves are separated into four categories (A, B, C, D). A and B are larger groups or centers with a higher cost, and C and D are termed squads which are designed to respond to smaller incidents at a lower cost. Relevant data concerning the historical rate and size of fire incidents from 1994–2006 are assigned and weighted to each subdistrict when determining the sizes and locations of stations and are captured in the cost constraints. Costs associated with each station, obtained from the already pre-built 60 total

stations, are depicted in Figure 35. In another model, the authors assign weights to various subdistricts based on the historical significance of revered structures and the increased adverse effect if said structures suffered fire damage. The historical rate of fires in these districts is of extra importance for this model because extra consideration must be taken regarding the “acceptable” amount of coverage and thus the size of responding stations (Atkas et al., 2013).

Station type	Size (square meters)	Cost (\$)	Annual capacity per station	Stations in operation in 2009
<i>A</i>	3,650	1,018,413	13,140	14
<i>B</i>	2,900	809,150	10,950	16
<i>C</i>	2,525	704,519	8,760	20
<i>D</i>	2,150	599,887	4,380	10

Figure 35. Istanbul station type and costs. Source: Atkas et al. (2013).

The authors then develop a map of Istanbul and its 790 subdistricts, identifying each subdistrict without a pre-built fire station an option for placing a new one. Mapping of “building footprint” data assists the authors with assigning each subdistrict’s “centroid” to assist in estimating the 5-minute coverage constraint and to avoid placing stations at irrelevant or unpopulated areas. With this data, they then created a proximity matrix where each cell is represented by a 1 if the subdistrict is reachable within 5 minutes of the other subdistrict and blank if it is not covered, as depicted in Figure 36. For example, if a station is located in subdistrict 156 (top row), it can service subdistricts 156, 159, 161, 211, 213, 218, and 219. This is only a small example of the total matrix which lists all 790 subdistricts as both rows and corresponding columns (Atkas et al., 2013).

	156	158	159	161	178	190	211	212	213	215	216	218	219	220
156	1		1	1			1		1			1	1	
158		1		1	1				1	1		1		1
159	1		1					1				1	1	
161	1	1		1			1		1	1				1
178		1			1	1	1			1	1	1		1
190					1	1		1	1			1	1	
211	1			1	1		1			1	1		1	
212			1			1		1	1	1				
213	1	1		1		1		1	1			1		
215		1		1	1		1	1		1		1	1	
216					1		1				1	1		1
218	1	1	1		1	1			1	1	1	1		1
219	1		1			1	1			1			1	
220		1		1	1						1	1		1

Table 2: In this proximity matrix example, the value in a cell is 1 if the representative point of a destination subdistrict can be reached from that of an origin subdistrict within five minutes; otherwise, it is blank.

Figure 36. Example of subdistrict matrix. Source: Atkas et al. (2013).

In their results, the authors considered three aspects of coverage, including the percentage of subdistricts ultimately covered (including percentages of those covered by two or more stations), the amount of service requests (historical fires) in each subdistrict, and a weighted amount of historical service requests for those districts with more historical locations. Results of each model are depicted in Figure 37. With respect to scenarios: (1) represents status quo, pre-existing stations and their coverage areas; (2) set covering model expanded from pre-built stations (keeping them) to obtain 100% coverage; (3) reports coverage for those new stations opened in second scenario; (4) from-scratch set covering model, assuming no pre-built stations and obtaining 100% coverage; (5) reports coverage for from-scratch model; (6) maximal-coverage model, obtaining as much possible coverage while considering city budget; (7) reports coverage from sixth scenario; (8) maximal-coverage model with weighted subdistricts based on historical significance; (9) reports coverage of eighth scenario; (10) 2005 coverage status used for comparison. The authors also generated a decision-making tool displaying the results of required stations,

their type, subdistrict location, and the impact on the overall coverage percentage, as depicted in Figure 38 (Atkas et al., 2013).

Scenario	Number of fire stations			Coverage (%)					Total cost (\$)
	<i>E</i>	<i>N</i>	<i>T</i>	C_{SD}	C_{double}	C_{triple}	C_{SR}	C_{HSR}	
1	60	—	60	58.6	15.1	0.4	56.6	18.2	47,293,423
2	60	149	209	100	37.2	4.3	100	100	136,676,586
3				100	37.2	4.3	100	100	
4	—	193	193	100	28.4	0.8	100	100	115,778,191
5				100	28.4	0.8	100	100	
6	60	64	124	85.9	35.6	2.8	93.9	71.1	85,686,191
7				85.9	35.6	2.8	93.1	70.7	
8	60	64	124	82.0	31.0	3.1	86.6	98.4	85,686,191
9				82.0	31.0	3.1	85.1	96.9	
10	50	—	50	46	3	0	43	9.2	40,771,394

Table 4: The table shows the results of our analysis of each scenario.

Notes: *E* = existing, *N* = new, *T* = total, C_{SD} = subdistrict, C_{double} = doubly covered, C_{triple} = triply covered, C_{SR} = service requests, C_{HSR} = heritage service requests.

Figure 37. Scenario results. Source: Atkas et al. (2013).

Station name	Station type	Location	Continent	Impact on coverage (%)
Beylikduzu squad	<i>D</i>	Beylikduzu	Europe	+0.71
Pendik 2nd squad	<i>D</i>	Pendik	Asia	+1.23
Tuzla Vernikçiler squad	<i>D</i>	Tuzla	Asia	+0.39
Zeytinburnu squad	<i>D</i>	Zeytinburnu	Europe	+0.80
Seyrantepe squad	<i>D</i>	Maslak	Europe	+0.66
West Ataşehir squad	<i>D</i>	Ataşehir	Asia	+0.73
Başıbüyük squad	<i>D</i>	Başıbüyük	Asia	+1.51
Abdurrahmangazi squad	<i>D</i>	Samandıra	Asia	+0.37
Hamidiye squad	<i>D</i>	Çamlıca	Asia	+0.42
Pınartepe squad	<i>D</i>	Pınartepe	Europe	+0.38
Total				+7.2

Figure 38. Station data table. Source: Atkas et al. (2013).

Scenario 1 in Figure 37 shows 60 existing stations, no new ones built, a 58.6% subdistrict coverage rate, relatively low rates of double and triple coverage, a 56.6% rate for service requests responded to, and a woefully low 18.2% coverage for weighted historical districts. Scenario 2 adds 149 stations and increases subdistrict and estimated service request coverage to 100% at a substantial cost of \$136,676,586. Scenario 4 also achieves 100% coverage for subdistricts, calls, and historical districts and at a lower cost, which is only possible if building from scratch and not being tied to pre-existing stations. Scenarios 6 and 8 are the same cost for having been constrained by the city budget, with (6) striving for maximum subdistrict coverage and (8) assigning more weight to historical districts.

The Marine Corps can leverage the same subjects and lessons from this study. Subdistrict coverage rates could be parallel to OSS coverage of locations with potentially qualified officer candidates. The scenarios can be applied to examine the status quo of OSS locations, expanding from while keeping already-established OSS locations, or potentially redrawing the map without consideration to already-established stations. Lastly, the Marine Corps too has budget constraints, and comparing optimal full coverage models with those that are more financially viable will assist the institution with trade-offs and weights of priorities.

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IV. METHODOLOGY AND RESULTS

A. APPLICATION PROGRAMMING INTERFACE

APIs are tools that allow communication between a client and a server (D. Reich, class presentation, January 22, 2021). Many websites use APIs to communicate with other websites to share and retrieve data. When typing in an address to a computer's internet browser, a request goes out to that site's server. The site is displayed after the browser receives a response from the server and interprets the code. In this case the browser is the client and the server is the operator of the visited website (Gazarov, n.d.).

As an example, consider a small business's website which contains a form used to set up appointments. The small business could use Google's calendar server, and the site could be coded to communicate that server to display availability, appointments, times, and details (Gazarov, n.d.). The small business's site would be coded with an API to retrieve Google's calendar program response, process it, and then display this information to the site and the client (Gazarov, n.d.).

Some servers only issue one type of response and connect in the same way, for example <https://nps.edu/> connects the user to NPS's website. Servers can use query strings to communicate more complex information, or parameters (D. Reich, class presentation, January 22, 2021). Location is an often used parameter and is relevant to this study. As an example, <https://forecast.weather.gov/MapClick.php?lat=36.598200000000008&lon=-121.896469999999997> would tell the forecast.weather.gov server to display the weather for location at 36.598200000000008 degrees latitude and -121.896469999999997 degrees longitude (D. Reich, class presentation, January 22, 2021). As maps are used often and in many different applications, there are multiple map APIs available. Many are free to use to a certain data or request limit, while also offering paid premium exclusive services. Many others require payment for any use. Each of these APIs offer programs to generate latitude and longitude data for inputted locations, be them generic such as a city name or more precise such as a specific address inside a city. This study uses a geospatial API from MapQuest, which can be used for free when registering as a MapQuest Developer. An

authentication code is required for the client to use an API to request information from the server, which is provided when registering as a Developer.

B. PYTHON CODING

Understanding the function of the desired program is important, but it is not necessarily coded in the order shown in Figure 39. As such, it may be useful to refer back to this figure. The first step is building the portion of the computer program which contacts the API and retrieves the desired information, which takes up the majority of the code.

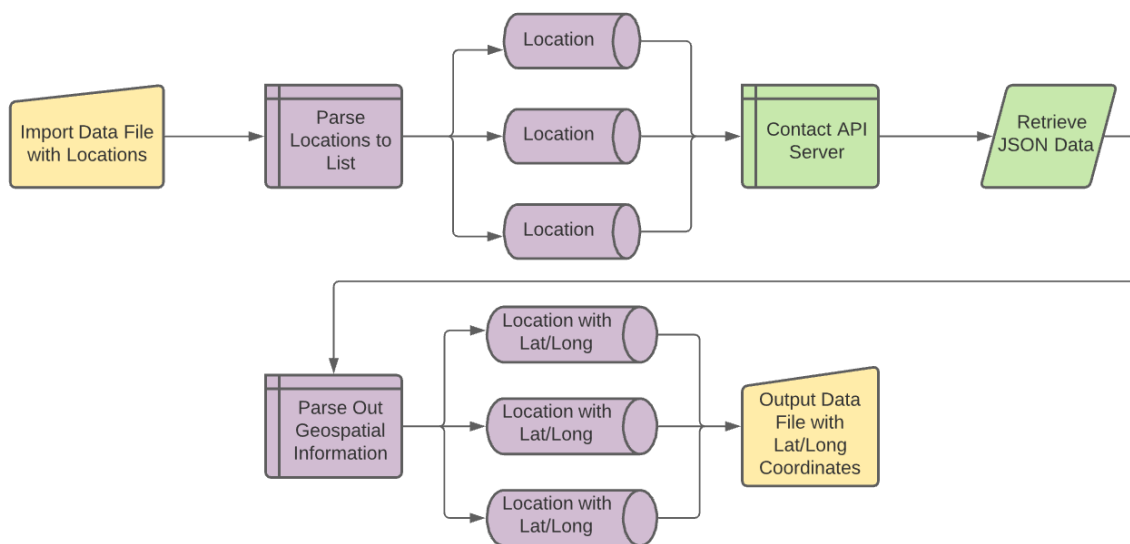


Figure 39. Computer program process flowchart.

1. Contact API Server

Two packages are imported into Python to assist for ease of use, depicted in Figure 40. This is done by making import statements which allow Python to load modules that will be used in subsequent lines of code. This is the first cell of the code, containing two lines; line 1 of this cell is 'import requests' line 2 of this cell is 'import json.'

```
In [1]: import requests
import json
```

Figure 40. Cell 1 of Python code in Jupyter Notebook.

The first import statement, ‘import requests’ loads a module designed to handle HTTP requests. ‘Import json’ loads a package used to convert JSON code, another plain text file language, into Python dictionaries.

```
In [2]: def buildGeocodingQueryString(location_of_interest, authentication_key):
url_base = 'http://www.mapquestapi.com/geocoding/v1/address?'
geocoding_url = url_base + 'key=' + authentication_key + '&location=' + location_of_interest
return geocoding_url
```

Figure 41. Cell 2 of Python code in Jupyter Notebook.

The next step is to define the ‘buildGeocodingQueryString’ function, started by ‘def’ on the top line of the code depicted in Figure 41. This function takes in two inputs, the ‘location_of_interest’ and my ‘authentication_key’. The tabbed lines inside the code fall within the function. The ‘url_base’ of the request will be the “base” of the URL, or the part which will always be the same. This base was obtained by registering as a developer for the MapQuest API program and running a test search on a generic location. After the base comes specific parameters which are added to the base, which is called the ‘geocoding_url’. It starts with the ‘url_base’ then adds ‘key=’ inside a single set of parentheses. This means that ‘key=’ will be added in directly as typed after the ‘url_base’. The next parameter ‘authentication_key’ is added, followed by ‘&location=’ (similarly inside single parenthesis to transcribe it exactly as written). Lastly, the ‘location_of_interest’ will be added to end the ‘geocoding_url’, which will be later inserted. The function is then instructed to return the completed ‘geocoding_url’. Nothing is returned at this point because this cell only defines a function; the function has not been executed yet.

What this completed function allows the program to do is to call not one specific location someone may do in an internet browser, but instead to call any location put into it along with an authentication key. It will pull the base URL, add ‘key=’, add the

authentication key, add '&location=', and then a location of interest which the user can define. Figure 42 runs this function for Manhattan, Kansas.

```
In [3]: buildGeocodingQueryString('manhattan, ks', 'v51vZ0QY1qLsKU8yGmsYt5AEA8ayAt91')
Out[3]: 'http://www.mapquestapi.com/geocoding/v1/address?key=v51vZ0QY1qLsKU8yGmsYt5AEA8ayAt91&location=manhattan, ks'
```

Figure 42. Cell 3 of Python code in Jupyter Notebook.

2. Retrieve JSON Data

Figure 42 shows a line of executed code and the corresponding output line. The input calls for the 'buildGeocodingQueryString' function and 'manhattan, ks' is entered where the function knows to look for the 'location_of_interest', and the MapQuest authentication key is placed where the function expects to find it. Because the function is directed to return the 'geocoding_url', the output line shows the complete URL based on the parameters. The output shows the base URL, followed by 'key=', then the actual key, then '&location=', then 'manhattan, ks', just as entered. Figure 43 depicts the outputted URL when viewed in an internet browser.

```

{
  "info": {
    "statusCode": 0,
    "copyright": {
      "text": "© 2021 MapQuest, Inc.",
      "imageUrl": "http://api.mqcdn.com/res/mqlogo.gif",
      "imageAltText": "© 2021 MapQuest, Inc."
    },
    "options": {
      "maxResults": -1,
      "thumbMaps": true,
      "ignoreRelatingInput": false
    },
    "results": {
      "0": {
        "providedLocation": {
          "location": "manhattan, ks"
        },
        "locations": {
          "0": {
            "street": "",
            "adminArea6": "",
            "adminArea6Type": "Neighborhood",
            "adminArea5": "Manhattan",
            "adminArea5Type": "City",
            "adminArea4": "Riley County",
            "adminArea4Type": "County",
            "adminArea3": "KS",
            "adminArea3Type": "State",
            "adminArea1": "US",
            "adminArea1Type": "Country",
            "postalCode": "",
            "geocodeQualityCode": "A5XAX",
            "geocodeQuality": "CITY",
            "dragPoint": false,
            "sideOfStreet": "N",
            "linkId": "282841941",
            "unknownInput": "",
            "type": "s",
            "latlng": {
              "lat": 39.190363,
              "lng": -96.549656
            },
            "displayLatlng": {
              "lat": 39.190363,
              "lng": -96.549656
            },
            "mapUrl": "http://www.mapquestapi.com/staticmap/v5/map?key=v5fVZDQY1qLsKUByGMsYt5AE8ayAt91&type=map&size=225,160&locations=39.190363,-96.549656|marker-sm=50318A-1&scalebar=true&zoom=12&rand=1909728093"
          }
        }
      }
    }
  }
}

```

f

Figure 43. Test of Cell 3 of Python code in Firefox.

The Mozilla Firefox browser is set to display JSON code into an easy to read format and shows the code worked. The browser used the key which the MapQuest server accepted. The results show it found Manhattan, determined it is a city located in Riley County, and gave latitude and longitude coordinates which the MapQuest API is set up to find.

3. Parse Out Geospatial Information

Now that a function is setup to generate MapQuest API URLs, a function is needed that actually connect to the API. This function is called ‘executeHTTPget’, as depicted in Figure 44.

```
In [4]: def executeHTTPget(url_string):
        response = requests.get(url_string)
        response_json = response.text
        return response_json
```

Figure 44. Cell 4 of Python code in Jupyter Notebook.

This function is based off a 'url_string'. The function is first instructed to obtain a response based on the 'url_string', and then also to obtain the text piece of the response, outputting in JSON plain text. The function is lastly instructed to return this JSON response, meaning the JSON as searched for in the browser in Figure 45. The code can make sense of the JSON text because the program first imported the JSON module in cell 1 in Figure 40.

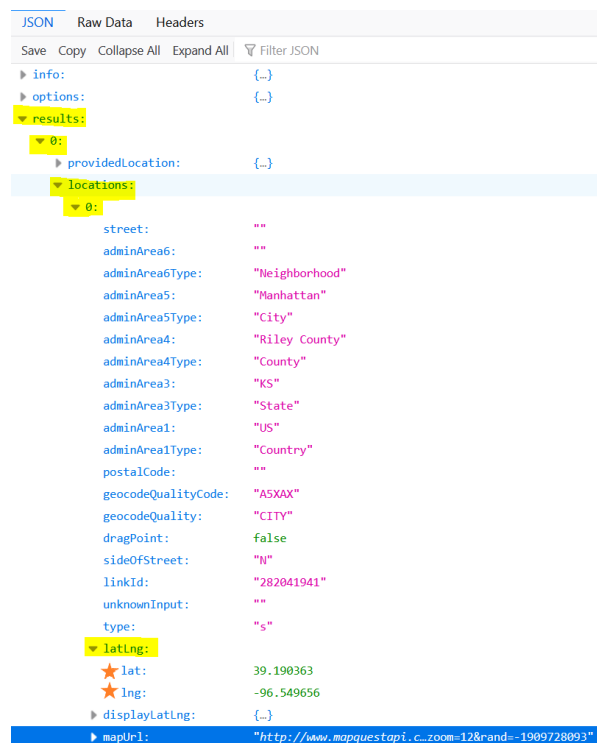


Figure 45. API call from Cell 5 of Python code viewed in Firefox.

As depicted in Figure 45, JSON code is organized into arrays (most of which are collapsed in the Figure). The latitude and longitude values needing to be extracted are

located (shown by orange star icons) but a response dictionary must be built so the program can locate, understand, and extract this information correctly. The arrays needing to be accessed are highlighted in the Figure. The first array needing access is ‘results’, and then also the ‘0’ array directly beneath it. JSON text arrays are always broken down with the first array being titled as ‘0’. After the first ‘0’ array, the program needs access to ‘locations’, then the ‘0’ array beneath that, and finally the ‘latlng’ array which contains ‘lat’ and ‘lng’. The required information for the response dictionary is now obtained, and that dictionary’s function is next depicted in Figure 46.

```
In [5]: def processGeocodingResponse(geocoding_response_json):  
        response_dictionary = json.loads(geocoding_response_json)  
        lat_long_dictionary = response_dictionary['results'][0]['locations'][0]['latlng']  
        latitude = lat_long_dictionary['lat']  
        longitude = lat_long_dictionary['lng']  
        return latitude, longitude
```

Figure 46. Cell 5 of Python code in Jupyter Notebook.

This function is defined as ‘processGeocodingResponse(geocoding_response_json)’. In it, the function is first instructed to run a response dictionary based on ‘json.loads(geocoding_response_json)’. This is part of the ‘import json’ module that was loaded in cell 1 of the code, and it allows Python to read through the JSON arrays in much the same way as was depicted in Figure 45. Next the ‘lat_long_dictionary’ is built, based on the arrays previously identified. Based on those, the dictionary function is instructed to lookup its own response dictionary in [‘results’][0][‘locations’][0][‘latlng’]. With those instructions, latitude and longitude variables are created, based off its search through the arrays, making latitude equal to the ‘lat’ value and longitude equal to ‘lng’. Lastly, the function is instructed to return those latitude and longitude values.

4. Location with Latitude and Longitude

An object is then created in the code to organize a data structure for the locations needing to be searched for later, which is also called a ‘class’ in Python. This will be used

to store the information when the program later looks for and categorizes multiple locations. This is depicted in Figure 47.

```
In [6]: class Location:
        def __init__(self, description, latitude, longitude):
            self.description = description
            self.latitude = latitude
            self.longitude = longitude
```

Figure 47. Cell 6 of Python code in Jupyter Notebook.

This is defined by coding ‘class Location’. Inside of the class, specific attributes for each individual location are defined with ‘def __init__(self, description, latitude, longitude)’. ‘__init__’ here means that when the code is initialized, it will define attributes self, description, latitude, and longitude. ‘Self’ is always the first argument when defining attributes inside of a class. The three tabbed lines in Figure 48 tell the function that when it creates a location (after automatically creating itself), it will then search inside itself for the description, latitude, and longitude, and then store those three attributes inside of each location.

5. Run Multiple Steps of the Process in a Single Function

Then a function is designed that will organize and combine many of the lines of codes and cells and commands from earlier on, called ‘getLocationObject’ which is depicted in Figure 48.

```
In [7]: def getLocationObject(location_of_interest, authentication_key):
        url_string = buildGeocodingQueryString(location_of_interest, authentication_key)
        response_json = executeHTTPget(url_string)
        latitude, longitude = processGeocodingResponse(response_json)
        location = Location(location_of_interest, latitude, longitude)
        return location
```

Figure 48. Cell 7 of Python code in Jupyter Notebook.

This function first reaches back to cell 2 of the code and assigns a ‘url_string’ based on the ‘buildGeocodingQueryString’ function. The results of this were demonstrated in

cell 3 of the code, but for this function keeps the 'location_of_interest' and 'authentication_key' generic so it will work with any location and any key, not restricted to one. After obtaining the 'url_string' the program then runs the 'executeHTTPget' function in cell 4, so the 'response_json' from that cell is added to this new function. The 'response_json' is processed by instructing this function to also grab the latitude and longitude which was demonstrated in cell 5. Lastly the function needs to assign these values to an object, which was first defined in cell 6. The function is finally instructed to return this location.

The 'getLocationObject' is tested by running this function on two locations, Lawrence, KS and Lincoln, NE, as shown cells 8 and 9 of the code and depicted in Figure 49. Two test variables are created, 'location1' and 'location2', and each are equal to the output of the 'getLocationObject' function and each are then assigned to one of the variables and include my MapQuest authentication key. The code then directs each cell to print what each location is. They both work, as cell 8 shows that 'location1' has a description of 'lawrence,ks', a latitude of 38.976067, and a longitude of -95.235957. The code now successfully parses out the geospatial information required for the study.

```
In [8]: location1 = getLocationObject('lawrence,ks', 'v51VZ0QY1qLsKU8yGmsYt5AEA8ayAt91')
print(location1.__dict__)

{'description': 'lawrence,ks', 'latitude': 38.973037, 'longitude': -95.235957}

In [9]: location2 = getLocationObject('lincoln,ne', 'v51VZ0QY1qLsKU8yGmsYt5AEA8ayAt91')
print(location2.__dict__)

{'description': 'lincoln,ne', 'latitude': 40.813599, 'longitude': -96.70261}
```

Figure 49. Cells 8 and 9 of Python code in Jupyter Notebook.

6. Import Data File with Locations

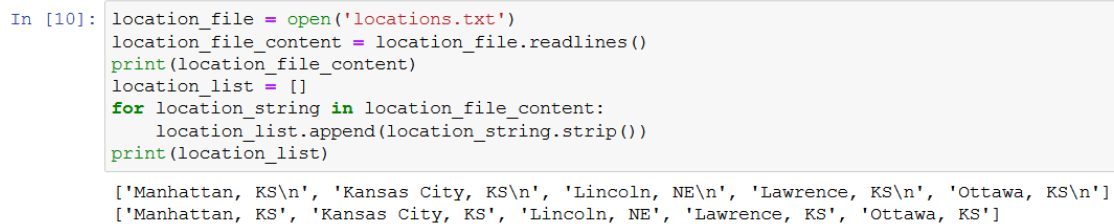
The purpose of coding these functions so far is because the objective is to design a process that can repeat the 'getLocationObject' function from cell 7 and other functions I'll discuss later on many different locations at the same time. Referring again back to Figure 39, the portion of the code which will be able to import the requested data which will now be understood and separated by location when read by the program. To

accomplish this, a plain text file of a short list of sample locations is created in a text editor, as depicted in Figure 50. This is saved as locations.txt.

A screenshot of a text editor window titled 'locations.txt'. The window contains a list of six locations, each on a new line, numbered 1 through 6. The locations are: 1 Manhattan, KS, 2 Kansas City, KS, 3 Lincoln, NE, 4 Lawrence, KS, 5 Ottawa, KS, and 6 is an empty line with a blue cursor. The text is in a light blue font on a dark background.

```
locations.txt
1  Manhattan, KS
2  Kansas City, KS
3  Lincoln, NE
4  Lawrence, KS
5  Ottawa, KS
6
```

Figure 50. Test Plain Text File viewed in Atom.

A screenshot of a Jupyter Notebook cell. The cell contains Python code that opens a file named 'locations.txt', reads its contents, strips the newline characters, and appends them to a list. The code then prints the list. Below the code, the output is displayed, showing the list of locations with their full paths and the list of locations without paths.

```
In [10]: location_file = open('locations.txt')
location_file_content = location_file.readlines()
print(location_file_content)
location_list = []
for location_string in location_file_content:
    location_list.append(location_string.strip())
print(location_list)

['Manhattan, KS\n', 'Kansas City, KS\n', 'Lincoln, NE\n', 'Lawrence, KS\n', 'Ottawa, KS\n']
['Manhattan, KS', 'Kansas City, KS', 'Lincoln, NE', 'Lawrence, KS', 'Ottawa, KS']
```

Figure 51. Cell 10 of Python code in Jupyter Notebook.

With that plain text file ready, lines of code are needed which will import, read, and separate it based on a set of instructions. Figure 51 shows cell 10 of the code which does this. The top line instructs Python to import the ‘locations.txt’ file, and the second line tells it to read the lines of content as this is a plain text file. A location list based on the text that Python has read is then created by telling it to strip it, meaning that Python will read each new line of text as a new and independent string. Lastly, Python then prints the ‘location_list’ as a test. The plain text below cell 10 is the output of this print and it shows that Python correctly read and separated the text by each line, meaning the program is now capable of both importing data and separating it based off the designed parameters. The strings it found are inside single parentheses and commas serve to separate each new string from the last.

7. Saving Locations with Latitudes and Longitudes

```
In [11]: location_objects_list = []
        for location_string in location_list:
            location = getLocationObject(location_string, 'v51VZ0QY1qLsKU8yGMSYt5AEA8ayAt91')
            location_objects_list.append(location)
```

Figure 52. Cell 11 of Python code in Jupyter Notebook.

With those strings which were successfully interpreted, next the program needs to create a list of objects based on that which will then be able to separate into description, latitude, and longitude, analogous to the “save location list to program” and “print list and information” steps depicted in Figure 39. The coding for such is shown in Figure 52. Python is first told that it is creating the ‘location_objects_list’. Then, for the ‘location_string’ in ‘location_list’ (each city which Python read as a separate string), it is instructed to run the ‘getLocationObject’ shown in cell 7 on every string Python found and include the authentication key. As this cell was not a function in itself and only contained instructions, there is no output. To check that these ran, cell 12 of code is created which tells Python that, for every location in this ‘location_objects_list’ which was created, print the location attributes that were assigned in cell 6. This is depicted in Figure 53. The short list of five cities that were created are printed. Each string is successfully determined to have had a description, latitude, and longitude attribute. The program is shown to be independently capable of all steps in Figure 39 except for the last one, “output data file.” Next, data needed for this study is imported.

```
In [12]: for location in location_objects_list:
        print(location.__dict__)

{'description': 'Manhattan, KS', 'latitude': 39.190363, 'longitude': -96.549656}
{'description': 'Kansas City, KS', 'latitude': 39.1127, 'longitude': -94.626804}
{'description': 'Lincoln, NE', 'latitude': 40.813599, 'longitude': -96.70261}
{'description': 'Lawrence, KS', 'latitude': 38.973037, 'longitude': -95.235957}
{'description': 'Ottawa, KS', 'latitude': 38.608498, 'longitude': -95.268637}
```

Figure 53. Cell 12 of Python code in Jupyter Notebook.

Column1	Region	District	RS	OSS	Address
1	ERR	1MCD	Albany	OSS Albany	2021 WESTERN AVE, SUITE 101A, ALBANY NY, 12203
2	ERR	1MCD	Springfield	OSS Amherst	6 UNIVERSITY DR, SUITE 205, AMHERST MA, 01002
3	ERR	1MCD	Portsmouth	OSS Boston	495 SUMMER ST, RM 107, BOSTON MA, 02120
4	ERR	1MCD	Pittsburgh	OSS Buffalo	520 LEE ENTRANCE RD, SUITE 208, AMHERST NY, 14228
5	ERR	1MCD	Baltimore	OSS Hyattsville	7305 BALTIMORE AVE SUITE 302, COLLEGE PARK MD, 20742
6	ERR	1MCD	New York	OSS Garden City	605 STEWART AVE, GARDEN CITY NY, 11530
7	ERR	1MCD	New York	OSS Manhattan	55 5TH AVE, SUITE 1301, NEW YORK NY, 10003
8	ERR	1MCD	New Jersey	OSS New Brunswick	303 GEORGE ST, SUITE 110, NEW BRUNSWICK NJ, 08901
9	ERR	1MCD	New Jersey	OSS Jersey City	101 HUDSON AVE, SUITE 3605, JERSEY CITY NJ, 07302
10	ERR	1MCD	Baltimore	OSS Newark	224 E DELAWARE AVE, SUITE 102, NEWARK DE, 21075
11	ERR	1MCD	Harrisburg	OSS Philadelphia	900 MARKET ST, SUITE 313, PHILADELPHIA PA, 19107
12	ERR	1MCD	Pittsburgh	OSS Pittsburgh	5837 ELLSWORTH AVE, PITTSBURGH PA, 15232
13	ERR	1MCD	Portsmouth	OSS Portsmouth	875 GREENLAND RD, UNIT 8-1, BUILD A, PORTSMOUTH NH, 03801
14	ERR	1MCD	Springfield	OSS Providence	1 DAVOL SQ, SUITE 301, PROVIDENCE RI, 02903
15	ERR	1MCD	Harrisburg	OSS Reading	76 COMMERCE RD, WYOMISSING PA, 19610
16	ERR	1MCD	Pittsburgh	OSS State College	242 S FRASER ST, STATE COLLEGE PA, 16801
17	ERR	1MCD	Albany	OSS Syracuse	344 W GENESEE ST, SUITE 200 SYRACUSE NY, 13202
18	ERR	4MCD	Detroit	OSS Ann Arbor	2144 S STATE ST, SUITE D, ANN ARBOR MI, 48104
19	ERR	4MCD	Louisville	OSS Covington	525 W 5TH ST, SUITE 119, COVINGTON KY, 41011
20	ERR	4MCD	Charleston	OSS Columbus	1335 DUBLIN RD, SUITE D209, COLUMBUS OH, 43215
21	ERR	4MCD	Lansing	OSS Lansing	301 M.A.C. AVE, EAST LANSING MI, 48823
22	ERR	4MCD	Frederick	OSS Fairfax	10521 BRADDOCK RD, SUITE C, FAIRFAX VA, 22032
23	ERR	4MCD	Cleveland	OSS Kent	265 WEST MAIN ST, SUITE 202, KENT OH, 44240
24	ERR	4MCD	Louisville	OSS Lexington	870 CORPORATE DR, SUITE 101, LEXINGTON KY, 40503
25	ERR	4MCD	Nasville	OSS Nashville	510 N THOMPSON LANE, SUITE E, MURFREESBORO TN, 37128
26	ERR	4MCD	Richmond	OSS Norfolk	4211 MONARCH WAY, SUITE 101, NORFOLK VA, 23508
27	ERR	4MCD	Raleigh	OSS Raleigh East	505 OBERLIN RD, SUITE 151, RALEIGH NC, 27605
28	ERR	4MCD	Raleigh	OSS Raleigh West	505 OBERLIN RD, SUITE 151, RALEIGH NC, 27605
29	ERR	4MCD	Richmond	OSS Richmond	100 ARBOR OAK DR, SUITE 106A, ASHLAND VA, 23005
30	ERR	4MCD	Charleston	OSS Roanoke	3555 ELECTRIC ROAD, SUITE K, ROANOKE VA, 24019

Figure 54. Sample of OSS locations viewed in Excel. Source: MCRC (2020).

Now that a series of functions was created which correctly connects to the MapQuest API, rips and interprets the JSON code which the server outputted, searches through arrays to display the needed attributes and can do all of that based on a text file which it imported, the program is used to first obtain the precise latitude and longitude of OSS locations. Figure 54 shows a small example of the most up to date locations of the 74 OSS locations. The Python functions are built to be based off of locations of interest which are retrieved from the MapQuest server. The entire list of addresses is converted into a plain text file called locations2.txt and then cell 10 is rerun to use this file instead of 'locations.txt'. When ran, Python correctly interprets the text strings for all of the OSS locations. With this being successful, rerunning cells 11 and 12 of the code generates descriptions, latitudes, and longitudes for each OSS locations.

8. Output Data File with Latitude and Longitudes

Next is to store and export this information, which is both the final piece of code and the last step of the chart depicted in Figure 39. Doing so in a Comma Separated Values (CSV), or '.csv' file allows this data to be easily used in a variety of programs. A CSV is a plain text file which separates each string of text with a comma, and no spaces. They can

be more difficult to work with in a text editor program, but they offer flexibility in that they can be read and interpreted by spreadsheet programs like Microsoft Excel and other visualization programs which work based on inputted data sets. Instructing Python to do this will be the final cell of code, as depicted in Figure 55.

```
In [13]: import csv
with open('data.csv', 'w',) as csvfile:
    writer = csv.writer(csvfile)
    writer.writerow(['Description', 'Latitude', 'Longitude'])
    for location in location_objects_list:
        writer.writerow([location.description, location.latitude, location.longitude])
```

Figure 55. Cell 13 of Python code in Jupyter Notebook.

Python is first told to import the csv module, allowing it to best read, process, and separate values appropriately. It is then told, with this module open, to create a new file called 'data.csv'. In said file, it is instructed to create columns for Description, Latitude, and Longitude. Then, based on each location Python read from the text file to create the 'location_objects_list', to put the 'location.description', 'location.latitude', and 'location.longitude' in each respective column. Once this cell is run, this new 'data.csv' file is created in the same file explorer folder that the Python code itself is stored in. Figure 56 shows a sample of the file in a text editor and Figure 57 shows a sample in Excel.

```
1 Description, Latitude, Longitude
2 "2021 WESTERN AVE, SUITE 101A, ALBANY NY, 12203",42.696975,-73.885689
3 "6 UNIVERSITY DR, SUITE 205, AMHERST MA, 01002",42.373023,-72.532933
4 "495 SUMMER ST, RM 107, BOSTON MA, 02120",42.341452,-71.035603
5 "520 LEE ENTRANCE RD, SUITE 208, AMHERST NY, 14228",43.003164,-78.785891
6 "7305 BALTIMORE AVE SUITE 302, COLLEGE PARK MD, 20742",38.97895,-76.93784
7 "605 STEWART AVE, GARDEN CITY NY, 11530",40.730928,-73.614769
8 "55 5TH AVE, SUITE 1301, NEW YORK NY, 10003",40.734877,-73.994421
9 "303 GEORGE ST, SUITE 110, NEW BRUNSWICK NJ, 08901",40.492759,-74.443383
10 "101 HUDSON AVE, SUITE 3605, JERSEY CITY NJ, 07302",40.71601,-74.034216
```

Figure 56. data.csv viewed in Atom text editor.

Descirption	Latitude	Longitude
2021 WESTERN AVE, SUITE 101A, ALBANY NY, 12203	42.696975	-73.885689
6 UNIVERSITY DR, SUITE 205, AMHERST MA, 01002	42.373023	-72.532933
495 SUMMER ST, RM 107, BOSTON MA, 02120	42.341452	-71.035603
520 LEE ENTRANCE RD, SUITE 208, AMHERST NY, 14228	43.003164	-78.785891
7305 BALTIMORE AVE SUITE 302, COLLEGE PARK MD, 20742	38.97895	-76.93784
605 STEWART AVE, GARDEN CITY NY, 11530	40.730928	-73.614769
55 5TH AVE, SUITE 1301, NEW YORK NY, 10003	40.734877	-73.994421
303 GEORGE ST, SUITE 110, NEW BRUNSWICK NJ, 08901	40.492759	-74.443383
101 HUDSON AVE, SUITE 3605, JERSEY CITY NJ, 07302	40.71601	-74.034216

Figure 57. data.csv viewed in Excel.

C. MAPPING

Tableau is an interactive data program which specializes in analytical visualization in order to help people clearly see and understand data (Tableau, n.d.). It can import a variety of file types, including plain text files like CSVs. To visualize the OSS location data geographically, the 'data.csv' file is imported and Tableau is set to measure the imported latitude and longitude values. By default, Tableau can treat latitudes and longitudes sums of measures, but setting these values as dimensions allows it see each value individually and then pair and map them. The generated map of generated OSS locations is depicted in Figure 58.

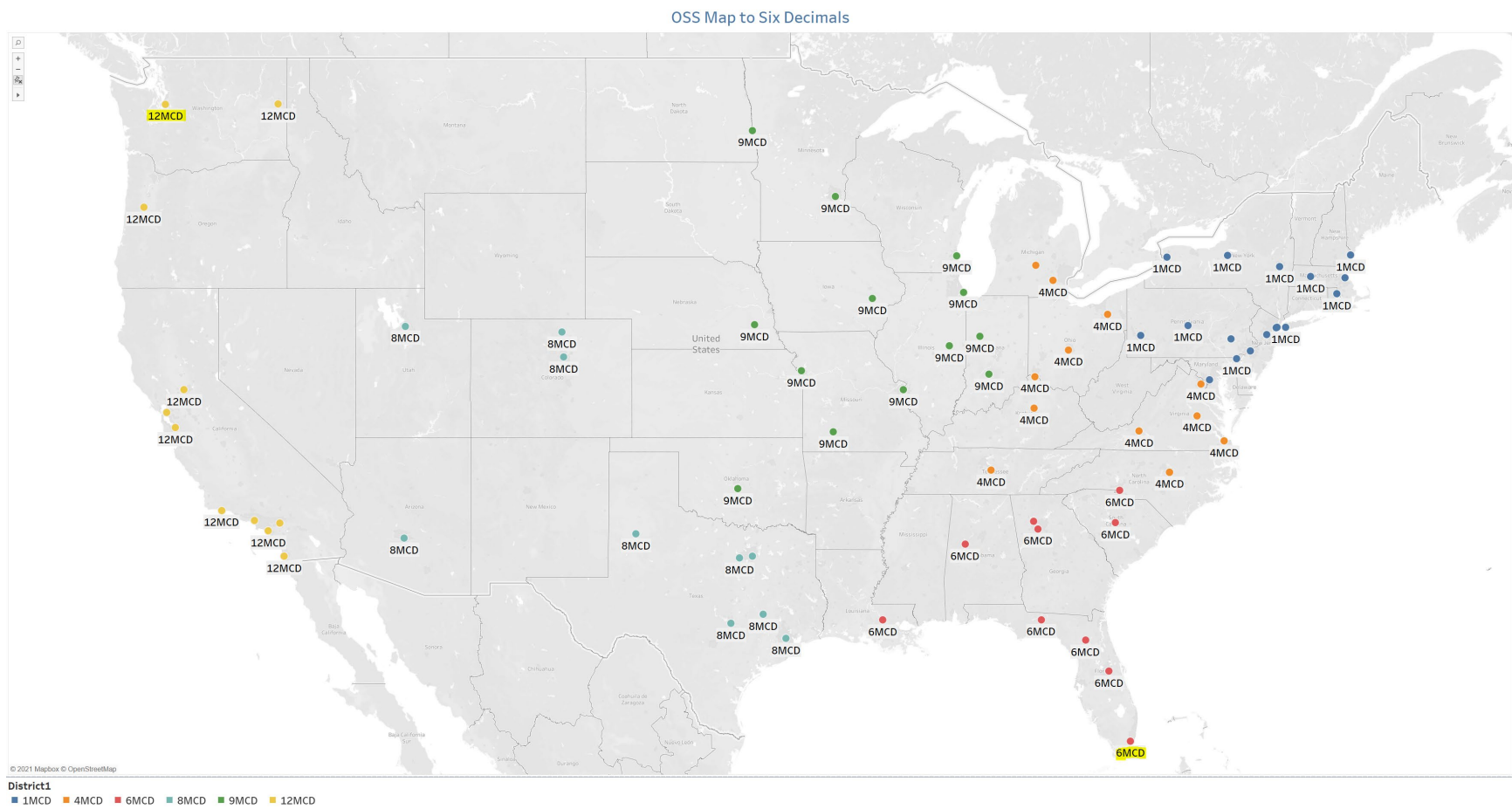


Figure 58. OSS map to six decimals .

Locations on this map are accurate to 6 decimal places (note that some of the points are not specifically labeled to avoid overlap). As discussed in the Background and Relevant Methods chapter, this makes these plots accurate to around 11cm for latitude and between 7.5cm to 10 cm for longitude. This level of geospatial precision is appropriate to map here because these OSS locations are publicly available and contain no personally identifiable information (PII). These longitudinal accuracy differences are important, however. For instance, the highlighted ‘6MCD’ point is OSS Miami, which is the OSS closest to the Equator. It has a latitude of 25.777257 and a longitude of -80.369502. The accuracy of latitude is virtually the same throughout the all the OSS locations, but the longitude here gives accuracy to around 7.5cm. The highlighted ‘12MCD’ point is OSS Seattle, the OSS which is the farthest north of the Equator which has a latitude/longitude of 47.664688/-122.31409. Longitude accuracy here would be around 10cm, or a nearly 25% more accuracy in the longitude precision when compared to the location of OSS Miami. While this level of precision moves an estimated geospatial location around 2.5cm, the 25% difference regarding the latitudinal degree is important when mapping prospective candidate addresses while striving to maintain anonymity.

D. OFFICER ACCESSION DATA

The data for this study was provided by MCRC. It lists information for officers who have successfully entered the Marine Corps from Fiscal Years (2006 – 2018 and contains the following parameters.

- Gender
- Ethnic Category
- Race (categorized by American Indian or Alaska Native, Asian, Black, Native Hawaiian or Pacific Islander, and White)
- Contract Begin Date
- Commission Date
- Home of Record (HOR) City

- HOR State
- HOR Zip Code

The raw data contained 60,636 total entries. Home addresses for these officers were not available. Of the total entries, 5 did not list gender data, 700 did not contain ethnic data, and 331 did not contain race data. Most relevant to this study, 1,790 did not contain HOR City and 1,594 did not contain state data. 11,265 of the entries were determined to be duplicates, leaving 49,370 unique entries. Of these:

- 1,226 are American Indian or Alaska Native (1,011 male, 215 female)
- 2,929 are Asian (2,469 male, 460 female)
- 4,113 are Black (3,327 male, 786 female)
- 408 are Native Hawaiian or Pacific Islander (345 male, 63 female)
- 40,490 are White (35,617 male, 4,873 female)
- 42,935 total are male, 6,430 total are female

For geospatial purposes, the data was cleaned to remove those officers without HOR City information. Entries were not kept for those officers with only zip code data. 47,826 officers remain in the data, and of these:

- 1,169 are American Indian or Alaska Native (965 male, 204 female)
- 2,849 are Asian (2,397 male, 452 female)
- 3,968 are Black (3,223 male, 745 female)
- 393 are Native Hawaiian or Pacific Islander (333 male, 60 female)
- 39,256 are White (34,259 male, 4,716 female)
- 162 males and 29 females remain with no race category,
- 41,619 total are male, 6,206 total are female, 1 no gender category

E. OFFICER ACCESSION CODING

These 47,826 officer data points are organized into a CSV file by listing their city, state, and zip code, and a new .txt file called 'locations.txt' is prepared which will run in the same Python code used to pull geospatial information for the OSS locations. As there are many city/state/zip combinations which have had multiple officers over this timeframe join the Marine Corps, duplicates are removed before running the code as running so many entries will take an extended period of time, stress the code and system, and run into transaction limits which would require a business-type account to be setup to handle so many transactions on a pay by month basis. Doing so reduces the amount of city/state/zip entries from 47,826 to 17,941.

City/state/zips are run as varying sets of around 200 combinations at a time, because as said larger entries stress the code and run up transaction limits, but also because some combinations cannot be easily read by the API and come back as list index errors in Python. This is because HOR information inputted by OSS staff at the time of each officer's accession may not be a viable location to the API or will be entered in a way that is unreadable by the server. When encountering such an error, Python reports the error as an output and does not continue further than the address that caused it. This is debugged by identifying individual addresses that cause the error as results are outputted alphabetically, setting these addresses aside for one by one processing at the end, and continuing later at the address after the one which caused the error. Figure 59 shows an example of outputted geospatial coordinates from inputted city/state/zip combinations.

```
In [12]: for location in location_objects_list:
        print(location.__dict__)

{'description': 'City State Zip', 'latitude': 34.95675, 'longitude': -87.66901}
{'description': 'ALLENTOWN, PA, 18101', 'latitude': 40.60263, 'longitude': -75.47027}
{'description': 'ALLENTOWN, PA, 18102', 'latitude': 40.60263, 'longitude': -75.47027}
{'description': 'ALLENTOWN, PA, 18103', 'latitude': 40.60263, 'longitude': -75.47027}
{'description': 'ALLENTOWN, PA, 18104', 'latitude': 40.60263, 'longitude': -75.47027}
{'description': 'ALLENTOWN, PA, 18109', 'latitude': 40.60263, 'longitude': -75.47027}
{'description': 'ALLENTOWN, PA, 18120', 'latitude': 40.60263, 'longitude': -75.47027}
{'description': 'ALLENTOWN, PA, 46383', 'latitude': 40.60263, 'longitude': -75.47027}
{'description': 'ALLIANCE, NE, 69301', 'latitude': 42.09712, 'longitude': -102.87093}
{'description': 'ALLIANCE, OH, 44601', 'latitude': 40.92155, 'longitude': -81.10584}
{'description': 'ALLISON PARK, PA, 15101', 'latitude': 40.56214, 'longitude': -79.95922}
{'description': 'ALLISON PARK, PA, 18516', 'latitude': 40.56214, 'longitude': -79.95922}
{'description': 'ALLPORT, PA, 16821', 'latitude': 40.96913, 'longitude': -78.20713}
{'description': 'ALLSTON, MA, 02134', 'latitude': 42.3534, 'longitude': -71.13217}
{'description': 'ALLYN, WA, 98524', 'latitude': 47.38174, 'longitude': -122.82983}
{'description': 'ALMA, AR, 72921', 'latitude': 35.47666, 'longitude': -94.22124}
{'description': 'ALMA, KS, 66401', 'latitude': 39.0134, 'longitude': -96.28953}
{'description': 'ALMA, MI, 48801', 'latitude': 43.37897, 'longitude': -84.65703}
{'description': 'ALMA, NE, 68920', 'latitude': 40.10371, 'longitude': -99.36316}
{'description': 'ALMOND, NY, 14804', 'latitude': 42.32131, 'longitude': -77.73706}
{'description': 'ALMONT, MI, 48003', 'latitude': 42.92156, 'longitude': -83.04517}
{'description': 'ALOHA, OR, 97006', 'latitude': 45.5088, 'longitude': -122.84234}
{'description': 'ALOHA, OR, 97007', 'latitude': 45.46023, 'longitude': -122.88814}
```

Figure 59. Officer city/state/zip geospatial coordinates outputted from Python.

After completing the code and debugging for locations which were not originally understood by the API server, geospatial coordinates are recompiled and each individual coordinate is assigned to the rest of the officer data, including duplicates so that each officer is accounted for, even many for a specific location. A completed CSV file with geospatial data for each officer is imported into Tableau and each point is plotted, as depicted in Figure 60.

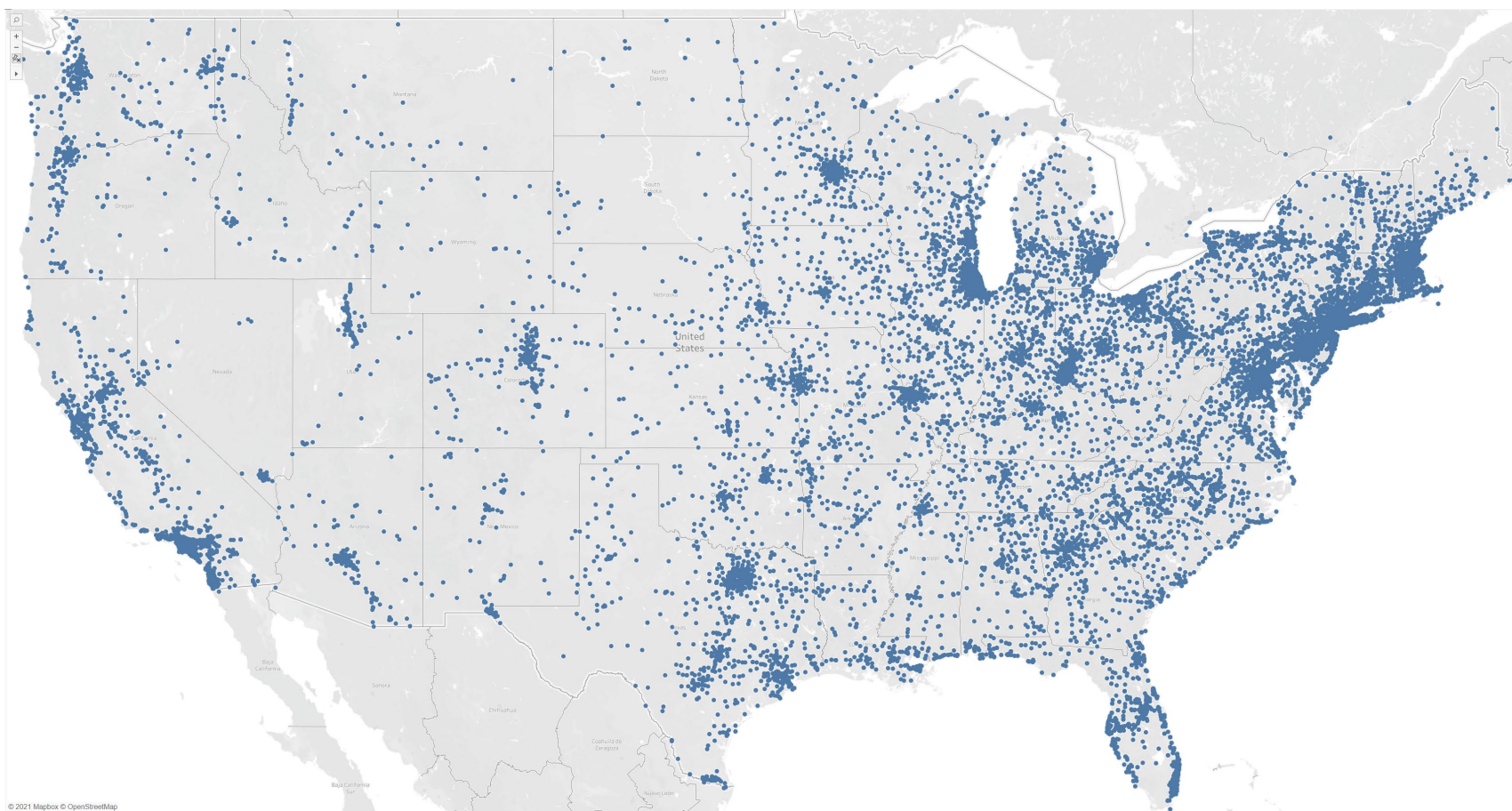


Figure 60. Initial results for officer geospatial locations.

Further debugging is required at this point. Tableau allows users to manually move their view throughout the world. This is useful because many officers joined from locations outside of the United States, but checking those points reveals some errors where the API incorrectly read or located certain locations. Figure 61 shows a small group of officers as having joined the Marine Corps from Uruguay, but the plotted points show data for cities like Long Beach, CA; Union, MO; and Santa Ana, CA. Many officers entered with HOR information from Santa Ana, CA, for example, but only some of those entries were errors. These and others like them were caused by a unique zip code being unreadable by the server, or if OSS locations combined ‘Santa Ana’ into something like ‘SANTAANA’ in their database.

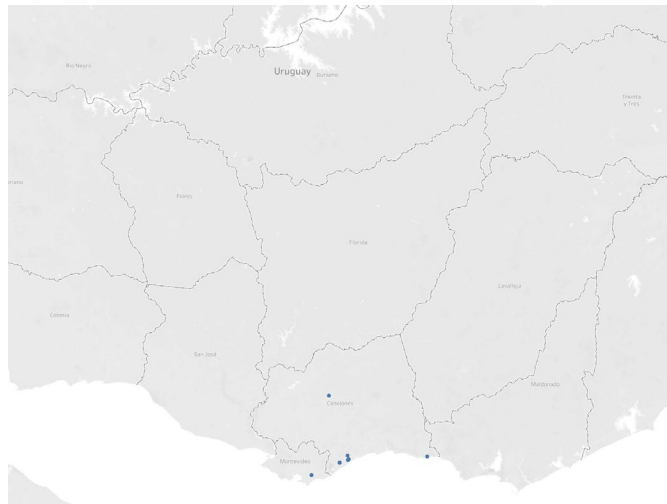


Figure 61. Geospatial initial errors.

F. MAP RESULTS AND FINDINGS

1. Female Breakdown

Figure 62 shows the densities of male (blue) and female (yellow) officers who have successfully joined the Marine Corps. As there are many more male officers who have joined, male plots are just as concentrated in and around the major cities, colleges, and population centers as females, which is where the Marine Corps has established their OSS locations (orange). As a result of the higher number of males, male plots also see a wider

variation, with more plots than female coming away from the population centers and OSS locations. At this scale, the female plots would be completely covered by male plots when only studying male plots. The variation is seen when the female plots begin to taper and male plots continue to be seen surrounding them. Figure 63 shows the same map when filtered only for females. With less noise and plots, OSS locations are labeled by their MCD, with some overlap when OSSs locations are located especially close together, which is seen in the areas of particularly high density of female accessions in the 1st and 4th MCD in the Northeast, the 6th MCD in the Southeast, the 8th MCD in the South, and the 12th MCD along the West Coast.

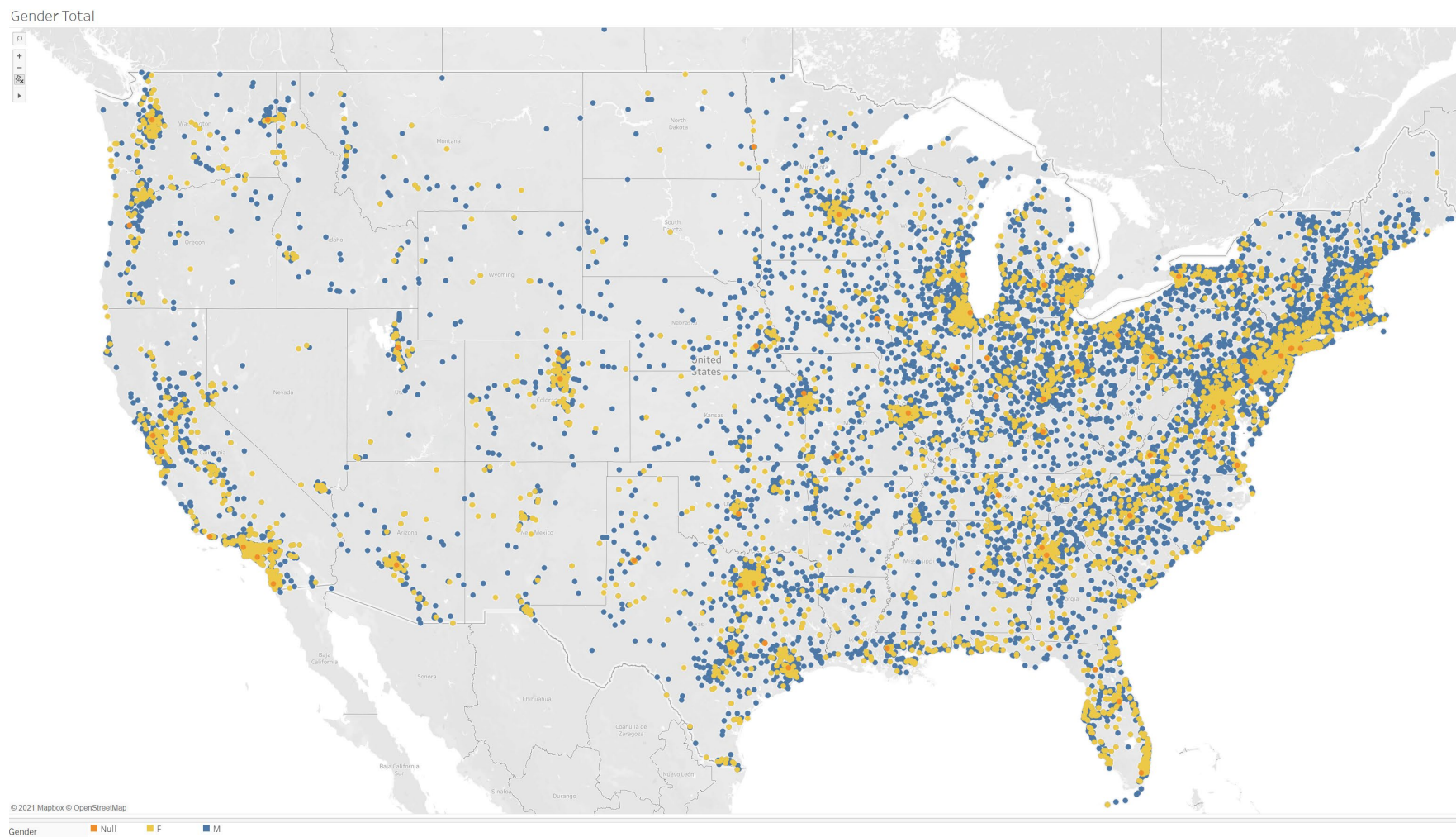


Figure 62. Male and female total map.

Gender Female Only

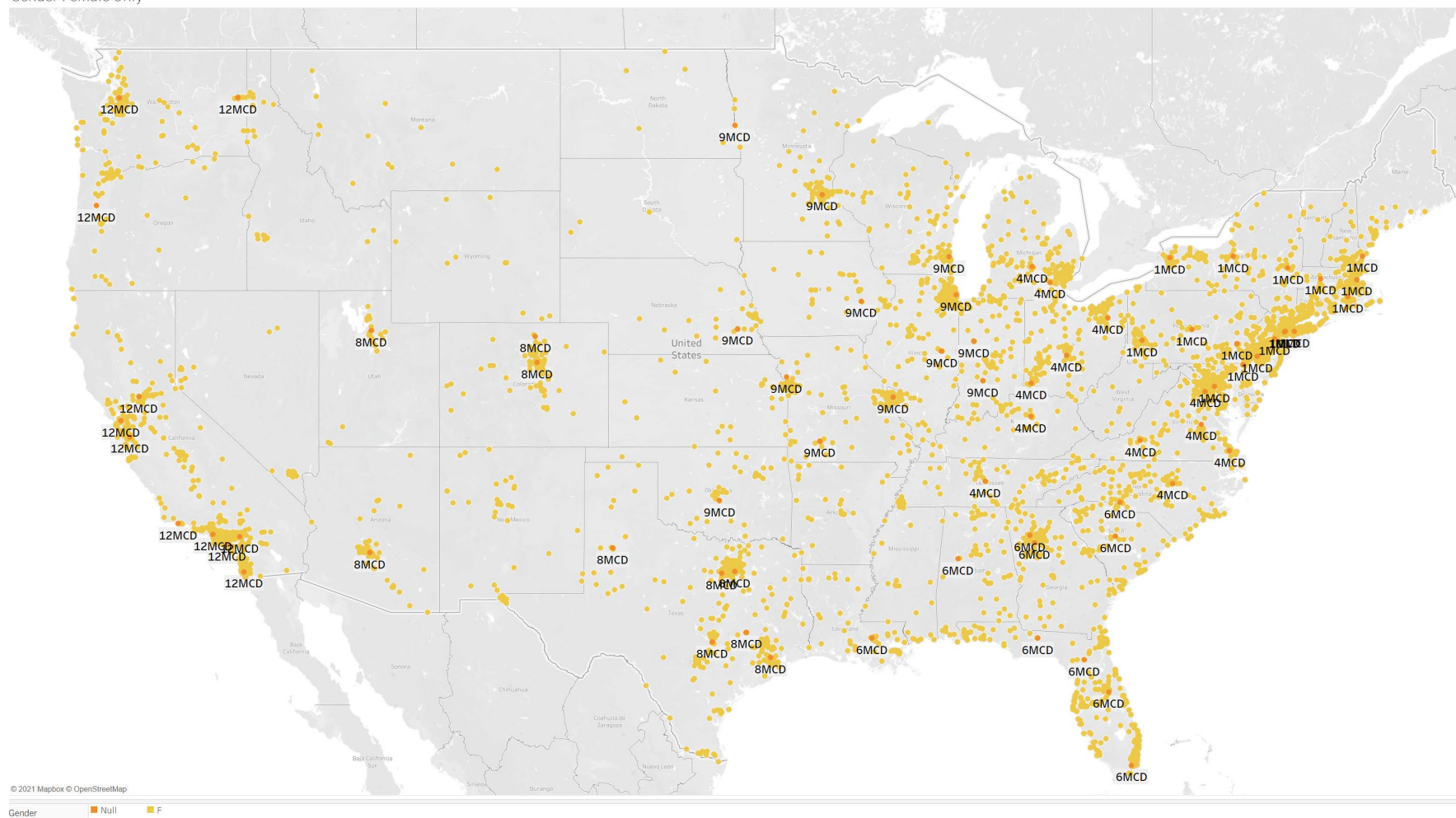


Figure 63. Female total map with OSS locations.

Figure 64 shows a female map broken down by race as categorized in the MCRC data, including American Indian or Alaskan Native (orange); Asian (red); Black or African American (teal); Native Hawaiian or Pacific Islander (green); and White (yellow). Null points (blue) are included as these are reported as female officers who declined to provide race information. OSS locations are also included.

At this scale, American Indian or Alaskan Native, Asian, and Native Hawaiian or Pacific Islander come in a small enough numbers to be crowded out at most places, and when seen they are heavily concentrated in the immediate areas around OSS locations. An exception to this relatively small number is the West Coast, where the Marine Corps finds the majority of their female officers. Their HOR information still has them in close proximity to these locations (due to the overall population density here), but their plots show heavy on the map due to the density of Asian female officers.

Of note, Black female officers are concentrated in the Northeast, West Coast, and Southeast. They remain similarly concentrated in densely populated and largely urban areas, but Figure 64 shows more variation in HOR city location than anywhere else in the country. Figure 65 provides more clarity to this region.

Gender Female Only

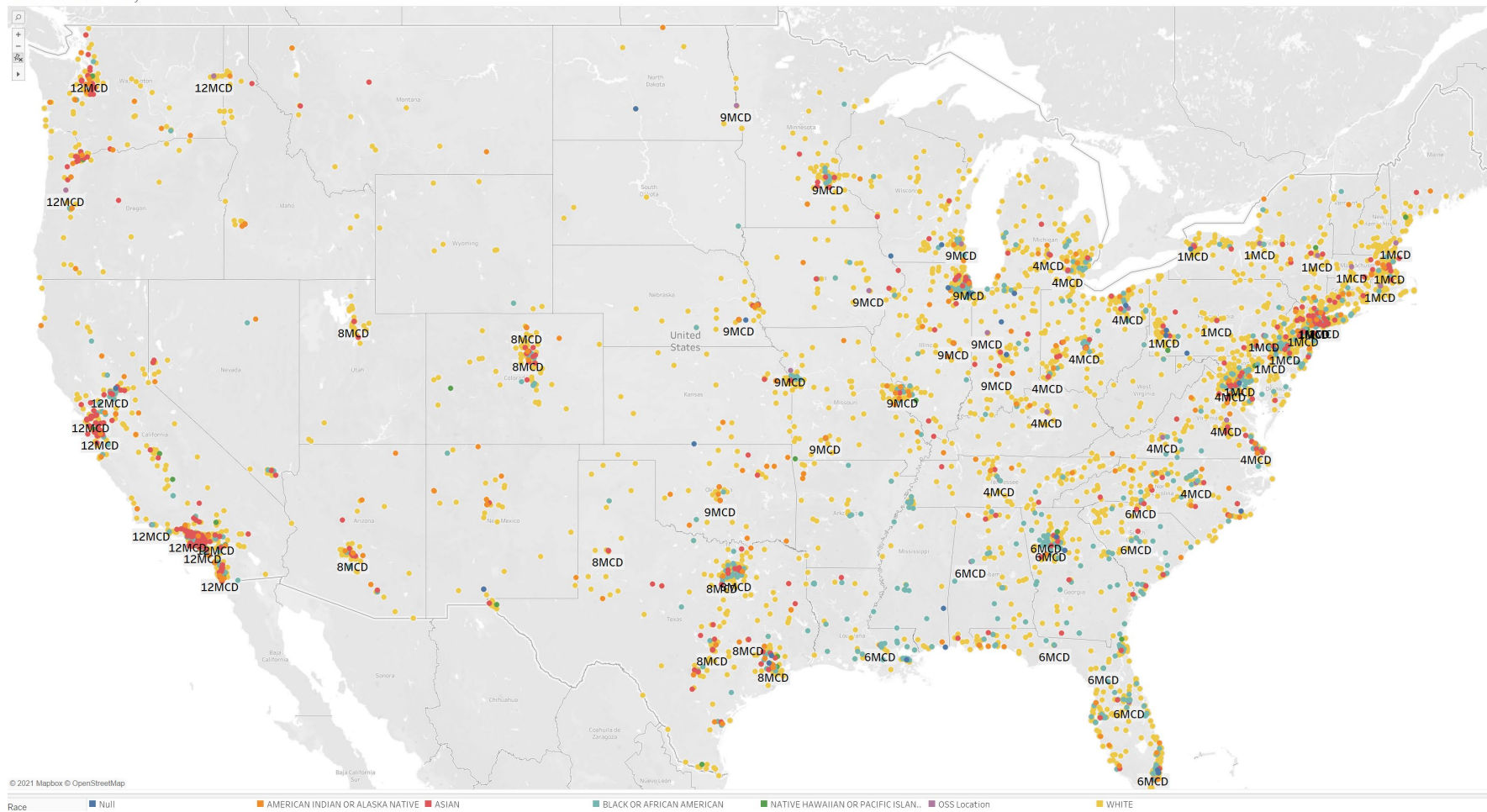


Figure 64. Female map by race with OSS locations.

Gender Female Only

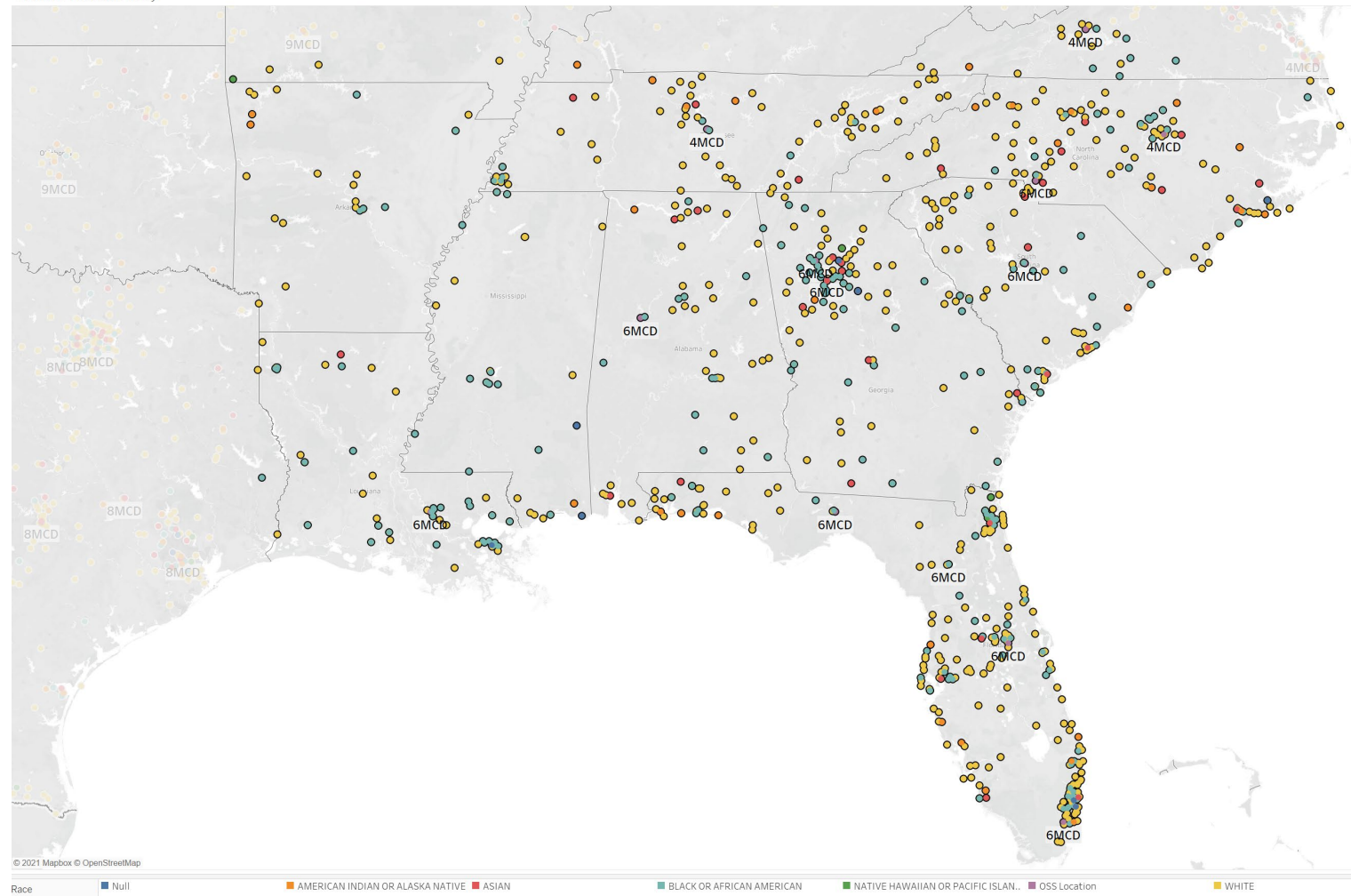


Figure 65. Southeast U.S. by female and race.

2. Race Breakdown

Figure 66 shows a map containing all male and female data points, organized by race categories in the MCRC data. Compared to Figure 64, it shows similar concentration in the Northeast, Southeast, and West Coast. The categories of American Indian or Alaskan Native, Asian, and Native Hawaiian or Pacific Islander remain heavily concentrated in densely populated urban areas. Most in the Asian and Native Hawaiian Native or Pacific Islander categories are concentrated in the Northeast and West Coast. Increased density is shown for American Indian or Alaskan Native is shown throughout the West Coast and states like Colorado, Texas, and the Midwest, containing parts of 8th and 9th MCDs. Now that male plots are included there is also a higher concentration of all plots in the 9th and 6th MCDs, particularly around cities including Milwaukee, Chicago, St. Louis, Indianapolis, Columbus, Cleveland, and Detroit. The majority of the plots and the variation away from cities are for white officers, but the urban centers remain a reliable source for obtaining diverse officers. This region is shown with more clarity in Figure 67.

The higher relative number of males shows the same high density and variation in the Southeast for the Black officer category. Figure 68 is isolated for black officers and shows more clearly the relative urban concentration throughout the nation when compared to the Southeast. Figure 69 shows the black density and variation for the Southeast only.

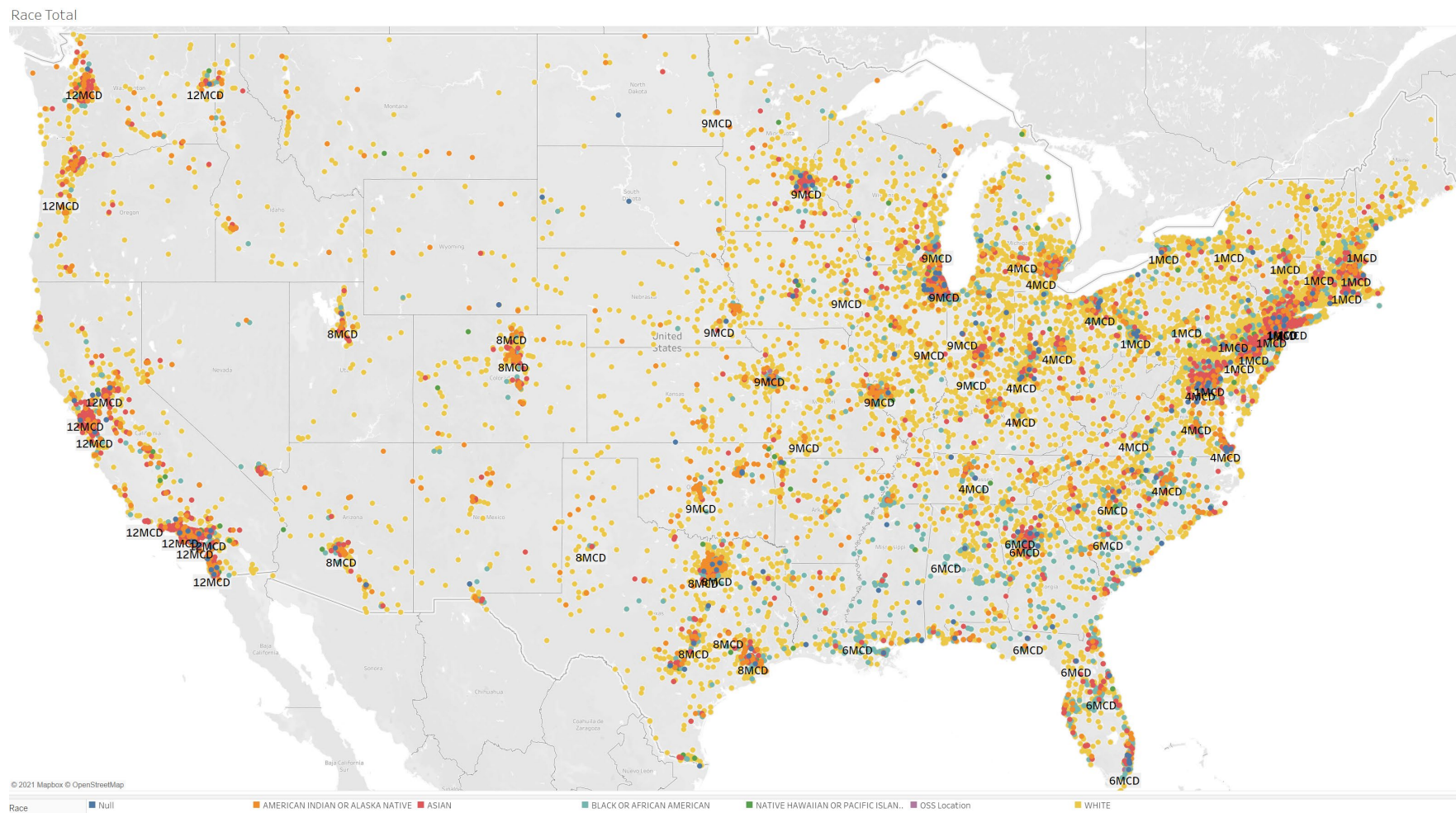


Figure 66. Total map by race with OSS locations.

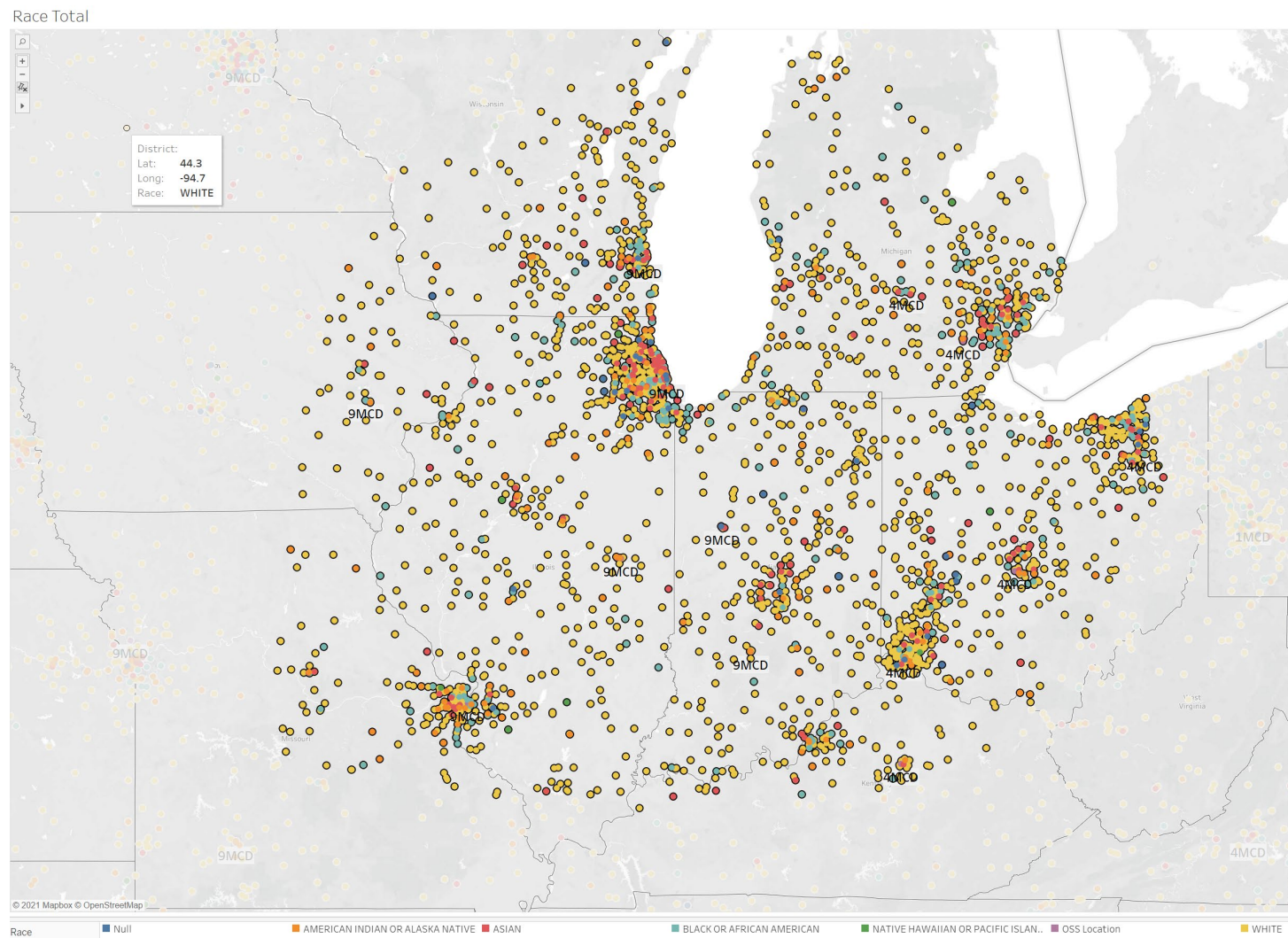


Figure 67. Concentrations in 9th and 4th MCDs.

© 2021 Mapbox © OpenStreetMap

Race

- BLACK OR AFRICAN AMERICAN
- OSS Location

Figure 68. Total male and female map by black category with OSS locations.

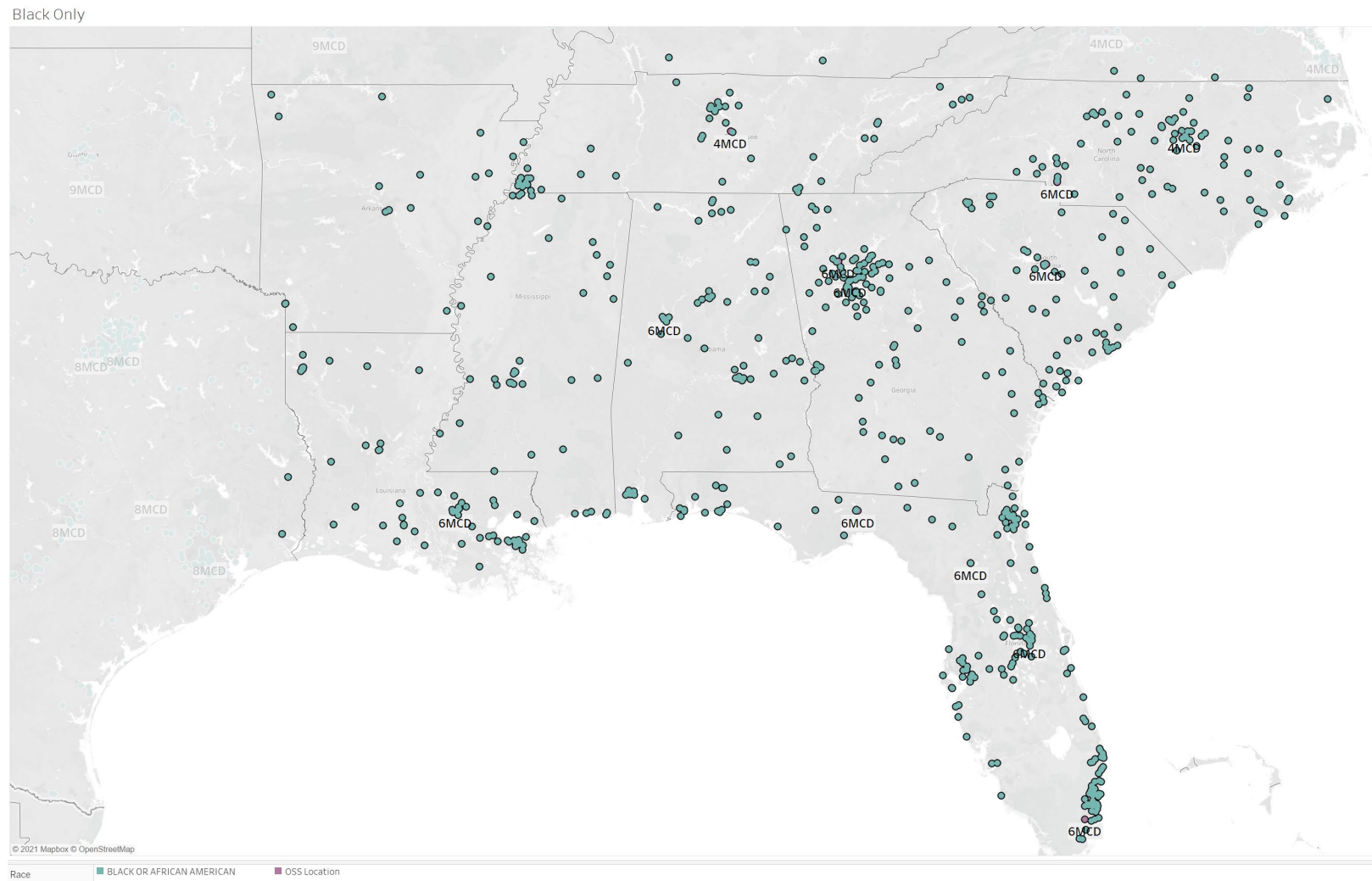


Figure 69. Southeast U.S. for black males and females.

3. Finding #1: Current OSS Structure May Not be Best Suited to Exploit Concentration and Variation of Black Officers in Southeast U.S.

The concentration of many black officers in the Southeast and the wider variation of them in this region is unique to any other diverse category in this study. Most of the other officers in diverse categories seem predictably concentrated in densely populated areas along either coast and/or in major urban areas. This holds true in part for black officers, but this concentration and variation in and around the 4th and 6th MCDs could be attributed for two main reasons.

The year after the passing of the Civil Rights Act of 1964 saw the creation of the Higher Education Act of 1965 (U.S. Department of Education, n.d.). The Act defined institutions known as Historically Black Colleges and Universities (HBCU), which are “...any historically black college or university that was established prior to 1964, whose principal mission was, and is, the education of black Americans” (U.S. Department of Education, n.d.). Of the 102 HBCUs listed by the Department of Education, Figure 70 shows that virtually all of them around the Southeast region (not all HBCUs are labeled due to overlap). Figure 71 shows HBCUs and OSS locations overlayed on the same map (labeled OSSs are yellow, HBCUs are green), while Figure 72 shows HBUCs, OSSs locations, and black officer locations. Here, OSSs are gold and labeled, HBCUs are red, and black officers are blue. Having this many plots increases the noise of the map, but the location and variation of HBCUs and black officers and their relationship to OSS locations is useful.

HBCU Locations

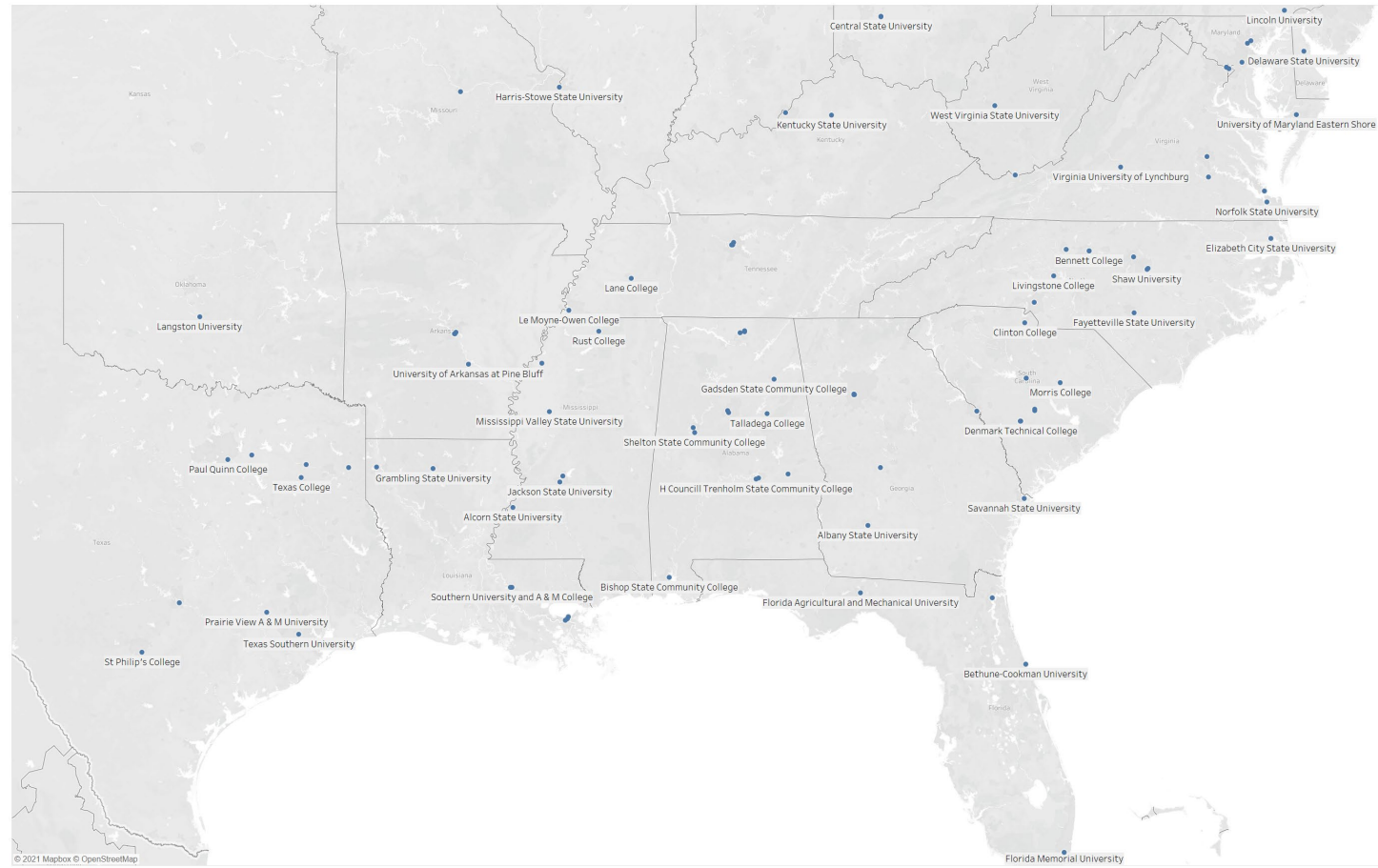


Figure 70. HBCU locations.

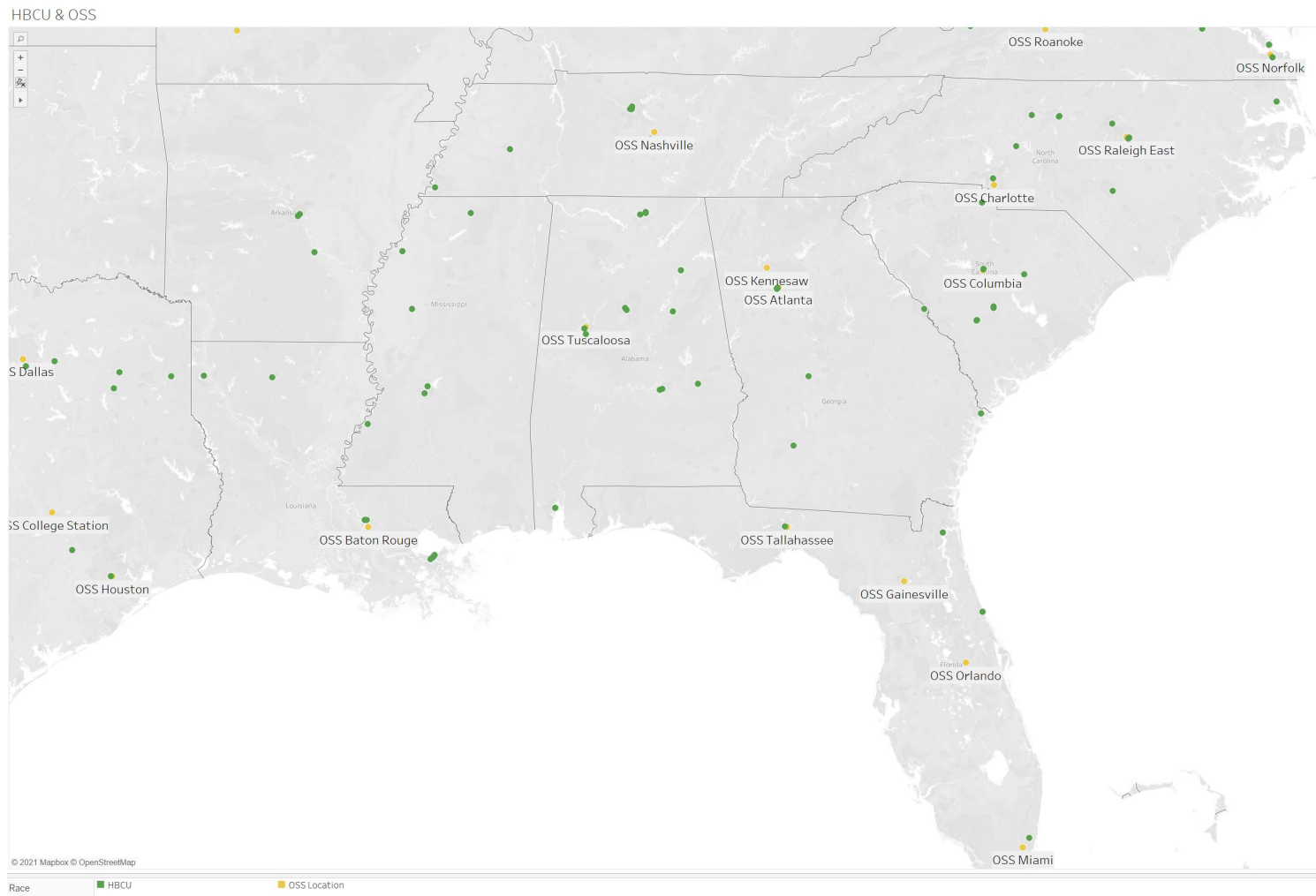


Figure 71. HBCU and OSS locations.

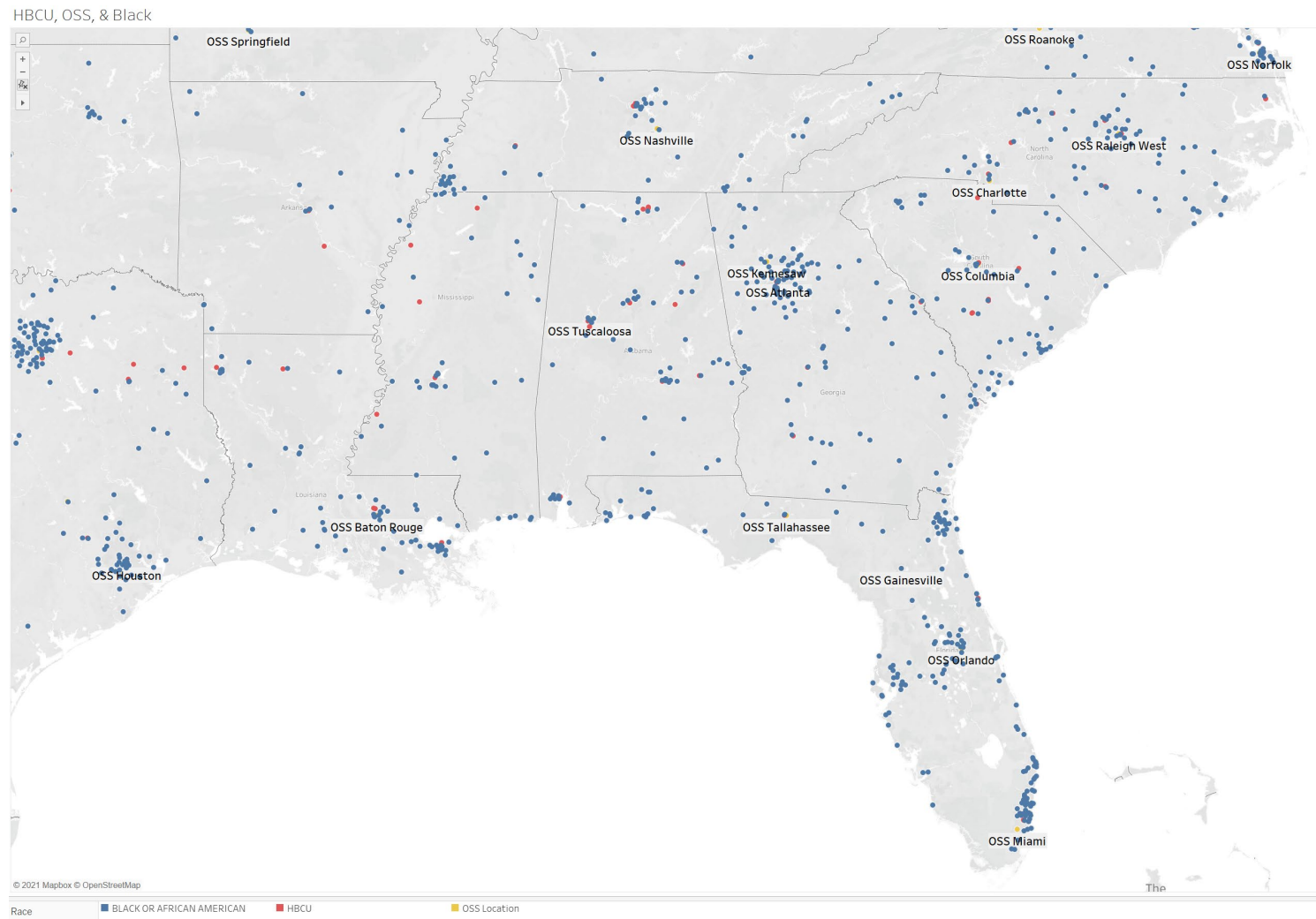


Figure 72. HBCUs, OSS locations, and black officer locations.

This concentration of HBCUs in largely one region of the U.S. naturally means that there is a large pool of potential black officer candidates located there, which was shown as true from the data provided by MCRC. Of the top 1% of schools identified in the 2015 QCP study by the CNA which are expected to provide the highest number of potential officer candidates, only two are included in the list of 102 HBCUs: Howard University and Morehouse College. None of the top 1% of schools from the male portion of the CNA study are listed as HBCUs.

The CNA study concluded that most of their findings for schools with the highest QCP were state universities with large student bodies, and virtually all of their top 1% schools for each of the diverse categories were as such. HBCUs tend to be much smaller in comparison, with the average student body being around 3,000, but some are quite large. North Carolina A&T State University has a student body of around 12,556, and St. Phillips College has around 12,926 (U.S. Department of Education, n.d.). That only two HBCUs appeared on the CNA list for females and none for males could be attributed to their relatively small size, but also the JAMRS, or propensity to serve, metric. The opportunity exists for increased attention to these schools and their surrounding areas.

The second reason for the concentration and variation in this region is that an overwhelming majority of the black middle class lives there permanently. When defining middle class by those homes in the middle 60% by income distribution, roughly 61.2% of blacks are considered middle class (Perry & Romer, 2020). As depicted in Figure 73, when considering the black middle class as a percentage of a city's overall population, all but three of these cities are located in this region.

Black middle class families are concentrated in the South and Mid Atlantic
Metro sizes and share of the Black middle class

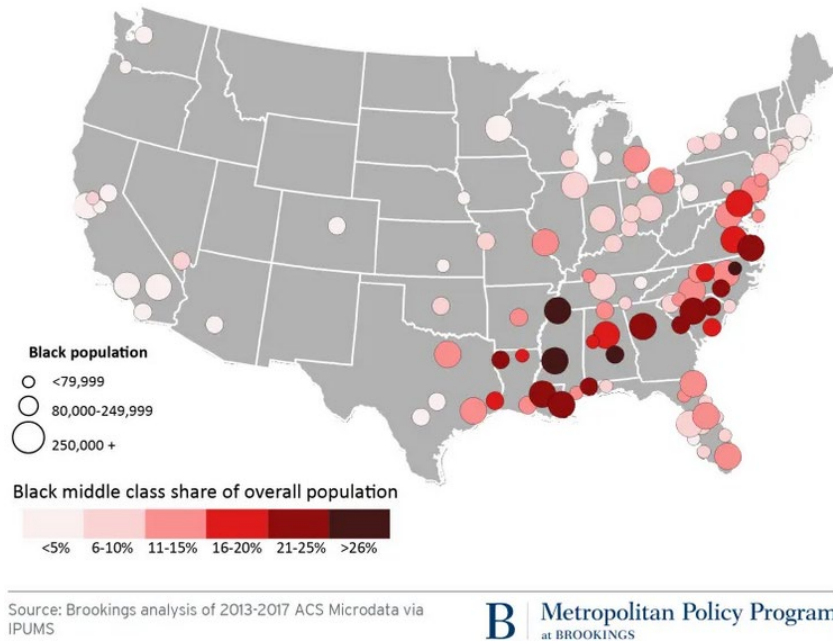


Figure 73. Black middle class as a percentage of population. Source: Perry & Romer (2020).

4. Finding #2: Top Universities and Counties Identified by QCP Receive Adequate Coverage and Officer Accessions

For females overall as a category, the CNA study identified the University of Central Florida (UCF), the University of Florida (UF), and Florida State University (FSU) as the top three QCP schools when adjusted for medical and propensity to serve weights. UCF is also the top total male school for QCP, with UF as seventh and FSU as ninth. UCF is in Orlando, FL, UF is in Gainesville, FL, and FSU is in Tallahassee, FL. As one example of top QCP schools receiving coverage by neighboring OSS locations, all three (and many other large nearby universities) are adequately covered and provide numerous new officers, as depicted in Figure 74. In fact, each of these universities has an OSS location inside of the city it is located in.

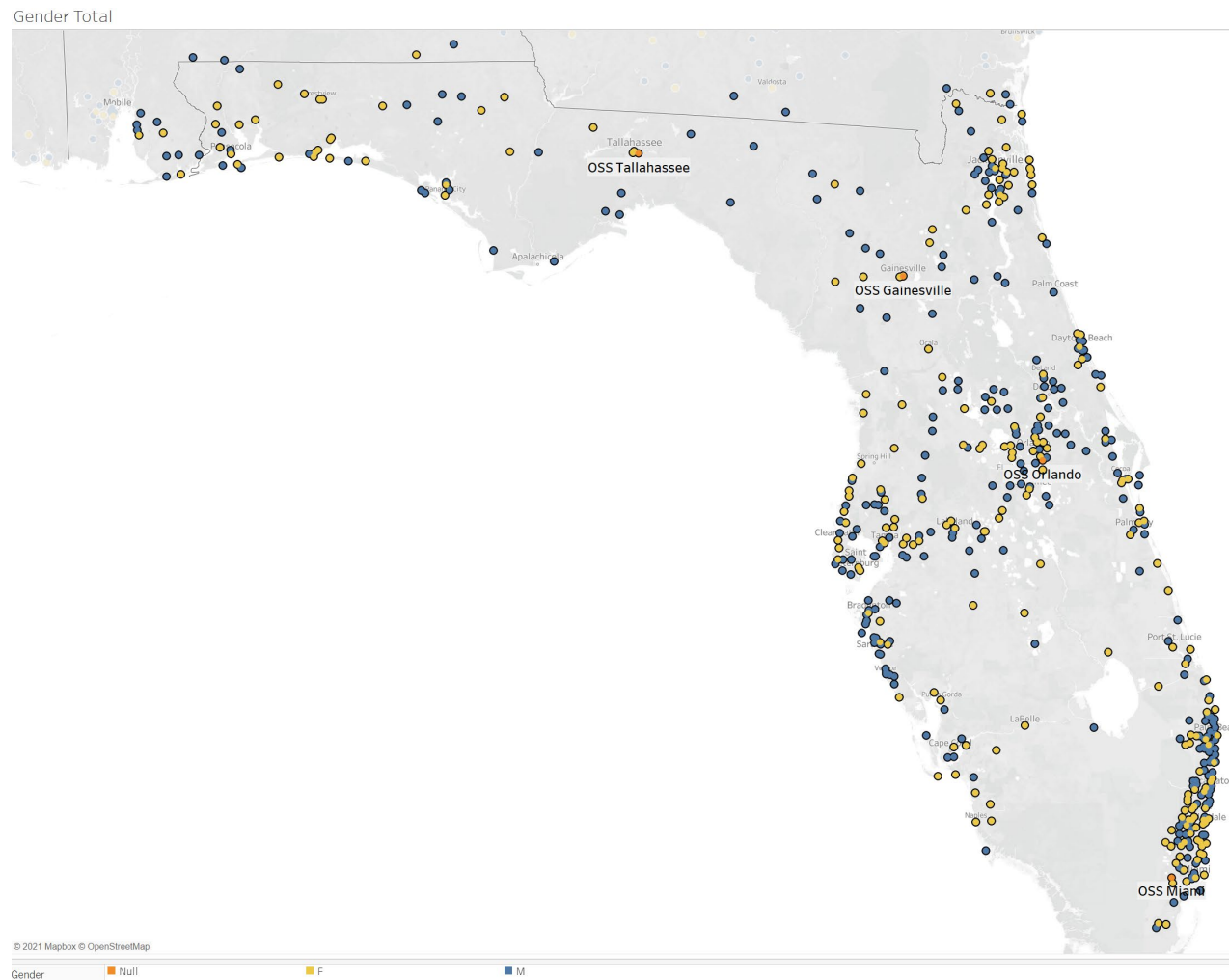


Figure 74. OSS and male/female officer locations in Florida.

Of the top 1% of universities for female QCP, 15 universities are identified and all but three have an OSS location located in the same city. Only the University of South Florida (USF), the University of Georgia (UG), and the University of Wisconsin (UW) do not. Each still receive adequate coverage, as USF is only 84 miles from OSS Orlando, UG is only 71.6 miles from OSS Atlanta and 85.2 miles from OSS Kennesaw, and UW is only 80 miles from OSS Milwaukee. The only top 1% university for males which does not have a local OSS location is Brigham Young University (BYU). BYU is in Provo, ID and is only 44.6 miles from OSS Salt Lake City. Each of the top 1% universities which do not have an OSS location in the same city are supported by one within a short driving distance which also serves either a neighboring university or universities and/or one of the top QCP counties identified by CNA. The MCRC structure adequately covers the top 1% QCP male and female universities, but the female universities less so.

Top 1% QCP universities for black males are not available in the CNA study. Of the top 1% black female universities, 15 are identified and 5 do not have an OSS location within their city, including USF, Florida Atlantic University (FAU), Southern Illinois University (SIU), the University of North Texas (UNT) and Georgia Southern University (GSU) USF is supported by OSS Orlando which again is 84 miles away. FAU is in Boca Raton, FL and supported by OSS Miami which is only 45.3 miles away. SIU is in Carbondale, IL and is 96.6 miles from OSS St. Louis. UNT is in Denton, TX and is only 39.8 miles from OSS Dallas. GSU remains relatively isolated, even compared to SIU. It is located in Statesboro, GA, and is 127 miles from OSS Columbia, 209 miles from OSS Atlanta, and 234 miles from OSS Tallahassee. The MCRC structure covers the top 1% black universities by QCP less compared to overall male and female structure when considering OSS locations in the same city and driving distances between the university and the nearest OSS location(s).

V. CONCLUSION

Given the Marine Corps' stated priorities and initiatives to increase female and diverse officer numbers, this study seeks to investigate the use of set cover models to maximize these accessions while minimizing the costs and resources to assist in decision making. This study finds the following.

A. SET COVER MODELS PROVIDE USEFUL INSIGHTS ON THE SPATIAL DISTRIBUTION OF OFFICER ACCESSIONS RELATIVE TO OSS LOCATIONS

Past research on this subject determined that diverse officer candidates are not equally distributed geographically. Using a computer program that is designed to communicate with access the MapQuest API server, I extract the precise geospatial locations of over 47,000 officers as they joined the Marine Corps and compared these with MCRC's physical OSS structure. I map these locations and officers based on gender and race and determine that the structure is adequately covering virtually all top school and county targets identified by the latest QCP study. The Marine Corps has locational access to diverse candidates throughout the country, with perhaps some need for more flexibility in the Southeast where diverse (black) officers' locations see higher variation. The Marine Corps has adequate access to female candidates, much more so than males.

B. FEMALES HAVE LOWER PERCENTAGES ON THE PROPENSITY TO SERVE METRIC

The MCRC structure is setup to as efficiently as possible access the majority potential officer candidates that the CNA identified (outside of arguable potential black officers in the Southeast). Recall that their school-level QCP is calculated using four data sources: IPEDS and Barron's Profile of American Colleges for school, student, and testing information; BRFSS for medical adjustment; and JAMRS for propensity to serve adjustment. Their county-level QCP uses PUMS for educational attainment estimates for counties, and then BRFSS and JAMRS. Even with only all males to compare with, in both cases this JAMRS measure has an overwhelming impact on the expected potential

candidates at identified schools and counties. Medical qualification has a notable effect on overall males and a significant effect on black females.

Using each of these measures, CNA produces estimates of an unadjusted QCP for a school or county, then a medically adjusted QCP and medically-and-propensity adjusted QCP for the same school or county. Figure 75 shows data for CNA's top 1% male QCP schools as an example, adjusted to show the percentage changes that the medical and propensity measures have on the unadjusted QCP, as well as the estimates of the propensity to serve for the unadjusted QCP. Figure 76 shows this same information for white females, and Figure 77 again for black females.

School	Male Total			Unadjusted to Med	Medical to Prop	Unadjusted to Prop
	Unadjusted	Med Adjusted	Med & Prop Adjusted			
University of Central Florida	4,509	3,866	219	85.74%	5.66%	4.86%
Pennsylvania State University-Main Campus	4,437	3,832	172	86.36%	4.49%	3.88%
Ohio State University-Main Campus	4,185	3,655	166	87.34%	4.54%	3.97%
Texas A & M University-College Station	3,935	3,451	181	87.70%	5.24%	4.60%
The University of Texas at Austin	3,726	3,288	163	88.24%	4.96%	4.37%
University of Maryland-College Park	3,443	2,996	166	87.02%	5.54%	4.82%
University of Illinois at Urbana-Champaign	3,290	2,926	124	88.94%	4.24%	3.77%
University of Florida	3,280	2,773	155	84.54%	5.59%	4.73%
Arizona State University-Tempe	3,156	2,696	138	85.42%	5.12%	4.37%
Florida State University	3,126	2,689	153	86.02%	5.69%	4.89%
Rutgers University-New Brunswick	3,066	2,711	121	88.42%	4.46%	3.95%
University of California-Berkeley	3,023	2,563	111	84.78%	4.33%	3.67%
University of Minnesota-Twin Cities	2,990	2,625	114	87.79%	4.34%	3.81%
Brigham Young University-Provo	2,973	2,599	134	87.42%	5.16%	4.51%
University of Michigan-Ann Arbor	2,938	2,546	110	86.66%	4.32%	3.74%
Avg				86.83%	4.91%	4.26%

Figure 75. Male QCP calculations. Adapted from Malone and Kelley (2015).

White Female							
School	Unadjusted	Med Adjusted	Med & Prop Adjusted	Unadjusted to Med	Medical to Prop	Unadjusted to Prop	
University of Central Florida	4,032	3,642	35	90.33%	0.96%	0.87%	
Ohio State University-Main Campus	3,304	2,984	21	90.31%	0.70%	0.64%	
Pennsylvania State University-Main Campus	3,127	2,824	16	90.31%	0.57%	0.51%	
Texas A & M University-College Station	2,952	2,666	19	90.31%	0.71%	0.64%	
Florida State University	2,923	2,640	25	90.32%	0.95%	0.86%	
University of Georgia	2,871	2,594	25	90.35%	0.96%	0.87%	
University of Minnesota-Twin Cities	2,766	2,498	16	90.31%	0.64%	0.58%	
University of Wisconsin-Madison	2,743	2,478	18	90.34%	0.73%	0.66%	
Brigham Young University-Provo	2,630	2,376	22	90.34%	0.93%	0.84%	
University of Florida	2,592	2,341	22	90.32%	0.94%	0.85%	
Michigan State University	2,473	2,233	16	90.30%	0.72%	0.65%	
Ohio University-Main Campus	2,468	2,229	16	90.32%	0.72%	0.65%	
Indiana University-Bloomington	2,431	2,196	15	90.33%	0.68%	0.62%	
University of South Florida-Main Campus	2,283	2,062	19	90.32%	0.92%	0.83%	
University of Michigan-Ann Arbor	2,265	2,046	14	90.33%	0.68%	0.62%	
			Avg	90.32%	0.79%	0.71%	

Figure 76. White Female QCP calculations. Adapted from Malone and Kelley (2015).

Black Female							
School	Unadjusted	Med Adjusted	Med & Prop Adjusted	Unadjusted to Med	Medical to Prop	Unadjusted to Prop	
University of Central Florida	698	542	9	77.65%	1.66%	1.29%	
Georgia State University	684	531	9	77.63%	1.69%	1.32%	
Florida International University	537	417	7	77.65%	1.68%	1.30%	
University of Maryland –College Park	520	404	6	77.69%	1.49%	1.15%	
FloridaState University	470	365	6	77.66%	1.64%	1.28%	
University of South Florida –Main Campus	445	345	5	77.53%	1.45%	1.12%	
Howard University	433	336	5	77.60%	1.49%	1.15%	
Florida Atlantic University	419	325	5	77.57%	1.54%	1.19%	
Southern Illinois University –Carbondale	418	325	3	77.75%	0.92%	0.72%	
Ohio State University –Main Campus	416	323	5	77.64%	1.55%	1.20%	
Morehouse College	388	301	5	77.58%	1.66%	1.29%	
University of North Texas	366	284	3	77.60%	1.06%	0.82%	
Georgia Southern University	353	274	3	77.62%	1.09%	0.85%	
University of Florida	343	266	4	77.55%	1.50%	1.17%	
Temple University	325	252	4	77.54%	1.59%	1.23%	
			Avg	77.62%	1.47%	1.14%	

Figure 77. Black Female QCP calculations. Adapted from Malone and Kelley (2015).

Without black (or any one race category) males to compare with, we can see multiple relevant differences when contrasting total males with individual race categories of females. First is a reminder that there are many more qualified female candidates than male. Only taking white females into account already brings female numbers close to male. Using only white and black females already passes the total number of males at multiple schools, including the top school (UCF) for each of these demographics. Second, we see that white females tend to be healthier than males, in that there tends to be a higher percentage of the unadjusted QCP that is medically qualified. However, the difference between males and black females is even wider, with black females coming in as by far the

least healthy race/gender category that the CNA reported numbers for. Averages percentages of the unadjusted QCP to be medically qualified and to have propensity to serve, by diversity category, is depicted in Figure 78.

Div Category	Unadjusted to Med	Medical to Prop	Unadjusted to Prop
Male Total	86.83%	4.91%	4.26%
Female Total	88.31%	0.86%	0.76%
Black Female	77.62%	1.47%	1.14%
Hispanic Female	90.69%	0.73%	0.67%
Other Female	85.69%	0.41%	0.35%
White Female	90.32%	0.79%	0.71%
Avg	86.58%	1.53%	1.31%

Figure 78. QCP percentage averages. Adapted from Malone and Kelley (2015).

The lower percentage of medically qualified black females is particularly unfortunate when including the propensity to serve metric, which actually turns out to be the second highest amongst all of the diversity categories that CNA produced data for. When considering the effect of this metric has on the both the unadjusted and medically adjusted QCP rate, black females' percentages dwarf the other female categories. While this is encouraging for this diversity group, it also shows the massive problem of the propensity to serve metric for all female categories.

Even with black females having the second highest propensity to serve metric of the categories presented by the CNA, their percentages are around only 33% of the male rates. Grouping all females overall, they are even less likely to have the propensity to serve. Consider the top QCP school for both males and females, UCF. There are more female college students than males, and they are more likely to be medically qualified. The unadjusted QCP for females is predicted to be around 6,464 females and 4,509 males. There are potentially nearly 2,000 more medically qualified females than males at UCF, around 5,674 for females and 3,866 for males. But when adjusted for medical and propensity to serve, CNA estimates 57 total qualified and interested female officer candidates at UCF, a school with a student body of around 66,000 in 2017 and over 70,000

in the fall of 2020 (University of Central Florida, 2020). The numbers become even more difficult to manage and plan around as the scope is narrowed to gender and racial categories. The 2015 CNA estimates that there are around 9 total black female officer candidates who are both medically qualified and open to service – and UCF is the top QCP school for black females. The 12th rated QCP school for black females is UNT. UNT reported record numbers of enrollment in 2020, with over 40,000 students, 55% of which are female and 45% male, with over 6,000 black students (Muller, 2020). Even still, CNA estimates that there are only 3 qualified and interested black females at UNT.

Without racial propensity estimates for male racial categories available, it is clear that a realignment of MCRC's OSS structure is at best unreasonable and at worst irresponsible. The cost-effectiveness curve discussed in the Set Cover Fundamentals section and any cost benefit analysis would find it difficult to justify the cost of such a realignment for such a small pool of largely disinterested populations while weighing the importance of recruiting and fielding enough officers for the total force. Any shifting of OSS locations, reallocating coverage areas, and reallocating resources should take secondary importance to improving propensities to serve.

C. THERE IS ROOM TO IMPROVE PROPENSITY TO SERVE

As stated at the end of Chapter 4, there is potentially an opportunity to gain more traction for black officer candidates specifically in the Southeast U.S., but the Marine Corps is clearly not an attractive career option for females and other specific racial minorities. Additional weight must be put behind an effort to enhance the service's attractiveness to these groups. A Memorandum published by senior Pentagon leadership was recently published to all major DOD leadership on this matter, which contains the 15 following recommendations which were generated by an appointed DOD Board on Diversity (Department of Defense [DOD], 2020):

1. Update recruiting content to represent all service members.
2. Develop and publish a data-driven accessions and retention strategy.
3. Increase the pool of qualified Reserve Officer Training Corps (ROTC) enrollment, scholarship, and commission applicants from minority serving institutions.
4. Remove aptitude test barriers that adversely impact diversity.

5. Evaluate demographic trends in performance evaluations.
6. Develop diverse pools of qualified candidates for nominative positions.
7. Establish a Diversity and Inclusion Center of Excellence.
8. Standardize a DOD human resources data system for diversity and inclusion analysis.
9. Offer internships in science, technology, engineering, and mathematics fields in conjunction with Junior ROTC programs.
10. Develop a diversity and inclusion organizational structure.
11. Develop a DOD diversity and inclusion mobile application and website.
12. Incorporate the value of cultivating diversity and inclusion into leadership and professionalism curricula.
13. Increase transparency of promotion selections and career opportunities.
14. Prohibit extremist or hate group activity.
15. Update the Uniform Code of Military Justice to address extremist activity (DOD, 2020).

The Marine Corps could also consider specific programs or task forces designed to put female and diverse Marine recruiters on the forefront of areas where recruits are likely to be found. Structural realignment to target HBCUs for recruitment, for instance, wouldn't be practical at the moment, but a "road show" similar to other traveling educational and informational programs the Marine Corps already operates could potentially serve to improve inroads to more diverse groups.

Overall, this study finds that at the margin, the likely benefit of re-optimizing OSS locations with respect to increasing diverse officer accessions is potentially lower than simply increasing their propensity to serve. Even if the MCRC structure is setup to as efficiently as possible access the majority of potential officer candidates that the CAN identified, the per-dollar gain in diverse Marines will likely be greater if propensity to serve is itself enhanced.

Additional research on this subject should be conducted. Mathematical models based on set cover problems with real world financial MCRC resources could be made. If possible, further set cover research should use officers' home address at the time of joining the Marine Corps and not be limited to their city, state, and zip code.

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