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THESIS

**TACTICAL UNMANNED AERIAL SYSTEM CAPABILITIES
IMPACT ANALYSIS IN SUPPORT OF THE EXPEDITIONARY
MARINE AIR GROUND TASK FORCE USING COMPUTER
MODELING AND SIMULATION**

by

Joshua Gordon

June 2019

Thesis Advisor:
Second Reader:

Susan M. Sanchez
Raymond R. Buettner Jr.

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ANALYSIS IN SUPPORT OF THE EXPEDITIONARY MARINE AIR GROUND
TASK FORCE USING COMPUTER MODELING AND SIMULATION**

Joshua Gordon
Major, United States Marine Corps
BS, U.S. Naval Academy, 2005

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June 2019**

Approved by: Susan M. Sanchez
Advisor

Raymond R. Buettner Jr.
Second Reader

W. Matthew Carlyle
Chair, Department of Operations Research

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ABSTRACT

The Marine Corps of the future is one that will increasingly rely on unmanned aerial systems (UASs) integrating directly with Marines' fire and maneuver. As UAS technology evolves, so, too, should the Marine Corps' understanding and utilization of this technology in an increasingly complex operation environment evolve. The most powerful measure of effectiveness for the operational contributions of UASs is in Marine lives that the UAS helps to preserve.

This research uses design of experiment principles and computer modeling to simulate a Marine Expeditionary Unit (MEU) conducting an amphibious assault against a peer-level adversary. Through a series of increasingly refined and focused experiments, a wide variety and range of UAS capabilities are explored to determine their impact on the Marines of that MEU. UAS capabilities explored include speed, stealth, air-to-ground missiles, ground support capability, and more.

Through this analysis, sensor range and the number of UASs employed simultaneously are determined to be the most important UAS attributes in saving Marine lives. These factors are found to be more significant than armament, airspeed, stealth, or rate of detection.

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LIST OF ACRONYMS AND ABBREVIATIONS

AAV	Amphibious Assault Vehicle
ACE	Aviation Combat Element
AvPlan	Marine Aviation Plan
C2	command and control
CAS	close air support
CMC	Commandant of the Marine Corps
COIN	counter-insurgency
ConOps	Concept of Operations
C-UAS	counter-UAS
DoD	Department of Defense
DoE	Design of Experiments
DP	design point
DTS	discrete time simulation
EW	electronic warfare
FoS	family of systems
GCE	Ground Combat Element
GCS	ground control station
GUI	graphical user interface
IADS	integrated air defense system
IDF	indirect fire
ISR	intelligence, surveillance, and reconnaissance
JSF	Joint Strike Fighter
knots	nautical miles per hour
m	meters
M&S	modeling and simulation
MAGTF	Marine Air Ground Task Force
MANA	Map Aware Non-Uniform Automata
MCCDC	Marine Corps' Combat Development Command
MEU	Marine Expeditionary Unit
MOC	Marine Corps Operating Concept

MoE	measure of effectiveness
MUX	MAGTF Unmanned Expeditionary
NM	nautical miles
NOLH	nearly orthogonal Latin hypercube
NSS	National Security Strategy
NPS	Naval Postgraduate School
OAD	Operations Analysis Directorate
OTH	over-the-horizon
OV	operational view
ROI	return on investment
SAM	surface to air missile
sec	second
TTPs	tactics, techniques, and procedures
UAS	unmanned aerial system
USMC	United States Marine Corps
USN	United States Navy
VMU	Marine Unmanned Aerial Vehicle Squadron
VTOL	vertical takeoff and landing

EXECUTIVE SUMMARY

The United States counts on its Marine Corps to be adaptive, lethal, and ready to fight and win against any adversary in any clime and place. Marines answer this call with an integrated fire and maneuver doctrine built into every Marine Air Ground Task Force (MAGTF)—a structure in which combat elements mutually support a common mission. Within this construct, unmanned aerial systems (UASs) fill a variety of ever-evolving and increasing roles. This research seeks to provide insight into those UAS capabilities that are most impactful in improving Marine survivability and MAGTF operational success.

This thesis uses advanced design of experiments and computer simulation modeling to provide quantitative analysis based on pragmatic assumptions about current and future UAS capabilities. The resultant analysis shows which attributes most benefit the Marine on the ground, and enhance mission accomplishment of a MAGTF in a realistic operational scenario against a peer-level adversary.

In this scenario, a Marine Expeditionary Unit (MEU), the smallest MAGTF, conducts an amphibious assault against a comparably-trained and realistically-equipped adversary. The Marine force is a conventionally-organized and equipped MEU assaulting a well-defended shoreline. The enemy is dug-in and incorporates a capable integrated air defense system near the shoreline. This anti-air capability is supported by indirect fire assets to defend against assaulting ground forces. The layered defense protects a cluster of enemy infantry units centered on an inland objective. To accomplish their mission, Marine forces launch UASs and assorted close air support (CAS) platforms to pave the way for surface and air assault forces.

Throughout this scenario, Marine UASs are employed in a variety of roles including intelligence, surveillance, and reconnaissance, CAS, and command & control. The specific UAS capabilities explored include, but are not limited to: overhead speed, sensor range, sensor fidelity, stealth, armament, quantity of UASs employed, and speed of enemy detection by a UAS. This research evolved through multiple iterations to provide the most tactically credible simulation possible. Using regression analysis, partition trees, and other statistical and graphing tools, this analysis concludes the following key findings:

- Improving a UAS's sensor range is the single most significant factor in improving Marine survivability and MAGTF operational success. In this scenario, the critical threshold was the ability for a UAS to detect and identify an enemy unit at least 10,500m away. This range considered a thinking enemy in a prepared defensive position; i.e., enemy units were also able to employ camouflage. Enemy units could also shoot back.
- The second-most significant factor was the quantity of UASs simultaneously employed. While this research did not specifically consider coordination between multiple UASs, there is a marked difference between operations using only one operational UAS and operations using two to six (the most assessed) at a time.
- Of other factors and capabilities explored, improved stealth and speed of detection were both found to be statistically significant, but had limited practical significance in determining the survival rate of individual Marines.
- UAS payloads that included AGM-114 Hellfire missiles actually reduced Marine survivability rate. Launch configurations with zero, two, and four missiles were explored; the fewer the number of missiles, the fewer number of Blue casualties were expected. It appears that a CAS role detracts from a UAS's capacity to provide an overarching command and control platform for other MAGTF CAS platforms to prosecute.

This thesis does not presume to take the place of the hundreds of hours invested by dedicated MEU staffs to develop their individual standard operating procedures, but does model what is believed to be a realistic and credible scenario. However, all computer simulation falls short of modeling the complexities of armed conflict, so there is great potential to expand upon and refine this research. Additional consideration could be given to coordinating the efforts between multiple UAS platforms. Interactions and decision criteria among the rest of the MAGTF assets could be refined and updated with classified inputs to increase their veracity. The responsibilities and interactions between aviation

assets alone typically takes a team of experienced aviators to synchronize their efforts. Similarly, adversary characteristics could be updated with classified inputs or varied over realistic ranges to refine recommendations or assess their robustness.

In summary, Marines exist to fight and win where and when our country needs us to. The findings reflected herein show that to best do so, the Marine Corps is more lethal and survivable using UASs with better sensors and in larger quantities. Other characteristics such as stealth and speed of detection are less impactful. This determination is made by focusing on the supported Marine warfighter and enabling them to accomplish their mission.

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“Your absolute best is the very least your Marines deserve.”

— LtCol Brad Ward, USMC, leader, mentor, friend

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To my fellow Marines, I speak often in this thesis about “the supported warfighter.” That’s each and every one of you. You are the reason the Marine Corps deemed it

worthwhile and gave me the great opportunity to study here at NPS. My commitment to you is to use the knowledge gained to contribute to keeping you alive and lethal as long as we are all called upon to do so.

Thank you, and Semper Fidelis.

THESIS DISCLAIMER

The reader is cautioned that the computer programs presented in this research may not have been exercised for all cases of interest. While every effort has been made within the time available to ensure that the programs are free of computational and logical errors, they cannot be considered validated. Any application of these programs without additional verification is at the risk of the user.

The views expressed in this document are those of the author and do not necessarily reflect the official policy or position of NPS, the DoD, or the U.S. government.

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I. INTRODUCTION

The United States Marine Corps (USMC) is at a critical decision point regarding the future of its unmanned aerial system (UAS) acquisition and employment strategy. However, the Marine Corps lacks quantitative analysis focused on determining the most beneficial systems and attributes to pursue for Marines to be effective against peer-level adversaries. As the smallest Service, it is uniquely critical to employ the Marine Corps' limited financial and training resources as efficiently as possible to see the maximum return on investment (ROI) in support of Marine warfighters.

A. PURPOSE

This research objectively assesses what specific UAS capabilities improve the survivability and mission accomplishment likelihood for Marines executing an amphibious assault, a trademark USMC mission, against an advanced, determined, and capable enemy. By approaching this question agnostically, the objective is to remove bias, preconceived notions, or external agendas from UAS acquisition and employment methodology. Instead of the Marine Corps' direction being determined by what industry presents as optimal, this study quantitatively shows what characteristics of tactical-level UAS most positively impact Marines engaged in expeditionary combat scenarios.

B. RELEVANCE TO THE MARINE CORPS

The results of this study directly support multiple facets of the Commandant of the Marine Corps' (CMC's) vision for the future posture of the Marine Corps. In written testimony to Congressional Defense Committees, General Neller states "while the Corps' fundamental purpose does not change, our concepts—and the organization, training, and equipment changes they drive—must adapt to effectively accomplish it" (Neller 2018). The "Modernize the Force" directive specifically addresses the Marine Air Ground Task Force (MAGTF) UAS Expeditionary (MUX) procurement, and prioritizes "investing in lethal, persistent, multi-role intelligence, surveillance, and reconnaissance (ISR) Vertical Take-Off and Landing (VTOL) UAS" (Neller 2018). This thesis, while not tasked or sponsored by any one organization, is in line with the intent of the CMC's initiatives and is inspired by

the 2016 Marine Corps Operating Concept (MOC) and the 2017 National Security Strategy (NSS).

The MOC represents the Marine Corps' vision of its own future role and responsibilities in an evolving and increasingly competitive world (Neller 2016). A major focus of the MOC is competition for the littorals, those parts of the world where the sea meets the land. The MOC is heavily predicated on the assumption of widespread unmanned system proliferation and advancement. These overarching components solidify the need for quantitative analysis clarifying where the Marine Corps can find the greatest ROI in its acquisition and implementation of UASs.

The NSS explicitly calls out China for its aggressive actions in reestablishing itself as a world power. These efforts are currently focused on establishing dominance in its home territorial waters and extending out through the hundreds of islands that surround the East and South China Seas. The Marine Corps, as the nation's amphibious force in readiness, needs to be prepared to counter this type of aggression when called upon. The initial and most basic building block of the Marine Corps' response will most likely be a forward-deployed Marine Expeditionary Unit (MEU) comparable to the force represented in this thesis.

C. LITERATURE REVIEW

Extensive and high-quality research regarding USMC UASs has been conducted by other Naval Postgraduate School (NPS) students, as well as operations analysts at organizations such as the Marine Corps' Combat Development Command (MCCDC) Operations Analysis Directorate (OAD). However, much of this research in the past decade has been focused on specific systems (i.e., what is being advertised by industry), the "ideal" system without regard to practical limitations, or specific employment techniques. This is evidenced by the very language in the ongoing acquisitions pursuit of future UAS capabilities: "The Government is currently evaluating and is willing to consider all options with regards to payloads and sensors early in the air vehicle design phase" (MUX RFI 2018). Through this capabilities-based research, we seek to define more suitable characteristics requirements.

1. MCCDC Studies

The following summaries exemplify the extensive and high-quality research previously conducted in USMC UASs. The fluid nature of combat requirements, developing technology, shifting national and Marine Corps objectives, and the long lead time required for DoD acquisitions makes the entire corpus of research valuable. This is a sampling rather than an exhaustive list.

In 2007, OAD analysts conducted a study to determine USMC UAS threshold and objective requirements within the then-current concept of a three-tiered USMC UAS family of systems (FoS) (MCCDC 2007). This FoS envisioned UAS tiers as: Tier I for Company to Platoon-level, Tier II for Regimental to Battalion-level, and Tier III for MAGTF-level units. Tier II and III required attributes were the focus of the study. Key recommendations were that Tier II ground control stations (GCSs) should operate at least two UASs simultaneously, each UAS should have at least a 50 nautical mile (NM) operational radius, and should fly at least 60 nautical miles per hour (knots). The Tier III attributes also required GCSs to control two UASs, each with at least eight hours flight endurance and cruise speed of at least 200 knots.

In 2014, OAD assessed developing UAS technologies to identify how a Group 4/5 UAS could fill current and future USMC (perceived) capability gaps (MCCDC 2014). This “Group” naming convention was based on UAS capabilities as opposed to the supported unit alignment of the USMC “Tier” system. The “Group” classification convention is further defined in Figure 1. This study also explored the potential for different payloads on then-currently fielded Group 3 UAS as an alternate solution. The sponsors for this study were the Fires and Maneuver Integration Division and Cyber Electronic Warfare Integration Division within MCCDC. The primary findings of this study were that Group 3 UAS were currently and would likely continue to be a good fit to support ground combat element (GCE) operations, but that a Group 4/5 UAS would better support aviation combat element (ACE) operations.

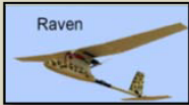
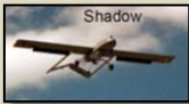
UAS Groups	Maximum Weight (lbs) (MGTOW)	Normal Operating Altitude (ft)	Speed (kts)	Representative UAS	
Group 1	0 – 20	<1200 AGL	100	Raven (RQ-11), WASP	
Group 2	21 – 55	<3500 AGL	< 250	ScanEagle	
Group 3	< 1320	< FL 180		Shadow (RQ-7B), Tier II / STUAS	
Group 4	>1320		Any Airspeed	Fire Scout (MQ-8B, RQ-8B), Predator (MQ-1A/B), Sky Warrior ERMP (MQ-1C)	
Group 5		> FL 180		Reaper (MQ-9A), Global Hawk (RQ-4), BAMS (RQ-4N)	

Figure 1. UAS group descriptions. Source: DoD UAS AIP (2011).

In 2017, OAD analyzed the MUX initial capabilities document (ICD), the starting document in a bid by the Marine Corps to acquire a Group 5 UAS tailored to its specific mission set (MCCDC 2017). This ICD posited gaps in Marine Corps capabilities that had never been aggregated on a single aviation platform, let alone a UAS. As an example, the study recommended a system that could carry multiple types of advanced guided missiles, operate an electronic warfare (EW) pod, carry hundreds of pounds of cargo, and fly for 24 hours at a time. Impressive as that would be, it creates a challenging technological shortfall. However, this takes nothing away from the impressive forward-thinking mentality of the MUX creators and study analysts. The measures of effectiveness (MoEs) used in this study focused entirely on what a theoretical MUX could do without discussion about those capabilities' impact to the supported warfighter.

Of the OAD studies, the oldest most closely resembles the goals of this thesis as its focus was on supporting the Marine on the ground. The 2014 study reflects an agenda by the sponsor; the ACE does not operate independently of the GCE within the scope of the MAGTF warfighting doctrine. The 2017 study, while thorough and very well done,

includes no mention of the supported warfighter. This is reflective of the financial climate within the DoD at that time, when each Service fought for relevancy and money as the major efforts in Iraq and Afghanistan continued to wind-down in that timeframe.

2. Past NPS Theses

The corpus of UAS research examined by NPS students is robust and extensive. This thesis builds on and expands that body of knowledge. Some of these theses were similarly focused on the impact of distinct capabilities or available systems. Others explored USMC capability gaps without focusing on the associated technological challenges. A third category examined optimal tactics, techniques, and procedures (TTPs) for Marine Corps UAS implementation.

Going back fifteen years, then-Captain Raffetto (2004) did a comparably impact-based study, albeit with different strategic goals in mind. However, the timeframe of this thesis had drastically different technological capabilities to assess as well as a different operational environment; the U.S. was still in the throes of Operation Iraqi Freedom and thinking about that low-tech, counter-insurgency (COIN) fight at the time. Raffetto used agent-based modeling and Design of Experiments (DoE) techniques to determine that a UAS's maximum flight time was the most significant factor for detection of enemy units. The second most significant factor was the sweep width of the UAS's sensor. Raffetto's work was highly relevant at the time of completion, but was centered around potential UAS offerings from industry and incorporated now-outdated technological assumptions.

Major Parker's thesis (2015) used similar modeling techniques as the ones we use in this thesis to determine the impact of system capabilities, but also looked at the TTPs used by amphibious assault vehicles (AAVs). Parker explored over 75 factors and determined, among other findings, that the self-deploying capability of future AAVs was the most significant factor in limiting Blue force casualties. Other findings related to optimal TTPs as opposed to differing capabilities. Parker did not incorporate UASs, but provided the bedrock of analytical tools we use in this thesis.

Captain Ekman (2017) studied the incorporation of UASs for logistics support of deployed Marines in a disaggregated environment. This research incorporated both

existing and prospective UAS capabilities in a variety of operational scenarios to determine preferred UAS characteristics and tactics in a logistical resupply role. Of all factors studied, Ekman determined that employment method was more significant than any particular UAS specification in predicting resupply success. This thesis used a similarly agnostic approach with regards to specific UAS platforms and focused instead on varying across a wide range of realistic decision factors.

Major Gulosh (2018) researched the potential of UAS “swarms” to enhance the efficacy of ground combat operations in his thesis. This dynamic and warfighter-oriented work considered homogenous as well as disparate UAS types and characteristics while conducting ISR operations in support of an infantry company. The findings from this research showed that UAS swarm technology is highly significant in reducing friendly force casualties during fast-paced and realistic combat operations.

Each of the above theses used advanced simulation techniques and delved deeply into unique facets of the Marine Corps’ utilization of UAS, capability gaps within the existing and future UAS community, the amphibious assault mission, and/or how best to support the Marine warfighter in an expeditionary environment. We built upon each of these works to address UAS capability needs in a uniquely Marine Corps mission against a peer-level adversary with the most realistic assumptions and scenario possible.

D. OVERVIEW

This thesis uses advanced DoE and Modeling & Simulation (M&S) techniques to provide quantitative analysis based on pragmatic assumptions about current and future UAS capabilities. The resultant analysis shows which attributes most benefit the Marine on the ground, and enhance mission accomplishment of a MAGTF in a realistic operational scenario against a peer-level adversary.

Chapter I addresses the background and motivation driving this research. Due to their highly interwoven nature, Chapter II defines both the operational scenario and the modeling application thereof. Chapter III examines the factors and analytical methods used throughout three rounds of experimentation, then presents and discusses the results. Chapter IV summarizes the most salient output points with succinct conclusions and

recommendations, not only for the Marine Corps UAS implementation plan, but also for future research opportunities.

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II. AMPHIBIOUS ASSAULT SCENARIO

In this chapter, we outline the phases of an amphibious assault mission. This type of mission is used in the opening vignettes of the MOC to highlight the importance of the amphibious assault mission to the Marine Corps. The operation is built around the smallest MAGTF, the MEU. We begin with an overview of the scenario, then provide more details about specific Blue and Red forces, and conclude with an explanation of the computer modeling implementation.

A. CONCEPT OF OPERATIONS

In this scenario, a Blue force conducts an amphibious assault against a well-trained and well-equipped peer-level Red enemy. The Blue force is a conventionally-organized and equipped MEU conducting an amphibious assault against a well-defended shoreline. The Red force is well dug-in (harder to find and kill) and incorporates a functioning integrated air defense system (IADS) near the shoreline and a cluster of infantry units centered on an inland objective. Red indirect fire (IDF) agents are randomly scattered throughout, reflecting a layered defense comparable to United States defensive doctrine. The operational view (OV)-1 of the scheme of maneuver is shown in Figure 2.



Figure 2 shows the starting locations of all agents just prior to commencement of Phase I.

Figure 2. OV-1: Amphibious assault concept of operations (ConOps) against peer-level, static enemy in defensive positions.

This operation is broken into four phases:

Phase I: Shaping. Aviation assets, led by the UAS, first reduce Red's IADS, then reduce Red's IDF capabilities to pave the way for the Blue assault forces. As this is operation is against a peer-level opponent, the UAS is pushing forward of manned aircraft and operating in a command and control (C2) role to find and fix enemy targets in order to direct CAS aircraft in their prosecution.

Phase II: Movement to Objective. This two-stage phase shows the transportation of infantry units from MEU shipping assets via AAVs and MV-22s to their appropriate starting positions to begin their Phase III actions.

- *Stage A: Surface.* AAVs carry their embarked infantry squads to the beach. Follow-on transportation by the AAVs moves the surface assault

force to the debarkation point in conjunction with the air assault force. The AAVs also carry the infantry's organic IDF mortar crews.

- *Stage B: Air.* MV-22 Ospreys launch from MEU shipping and insert their embarked infantry squads into the landing zone in order to flank the enemy position and not overlap their fields of fire.

Phase III: Assault. Both surface and air assault forces advance in parallel towards the Blue objective in a simulated urban environment. CAS assets other than the UAS are not incorporated in this Phase. The mortar systems and infantry units receive direction and targeting information from the UAS. Surviving CAS agents continue to fly a perimeter around the objective area to ensure no reinforcements arrive to assist Red.

Phase IV: Consolidation. Blue ground forces consolidate on their objective once all Red infantry are killed.

The specific TTPs used by units other than the UAS are simplified in order to focus analysis on the impact of the UAS to those forces. Specialists in the infantry, IDF, CAS, and other warfare fields would undoubtedly be able to identify better TTPs for their individual components of this operation. However, as we will discuss in more detail in Chapter III, the overall interplay of their interactions and supporting relationships are effectively captured within the simulation model.

B. BLUE (FRIENDLY) FORCES

Detailed planning for an amphibious assault is a focus of effort for dozens of Marine and Navy officers across months of work-ups and deployment on MEUs. Acknowledging that the details of such an operation will differ for every organization and specific scenario, the following is a simple, yet realistic implementation highlighting the effects of different configurations of a MEU's organic UAS assets throughout the operation. An overview of Blue units is depicted in Table 1 and reflects a realistic representation of MEU assets that would be available for this type of operation.

Table 1. Blue Table of Organization (without UAS)

Qty	Agent Type	Sensor Range (m)	Sensor Fidelity (%)	Weapon	Weapon Quantity	Weapon Range (m)	Weapon Fidelity (%)	Notes
4	JSF	500-10000	10-50	AGM-65 Maverick	6	1000-24000	40-95	Two CAS sections
4	AH-1Z	500-10000	10-50	AGM-115 Hellfire	8	1000-7000	40-95	Two CAS sections
9	MV-22	1500	30	door guns	100	1500	5	Air Assault
9	AAV-7	1500-2000	25	25mm	200	100-2000	5-50	Surface Assault
36	Infantry	100-1000	50-100	M-4/IAR	30	10-500	10-100	Air and Surface Assault elements of GCE
2	Mortar	100-1500	50-100	81mm	30	500-14000	50	Mortar sections fire in support of infantry maneuver Range enhanced for modeling Primary cueing from UAS
3	LHx ship	n/a	n/a	n/a	n/a	n/a	n/a	LHD, LSD, and LPD are not relevant in this scenario

Infantry and mortar agents represent those types of forces and do not reflect specific quantities.

The ranges shown in Table 1 reflect the maximum and minimum sensor and weapon engagement ranges for each agent type. Similarly, the fidelities shown are the probabilities of classification per detection event and probability of hit per shot for sensor and weapons, respectively, where the high fidelities are associated with the low distances and vice versa. These values are fixed for Blue agents other than the UAS. We will discuss the UAS capabilities in greater detail in Chapter III. During a simulation run, the fidelities are interpolated between the Table 1 values by using the actual simulation distances (between agents), and random draws determine the outcomes.

1. Blue Aviation Combat Element (ACE)

Blue ACE agents represent the MEU's aviation combat power. Within a MEU ACE, each type of aircraft plays distinct and complementary roles, both in real-world operations and in this simulation scenario.

The UAS starts the scenario in its patrol box just off the coast of the objective. Time on station, flight range, and related capabilities are addressed in Chapter II, Section E, Assumptions. Operational UAS capabilities are addressed in greater detail in Chapter III, Sections E.1 and F.1, the factor explanations for Experiments 2 and 3, respectively.

The F-35B Joint Strike Fighters (JSFs) in this model are employed in two separate CAS sections. The first section launches as soon as the UAS agent(s) classify the first Red agent. The second section launches after 40 minutes of simulated time. JSFs throughout

the model have 70% “personal concealment per detection event” to signify their stealthy properties. For modeling simplicity, these JSFs carry six AGM-65 Maverick missiles each and can reload throughout the scenario at the ship. JSFs target Red units in the following order: surface to air missiles (SAMs) launchers, radar sites, and howitzers.

The AH-1Z Cobras in this model are employed in two separate CAS sections. The first section launches as soon as the UAS agent(s) classify the first Red agent. The second section launches after 40 minutes of simulated time. For modeling simplicity, these Cobras carry eight AGM-114 Hellfire missiles each and can reload throughout the scenario at the ship. Cobras target Red units in the following order: radar sites, SAM launchers, howitzers.

MV-22 Ospreys are used solely to deliver the air assault component of the GCE to their landing zone. They are equipped with heavy machine guns for self-defense, but are not a significant threat to Red forces.

2. Blue Ground Combat Element (GCE)

While the ACE is a critical enabling force for most MAGTF operations, the GCE typically represents the battle-winning combat power of a MEU and would be deemed “the Main Effort” for an amphibious assault. Much like their aviation counterpart, the GCE uses several unique and complementary agent types. This research focuses on the utilization of assorted UAS configurations and the subsequent impact to Blue forces as a whole, so many GCE units and their movements are simplified.

Amphibious assault vehicles (AAVs) are used solely to deliver the surface assault component of the GCE to their disembarkation point. They are equipped with 25mm turret guns for self-defense, but are not primary combatants. In this thesis, we make no distinction between the current AAVs and the future Amphibious Combat Vehicles the Marine Corps would likely be using in this type of operation.

Each infantry unit modeled roughly reflects a fireteam of U.S. infantry Marines. These units deploy either via Osprey or AAV into the objective area and move together through comparable-type Red infantry forces, reinforced with any other surviving Red assets, towards Blue’s primary objective.

Mortar agents are analogous to the mortar sections organic to MEU infantry battalions; elements which could and would operate forward in support of specific infantry fire and maneuver towards an objective. These mortar systems receive direct communications from the UAS regarding classification and targeting information. These communications reflect a realistic call-for-fire interaction between an overhead ISR platform and supported IDF unit.

C. RED (ENEMY) FORCES

Red forces are equally as competent as Blue forces in this scenario, but are in a defensive posture compared to the Marines' offensive posture. This means that Red units are harder to detect (reflecting well-established camouflage) and harder to kill (reflecting effective defensive positions) than their maneuvering Blue counterparts where applicable. Details about Red units are shown in Table 2.

Table 2. Red Table of Organization

Qty	Agent Type	Sensor Range (m)	Sensor Fidelity (%)	Weapon Range (m)	Weapon Fidelity (%)	Notes
3	Radar	5000-20000	20-90	1000-7000	10-50	Primary function is sensor and fire control for SAM launchers
8	SAM	5000	10	5000-20000	10-80	Relies on radar for primary target cueing
10	Howitzer	1000-12000	10-80	500-15000	50	IDF
40	Infantry	100-1000	50-100	10-500	10-100	Capable and well dug-in light infantry

As with the Blue ground forces, Red units are simplified in their variety, diversity, and tactics. However, Red does employ an effective IADS. Incorporating more complex and potentially classified components of any/all these into Red units may be useful for subsequent studies. The maximums and minimums shown for ranges and fidelity are modeled the in same way as Blue agents; the capabilities are fixed. The ranges used reflect the real-world challenges of detecting, classifying, and hitting targets at greater ranges.

The generalized Red radar systems do not represent any specific enemy air-defense radars. They have a long detect and classification range, but more importantly, provide integrated targeting information to the SAM sites in the area. Targeting fidelity improves as Blue agents get closer. The radar's actual weapons reflect short-range self-defense systems; their primary function is to cue SAM sites. Red radars target all Blue airborne agents.

Surface to Air missiles sites are the second part of Red's IADS. As appropriate for a peer-level adversary, these advanced systems are effective against all Blue systems. However, without functioning radar agents cueing them, the SAM agents are unable to engage at their maximum effective range; this represents the weakness in an integrated system. SAM sites target all Blue airborne agents.

Red's IDF assets represent the powerful and effective artillery systems historically used by major U.S. adversaries. These howitzers are highly capable against Blue ground vehicles and personnel, but are vulnerable to attack from the air.

The Red infantry units are analogous to Blue's, but they require two hits to kill instead of one. This adaptation reflects the challenge of attacking an enemy in a prepared fighting position.

D. MANA IMPLEMENTATION

This study uses Map Aware Non-Uniform Automata (MANA) M&S software to simulate a hypothetical battlefield scenario. The movements and actions of agents representing friendly (Blue) and enemy (Red) forces are modeled using discrete time simulation (DTS) in a variety of unique agent states to portray common combat situations. One of MANA's greatest strengths is the flexibility inherent in its graphical user interface (GUI) and the interaction modeling possible between agents. This particular theoretical battlefield was adapted from Major Parker's thesis. An excellent description of both MANA and the battlefield can be referenced there. The MANA agents used in this model are shown in Table 3.

Table 3. MANA Agent Classifications for Blue and Red Units

MANA Agent Classifications					
Agent	Description of Blue Agents	Allegiance	Class	Threat	Targets
JSF	Joint Strike Fighter	1	5	3	4, 2, 3
AH-1Z	Super Cobra	1	5	3	2, 4, 3
MV-22	Osprey	1	6	3	3, 1
AAV	Amphibious Assault Vehicle	1	7	3	3, 1
Infantry	Marine infantry fireteam	1	1	1	1, 3, 7
Mortar	IDF asset organic to infantry units	1	3	2	3, 2, 4, 1
Agent	Description of Red Agents	Allegiance	Class	Threat	Targets
RedRadarSite	Advanced Surface to Air targeting and tracking radar	2	2	3	5, 6, 8
RedSAMLauncher	Medium-range advanced SAM launcher	2	4	3	5, 6, 8
RedHowitzer	IDF	2	3	3	7, 2, 3, 1
RedInfantry	Dug-in infantry units	2	1	1	1, 3, 7

This model incorporates an advanced designed of experiments tool pioneered at NPS in its analysis. The nearly orthogonal Latin hypercube (NOLH) design models hundreds of possible configurations across multiple decision factors of UAS capabilities and utilization in a realistic MAGTF scenario. The data from an initial test run and two subsequent unique experiments reflect over 179,000 individual model simulations. The outputs from each of these three experiments were collated and analyzed using JMP statistical analysis software (JMP Pro 14.3 2018).

The final MoEs, or dependent variables, used in this study were the number of Blue (friendly) forces killed, number of Red (enemy) forces killed, time until 50% of Red forces killed, time until first Red classified, time until last Red classification, number of Red units classified by UAS, and number of Red units classified by in total by Blue forces. These MoEs will be discussed further in the Analysis.

E. ASSUMPTIONS

This model focuses on the impact to ground forces of varying UAS capabilities, so some real-world planning factors are only addressed in the following assumptions:

- The threat to Blue ships from Red forces is assumed to be zero. This simplification represents the un-modeled protection that would be provided by other United States Navy (USN) ships providing a defensive screen against anti-ship Red assets.
- In Experiments 1 and 2, the UAS is treated as 100% undetectable. Effectively, this gives it total survivability even against a dangerous and otherwise effective enemy. In Experiment 3, this factor is varied and is discussed further.
- The Red air threat (i.e., enemy aircraft) is not considered. It is unlikely an operation as risky as an amphibious assault would be conducted against an enemy with a viable aviation component.
- UAS endurance and shipboard launch/recovery capabilities are not addressed in this research. These capabilities are absolutely relevant to the larger UAS discussion, but diligent MEU planners would ensure UAS availability during critical phases of the assault based on their available assets.
- There are no neutral agents in this scenario. The challenge of discerning enemy from neutral or friendly agents is represented by the probability of classification per detection event for each unit type.
- Unclassified approximations of Blue and Red sensor and weapons capabilities accurately reflect realistic interactions.
- The Phase III assault is conducted with only UAS for CAS support. This represents the persistent danger manned CAS platforms face in an urban

environment, particularly when loitering overhead persistently as is often required to prosecute ground targets in a cluttered urban environment.

- The JSF's capabilities are drastically limited in this scenario from what F-35 advocates believe it to be capable of. Again, this reflects the threat posed by a rapidly developing and adapting peer-level adversary. Against a true peer, the risk to aircrew would rapidly become prohibitive, so they are incorporated as highly capable CAS platforms instead of airborne quarterbacks as depicted in the MOC. Many of the F-35's sensor and communications capabilities are instead attributed to the UAS in this thesis as they are not dependent on any particular JSF-qualities.
- Communication fidelity, specifically regarding GCS to UAS communications, is assumed to be 100% throughout this scenario. While this will rarely come to fruition in real-world operations, particularly against the type of peer-level, EW-capable adversary modeled here, the degradation in such a conflict would likely be felt by all units and both sides. Thus, the net effect for this scenario is assessed to be null.

F. LIMITATIONS

MANA as a modeling tool has extensive flexibility and range, but like all analysis tools, also has its limitations. Below are a few of the most significant:

- The flight paths of aircraft agents can be visually erratic; it is not uncommon to see a jet stop in mid-air, then turn 180° and take off in the opposite direction. This incongruity is a result of the underlying DTS used and personality employed by each aircraft in their assorted agent states. As Al Rowaei et al. (2011) discuss, "the use of DTS can compromise the modeling accuracy of changes in agent sensor range and detection, as well as the ability of agents to travel to specific target destinations in a spatial simulation environment." These potential shortcomings are addressed by choosing an appropriate time step. The five second time step used in this research represents only 1/4800th of the overall simulation time. Further,

this interval is reasonable based on the speed of agents and ranges employed by individual sensor and weapons systems in this model; there are not conflicts in which agents pass their objectives, close too rapidly with enemies, or otherwise defy reality. By incorporating correctly sized time steps as a mitigation measure, we appropriately address Al Rowaei et al's concerns regarding indiscriminate DTS methods.

- The ability of UAS to act as an airborne retransmission site to pass communications and coordinate over-the-horizon (OTH) activities is a potentially critical capability for long-range MEU operations. However, as with most person-to-person interactions, this is uniquely challenging to represent with M&S tools. As a workaround, the UAS is granted near-ubiquitous communications capacity and capability with other Blue forces. For CAS and IDF agents, this communication is near-instantaneous. For infantry units, there is a simulated five-minute delay representing the real-world consideration of passing UAS observations through intermediaries down to the fireteam in the middle of an assault.
- Many MEU operations function on an execution checklist: a series of brevity terms and pre-established codewords signifying completion of a different aspect of an operation. i.e., “Cobra 21 passes ‘Chargers’ at time 3–4” to signify that whatever task was coded to “Chargers” was successfully executed at 34 minutes past the hour. Again, this level of interaction does not model well in MANA. To work around this limitation, this model uses preplanned timing, an impossibility to perfectly execute in real world operations, to synchronize scenario elements such as the surface and air assault forces.
- Stealth is modeled comparably to established defensive positions via a personal concealment property in MANA. Just as JSFs enjoy a 70% “personal concealment per detection event,” so too do static, prepared defensive positions. This nod to a peer-level threat and its inherent competence is one of the unique facets of this research.

III. ANALYTICAL METHODS AND RESULTS

In this chapter, we use a data farming approach to explore the use of a tactical UAS as described in the scenario of Chapter II. Conducting several well-designed simulation experiments enables us to quantitatively assess the most critical capabilities for a tactical UAS to possess in this realistic and challenging combat situation. We begin in Section A with an overview of the robust DoE approach and vocabulary. In Section B, we describe the assorted analytical methodology we used throughout our research. As each experiment built on and refined the specific model used, we present an overview of all MoEs used throughout the experimental evolution in Section C. We address specific factors, factor levels, and significant results within their respective experiments in Sections D-F.

A. DESIGN OF EXPERIMENTS

Computer simulation models are powerful analytical tools for gleaning insight about complex factors and their interactions, but only if employed correctly. When incorporating a variety of widespread decision and noise factors—characteristics which in the real world either can be controlled or are inherently uncontrollable, respectively—even the most powerful computers in the world can rapidly fall short of the computational power requirements to return timely results. By incorporating an efficient DoE, we effectively explore a large space of relevant potentialities and isolate robust results. Put in layman’s terms, a robust DoE looks at many relevant combinations of factor levels to give us high confidence that our results reflect realistic outcomes (Sanchez et al. 2018).

The following basic nomenclature codifies specific key terms to limit ambiguity. These are paraphrased from DoE/data farming source material, where more detailed definitions can be found (Sanchez et al. 2018).

- *Factors*: The input choices that we believe may impact output. These can be quantitative or qualitative, discrete or continuous, depending on the circumstances of a given experiment.
- *Levels*: The variety of values which a given factor may assume during the experiment.

- *Design Point (DP)*: A particular and unique combination of factor levels.
- *Responses or MoEs*: The experimental outputs resulting from a given DP.

B. METHODOLOGY

Our primary analytical tool for the output from our MANA simulations is the JMP data analytics software (JMP Pro 14.3 2018). We use its powerful and intuitive GUI to dynamically and interactively explore the large quantities of data generated using advanced statistical techniques, a host of graphing options, and visual pattern identification. The following summaries are drawn from the JMP 14 software documentation and provide insight into some of the most significant techniques we used in this research. More detailed explanations are available in the comprehensive JMP 14 source documentation available from SAS.

The distribution tool provides histograms and boxplots for quantitative factors and MoEs, or frequency distributions for qualitative factors and MoEs. These visualizations are reinforced with customizable summary statistic output. We use the distribution tool as an effective first visualization of the MoEs to determine how they vary over the design points in terms of either raw output or as summaries across random replications.

Once we have developed some initial understanding of the experiment results, we fit metamodels to better understand the specific effects of the input factors on the MoEs. In the simulation community, the term ‘metamodel’ refers to a mathematical or statistical model of a simulation model’s behavior. Because we are interested in complex interactions and non-linear behavior, we initially use stepwise regression to identify significant terms from second-order metamodels (those containing main effects, quadratic effects, and two-way interactions among the factors). This regression technique is very flexible. In our final experiment, we use a third-order metamodel which adds cubic and three-way interactions as possibilities for the step-wise regression.

Once we identify significant predictive factors and terms, we fit a standard least-squares regression metamodel, further refine it if necessary, and discuss its implications. Related regression visualization tools, such as prediction and interaction profilers, provide further insights.

As an alternative to and verification of the conclusions from the fitted regression metamodel, we also use partition trees to construct non-parametric metamodels. These powerful tools are ideal for exploring computer modeling output data as they do not require any pre-existing relationship framework, they can handle large quantities of data, and their outputs are easily interpretable (JMP Pro 14.3 2018). They are often simpler to explain to non-technical audiences than regression models.

C. MEASURES OF EFFECTIVENESS

We built this model to determine the effects of UAS capabilities on the supported warfighter, so the most operationally, analytically, and morally significant MoE in all three experiments is the number of Blue casualties. We define a casualty in this thesis as a single agent killed in action. The response variable for this MoE is “Alleg1Cas.Blue.” This translates to mean that Blue forces are all aligned with “Allegiance 1.” The number of potential Blue casualties varies across the three experiments because we alter specific numbers of Blue agents as we represent a more realistic and credible scenario.

We also track the number of Red casualties, denoted as “Alleg2Cas.Red,” across all three experiments. Again, this MoE counts the number of individual Red agents killed in a given simulation; wounded agents are not considered. The key output we seek with this MoE is any indication of a “no-win” scenario in which both Blue and Red forces suffer unacceptable losses. This would be a rare event based on the model as crafted, but we will let the results speak for themselves in subsequent analysis.

To address the efficiency enabled by UAS capabilities, we use several forms of time-related MoEs throughout our research. The “RedKillTime” response tells us how many seconds it took for half the Red force to be killed. Other time-related MoEs include “TimeFirstRedClassified” and “TimeLastRedClassified.” Again, these provide a metric to assess the efficiency of Blue forces. However, the time-related MoEs are not particularly effective in this particular scenario due to timing limitations of using MANA agents as discussed in Chapter II, Section F.

We also include an MoE tracking the quantity of Red agents classified by all Blue units, “NumRedAgtsClassifiedByBlue,” to compare against those classified specifically by

the UAS, “NumRedAgtsClassifiedByUAS.” The classification threshold is important in our MANA characterization as both Red and Blue agents require a positive classification of enemy agents prior to shooting at them. This reflects the very realistic fog of war; e.g., a squad on patrol receives fire from an unknown location in a tree line to the East.

D. EXPERIMENT 1: MODELING PROOF OF CONCEPT

Experiment 1 is a limited-scope experiment to verify that UAS incorporation in the operation is making both a statistically significant and a practically important impact on the simulated forces. The only factor we adjusted in Experiment 1 is a binary one, “UAS.Active.” This “Yes” or “No” factor indicates whether a UAS agent is part of the operation or not. With 200 replications of the base model changing only this factor, we see an impact to the number of Blue and Red casualties as shown in Figure 3.

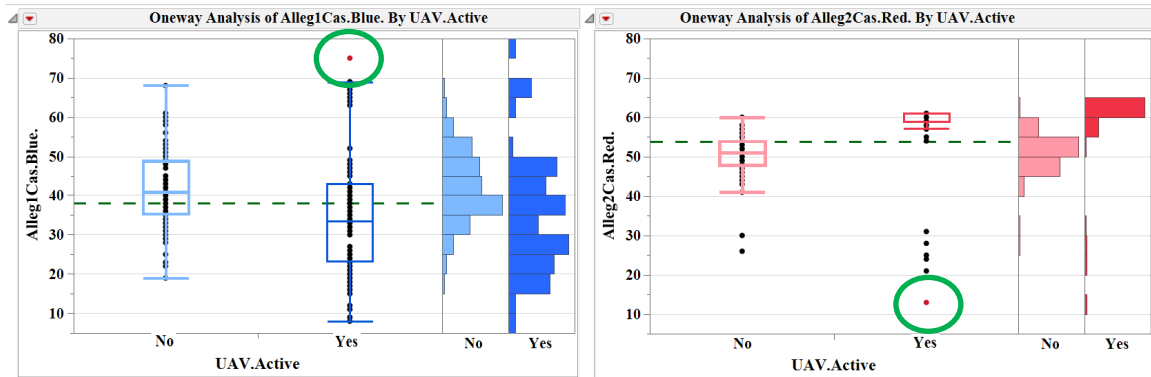


Figure 3. Boxplots and histograms of Blue (left) and Red (right) casualties when only accounting for UAS absence or presence.

As we look at the left side of Figure 3, the mean of Blue casualties is 41.7 without a UAS and 34.6 with a UAS. This is statistically significant with a p -value <0.0001 . Using this one factor only has an R-squared value of 0.074 for Blue casualties. This means that less than 10% of the total variability of Blue casualties is explained by the UAS.Active factor.

Red force casualties are also heavily impacted by the UAS.Active factor, as shown on the right side of Figure 3. There, we see that Red has a mean casualty count of 50.5

without a Blue UAS as opposed to 57.1 with a Blue UAS, a statistically significant different with a p -value <0.0001 . Particularly with a UAS operational, we see a distinct grouping of results above the mean with only eight outliers preventing the mean from being significantly higher. While the R-squared for Red casualties is somewhat better at 0.14, there is still a lot of unexplained variability in this experiment.

The circled outliers on both the left and right sides reflect two unique simulations with identical results. For these two simulation seeds, even with an operational Blue UAS, Red IADS killed all Blue CAS agents early in the fight leading to identical defeats of Blue by Red with 75 and 13 casualties, respectively. This reflects the stochastic qualities built into the model. Also, this is realistic for real-world operations; sometimes even a better-equipped and numerically superior force loses due to unforeseeable circumstances. Therefore, we do assess these simulations to be valid and pertinent.

Experiment 1 served its purpose well. We see solid evidence of a significant impact to Blue forces based solely on the presence or absence of a UAS directing the fight. This initial experiment confirms that our baseline MANA model reasonably reflects the interactions between Blue forces conducting an amphibious assault against a peer-level Red adversary. This confirmation paves the way for our next experiment.

E. EXPERIMENT 2: MODEL REFINEMENT

While still an evolving model, we reach a significantly improved level of realism and operational credibility in Experiment 2. The baseline ConOps for all Blue and Red forces remain the same. However, this experiment is where Red forces in prepared defensive positions became harder to kill than their assaulting and mobile analogous Blue forces. Blue CAS agents, while still primarily relying on C2 from the UAS, became more realistically capable of operating within their own cockpits and sections to prosecute Red targets of their own accord. These assorted refinements are critical steps in linking the power of computer simulation with real-world tactics and outcomes. The known shortfall of Experiment 2 is that it still incorporated only a single UAS and that system was not targetable by Red agents.

1. Factors

With Experiment 2, we begin in earnest the process of identifying the most impactful UAS capabilities and their associated performance thresholds for those most significant factors. We use four distinct decision factors, shown in Table 4, for the Experiment 2 modeling.

Table 4. Decision Factors for Experiment 2

Experiment 2 Factors				
Factor	Min	Max	Unit	Type
OverheadSpeed	20	150	knots	Continuous
SensorRng	1000	20000	meter	Continuous
AvgTimeBetwDet	5	300	second	Continuous
Pclass	10	90	percent	Continuous

Further information on each of the Experiment 2 factors is as follows:

- *OverheadSpeed*: The overhead speed of a UAS is how fast it flies, in knots, while operating in the objective area. As discussed in Chapter II, Section E, Assumptions, this is the only measure of speed evaluated for the UAS. The speed used during travel from its launch and recovery location is not considered in this model.
- *SensorRange*: The maximum effective range of the UAS's sensor measured in meters (m). This factor does not differentiate on target size, camouflage, atmospheric conditions, or other potential noise effects. Instead, this all-encompassing term defines the range in which it is possible for a UAS sensor to detect and subsequently classify enemy agents.
- *AvgTimeBetwDet*: We use the average time between detections instead of attempting to model the efficacy of a UAS's GCS crew. All human-in-the-loop unmanned systems incorporate a GCS to varying degrees. This factor holistically captures the effect of the team size, training, and equipment

quality using seconds (secs) as the performance measure. e.g., A highly-trained and well-staffed GCS team will find, or detect, potential targets more quickly than a single operator with minimal training using the same system.

- *Pclass*: We use the probability of classification to represent the quality of sensors used by a UAS. For a given detection event, this is the probability (by percent) that the GCS crew will be able to classify the detected agent as an enemy or not.

We use an NOLH to set these four factors at 65 nearly orthogonal DPs, 64 unique and one center point, to fill the design space as shown in Figure 4. An NOLH enables a far more efficient DoE than the full factorial version of these four factors, which would have over 17.8 million DPs.

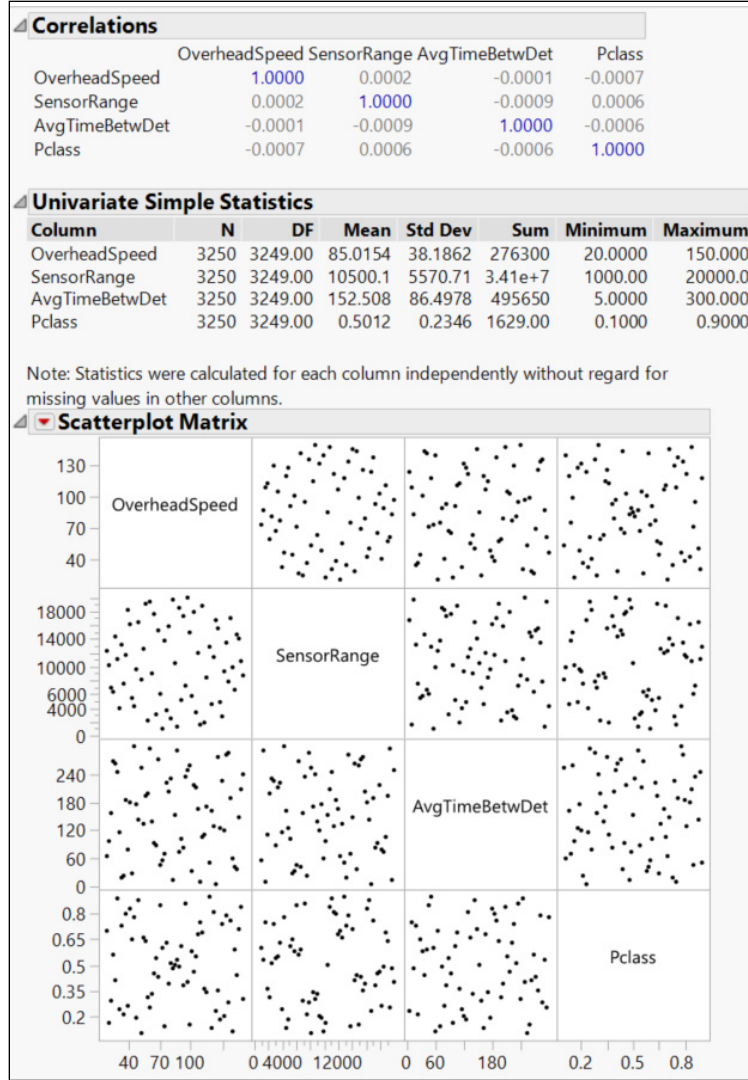


Figure 4. NOLH of Experiment 2 decision factors.

The NOLH is nearly orthogonal; the magnitude of the correlation between each factor and any other is less than 1/1000. While not perfectly orthogonal, this nearly-orthogonal design shows that there is no unintended correlation between factors. The lower portion of Figure 4 shows well-filled pairwise scatterplots of each factor's unique levels compared with the levels of each other factor.

2. Output

We use 50 randomly generated simulation seeds for each of the 65 DPs to generate a total of 3,250 simulated assaults. The unfiltered output for our primary MoEs, the number

of Blue and Red casualties, is shown in Figure 5. Blue and Red demonstrate heavy right and left tails respectively; this was anticipated based on our scenario in which Blue attacked at the time and place of their choosing. Additionally, however, we see that both Red and Blue have significant numbers of outliers and Blue even shows unexpected hints of bimodality as seen in the 60–75 casualty range of its distribution. This initial look at the distribution of Blue and Red casualties raised more questions than it answered, so we tried a different take on its analysis.

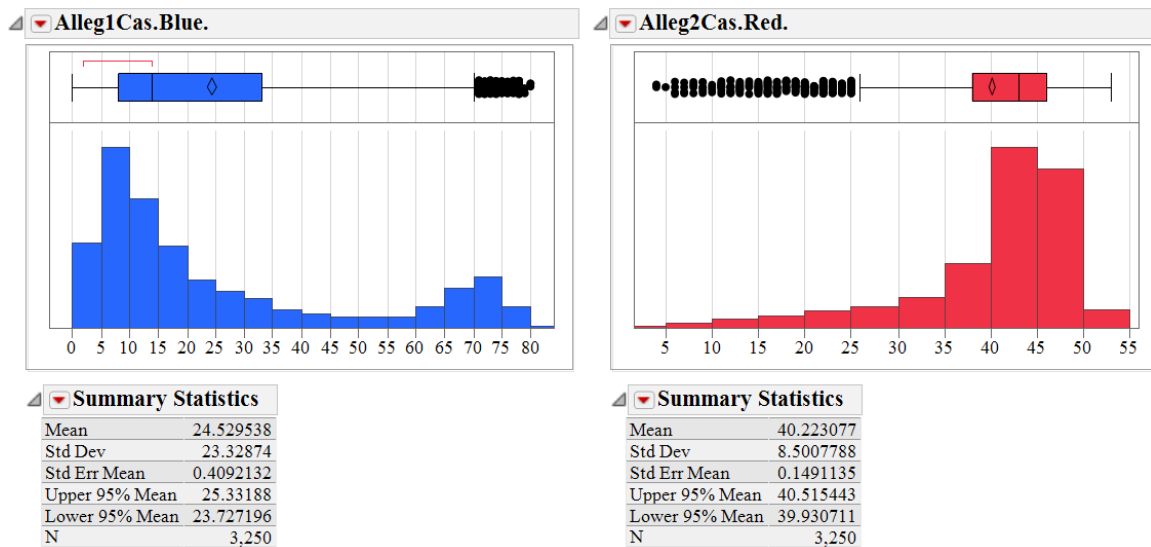


Figure 5. Experiment 2 unfiltered output including histograms and summary statistics.

To better understand the effects occurring for each of our 65 DPs, we took the mean of Blue and Red casualties for each DP and plotted their distribution as shown in Figure 6. The horizontal scales on these histograms is artificially expanded to maintain consistency and aid comparison with Figure 5.

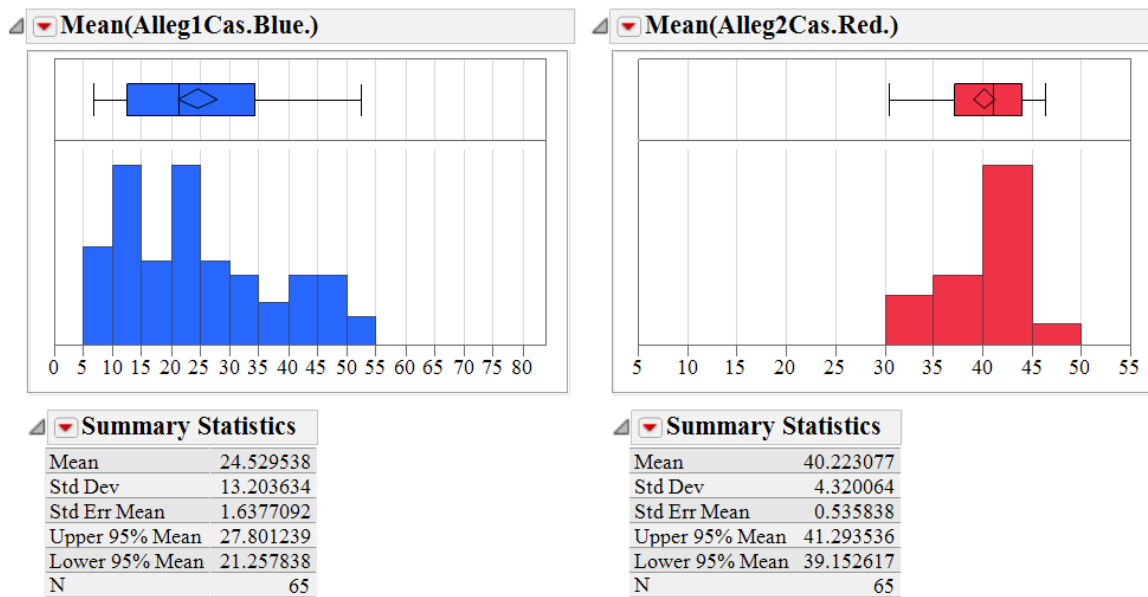


Figure 6. Experiment 2 histograms and summary statistics for expected Blue and Red casualties, by design point.

We still see notable variability on the left side of Figure 6 in the Blue casualty numbers—a Marine commander would have understandable concerns about a model that predicted somewhere between 15 and 43% total force casualties. These represent the lower and upper quantile values respectively out of the total Blue force. However, these MoEs do give us a sense that our decision factors are steering us towards an advisable configuration of UAS to support our MAGTF however. Prior to the analysis of our definitive model in Experiment 3, we will examine our primary MoE, the number of Blue casualties, in the Experiment 2 output with regression, partition trees, and impact analysis.

3. Regression

We begin our examination of Experiment 2 results with a stepwise regression metamodel for expected Blue casualties. There are 14 potential metamodel terms: four main effects, four quadratic effects, and six two-way interactions. Figure 7 shows the resultant regression metamodel summary.

Effect Summary

Source	LogWorth		PValue
SensorRange	31.129		0.00000
Pclass	13.720		0.00000
AvgTimeBetwDet	13.700		0.00000
SensorRange*SensorRange	10.360		0.00000
OverheadSpeed	8.501		0.00000
Pclass*Pclass	3.282		0.00052
SensorRange*AvgTimeBetwDet	2.269		0.00539
AvgTimeBetwDet*Pclass	2.059		0.00873
OverheadSpeed*OverheadSpeed	2.024		0.00945
AvgTimeBetwDet*AvgTimeBetwDet	1.646		0.02258
OverheadSpeed*SensorRange	1.480		0.03313
SensorRange*Pclass	0.091		0.81023

[Remove](#) [Add](#) [Edit](#) ☐ FDR

Summary of Fit

RSquare	0.953051
RSquare Adj	0.942217
Root Mean Square Error	3.173897
Mean of Response	24.52954
Observations (or Sum Wgts)	65

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	12	10,633.673	886.139	87.9663
Error	52	523.828	10.074	Prob > F
C. Total	64	11,157.501		<.0001*

subsequent Experiment 2 metamodeling.

Figure 7. Experiment 2 initial regression metamodel for expected Blue casualties (as determined by stepwise regression).

The resultant least squares regression model only omits two of the possible 14 terms: OverheadSpeed*AvgTimeBetwDet and OverheadSpeed*Pclass. Using the remaining 12 terms, this model achieves an impressive R-squared of 0.953 as highlighted in Figure 7. The most significant factors, SensorRange, Pclass, and AvgTimeBetwDet, are now readily apparent along with the less-noteworthy contributions of SensorRange² and OverheadSpeed. To gain a better appreciation of what each of these terms practically mean in this metamodel, we turn to the intuitive visuals in Figure 8.

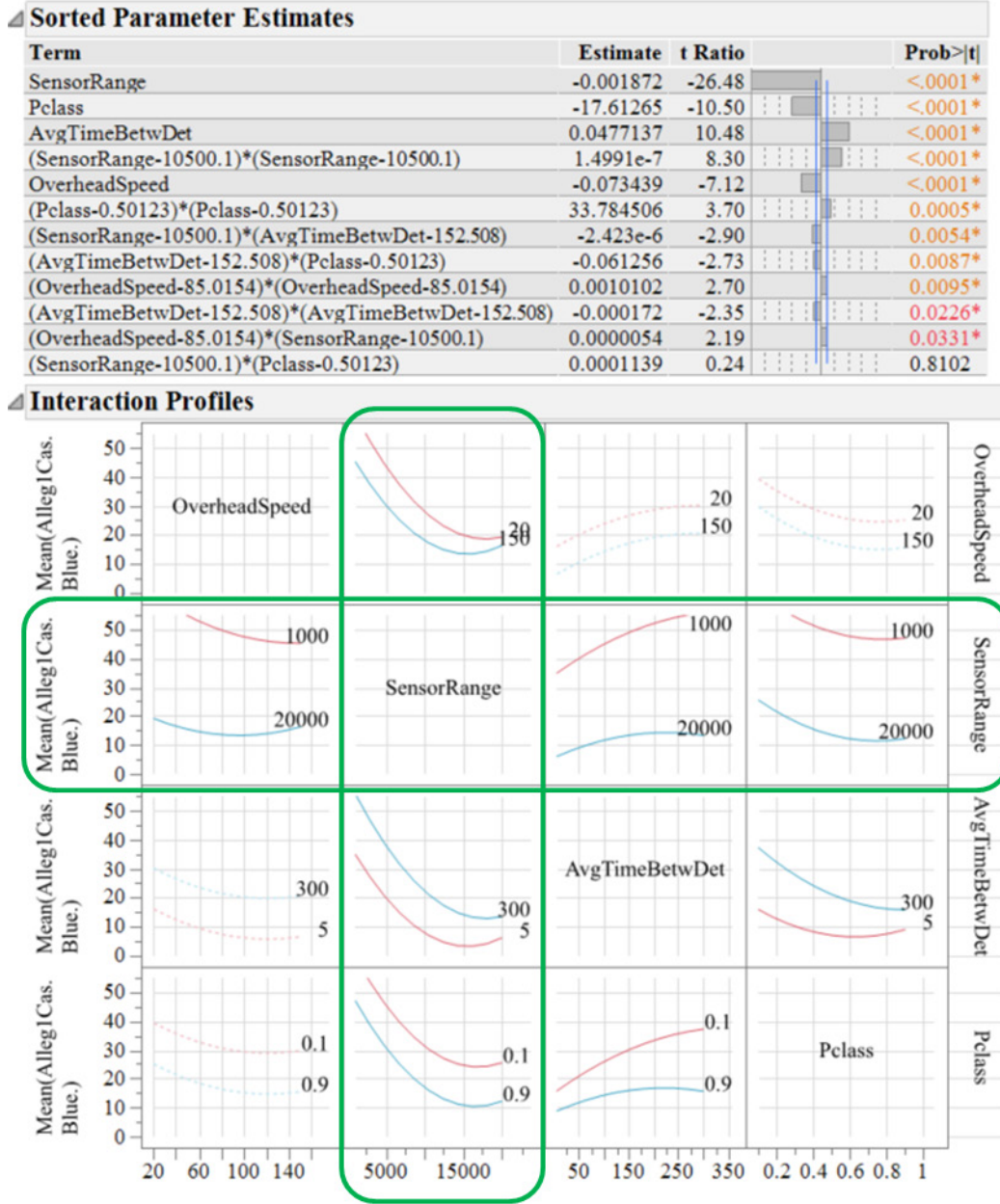


Figure 8. Parameter estimates and interaction profiles of Experiment~2 initial regression metamodel for expected Blue casualties.

We sort the parameter estimates by their respective contributions to the metamodel as shown in the upper portion of Figure 8 and see a clear visual representation of each factor's influence. SensorRange is readily identifiable as the single most significant predictor of Blue casualties. SensorRange's quadratic term is also one of the strongest contributors.

To gain an appreciation for what these contributions translate to on a practical level, we look to the lower portion of Figure 8, specifically the green-outlined portions. No term other than those incorporating SensorRange spans as wide a range of MoE response or changes as rapidly. However, we also see potentially misleading effects within these interactions.

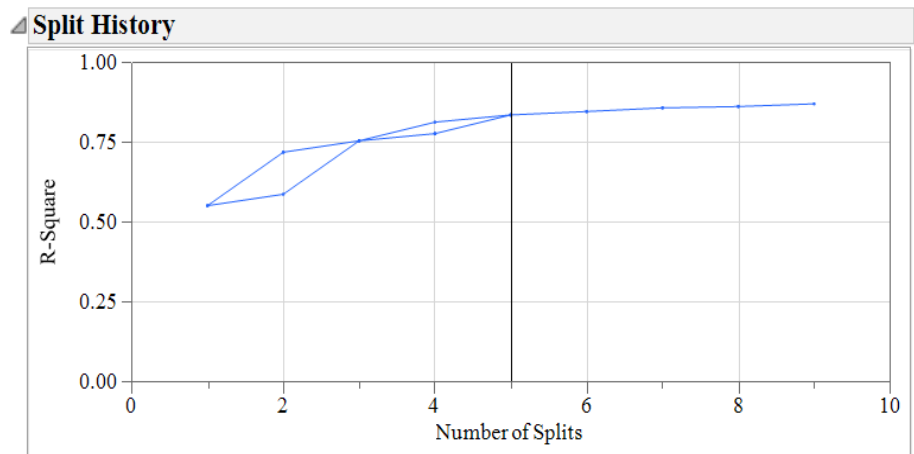
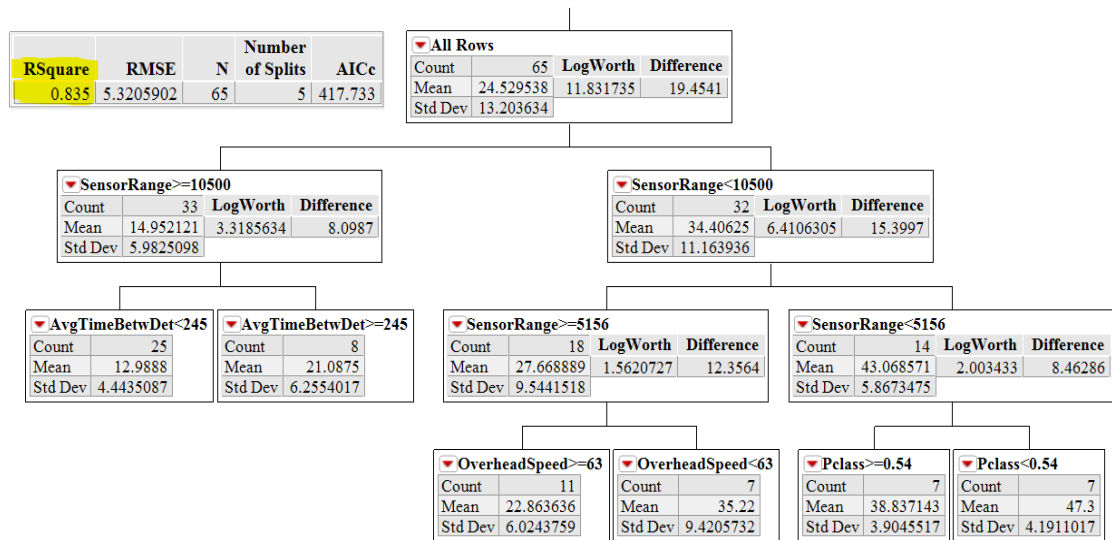
Using solely the interaction profiles in the lower portion of Figure 8, it appears that the mean quantity of Blue casualties increases when SensorRange improves above ~15,000m. This does not correspond with the rest of our findings or our expectations. We will explore this conundrum further using partition trees and in Section F.

4. Partition Tree

We use a partition tree to split (or partition) the output data without making parametric assumptions about the relationship between our input factors and the response values. Our partition tree for Experiment 2 is shown in Figure 9.

As shown in the upper highlighted portion, we achieve an R-squared of 0.835 for this model with only five splits in our data. We initially split the response values by all DPs with SensorRange $\geq 10,500\text{m}$ on the left branch and DPs with SensorRange $< 10,500\text{m}$ on the right branch. This one metric divides the 65 aggregated responses into a group of 33 with a mean of 14.9, and a group of 32 with a mean of 34.4, and looking at the split history, accounts for more than 50% (R-squared of ~0.55) of the model's variability.

Continuing down the left, or preferred (because it represents fewer Blue casualties) branch, we determine that ensuring an AvgTimeBetwDet < 245 secs along with our SensorRange $\geq 10,500\text{m}$ allows us to predict that expected Blue casualties can be reduced to just under 13. This translates to an ~16% expected casualty rate for Blue forces. That would still be a significant loss of life for any Blue commander to accept. By comparison, we see that the right branch of DPs never predicts a casualty quantity less than 22 fatalities, or just over 25% of the total force. These real-life human considerations illustrate the importance of these data.



Column Contributions

Term	Number of Splits	SS	Portion
SensorRange	2	8016.12819	0.8603
OverheadSpeed	1	653.129923	0.0701
AvgTimeBetwDet	1	397.508738	0.0427
Pclass	1	250.669829	0.0269

and column contributions for Experiment 2 factors.

In the lower highlighted portion of Figure 9, we break down the “column contributions” of each factor in determining our expected MoE response. This simple bar graph does exactly what the name implies in showing that SensorRange accounts for more than 86% of the predictive value of this partition tree.

5. Impact Analysis

To synchronize the findings of these two methods and summarize our Experiment 2 analysis, we plot each of the DP means in Figure 10. As indicated with both regression analysis and our partition tree, we can clearly see the significance of a higher SensorRange in reducing Blue casualties.

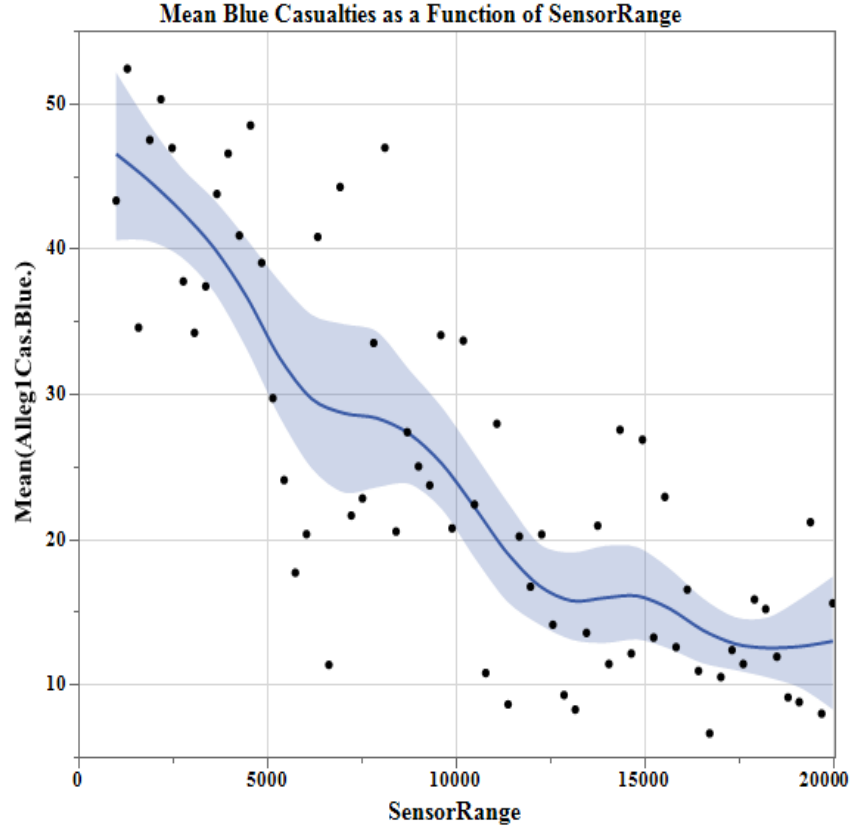
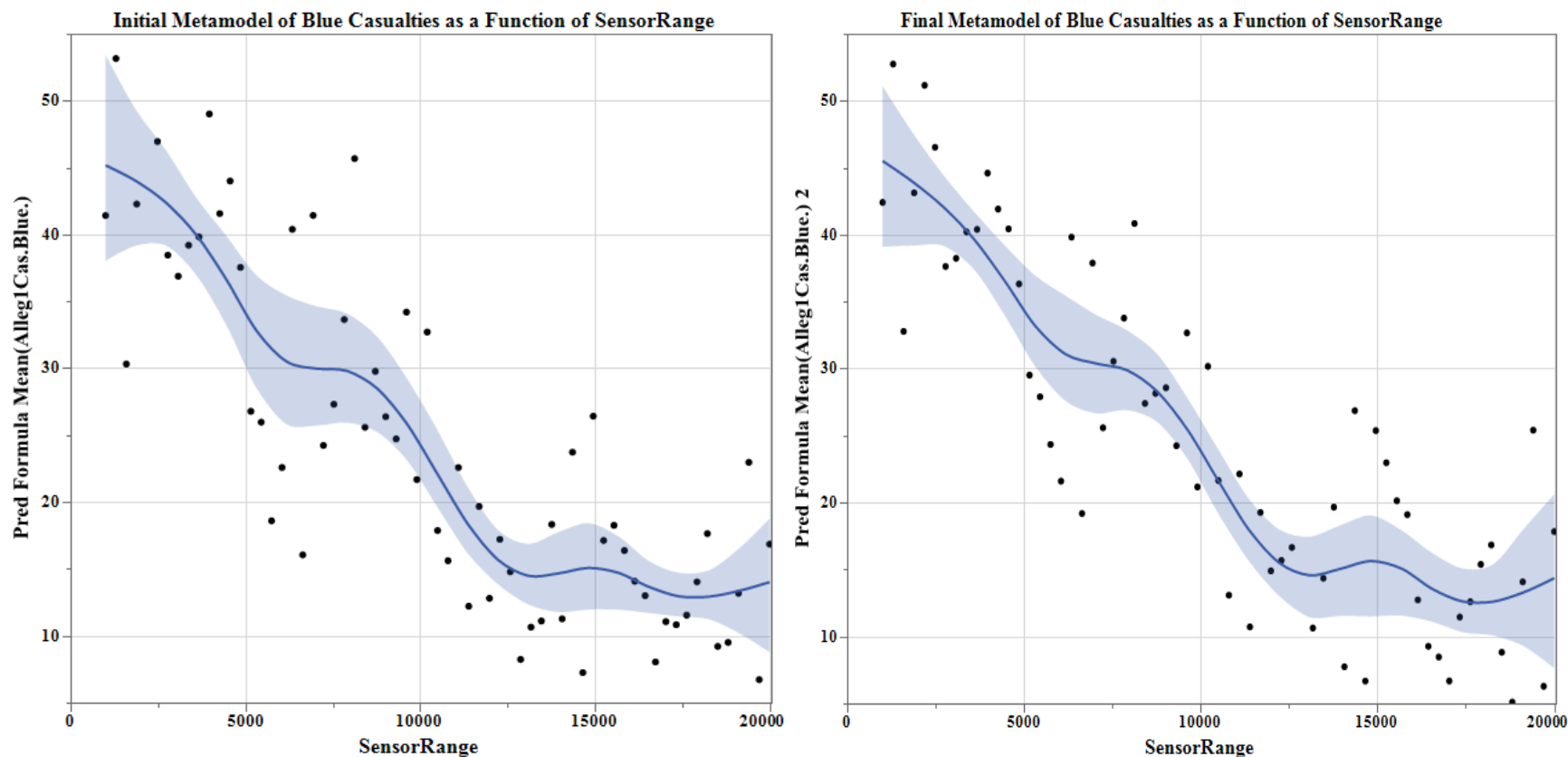


Figure 10. Experiment 2 Blue casualty means for each DP with 95% confidence interval band.

The Figure 10 graph only shows Blue casualties as a function of SensorRange however. The blue shaded region represents a 95% bootstrap confidence interval for each SensorRange value. These results correspond with the overwhelming weight our partition tree placed on this factor. This does not include the regression metamodel we used in Section E.4. We bring these elements together in a side-by-side comparison in Figure 11.



The left plot incorporates all terms from our first metamodel included in Figure 7, while the right plot shows the refined results using only the most significant terms.

Figure 11. Smoothed predictions versus Sensor Range of initial and final metamodels of expected Blue casualties for Experiment 2.

When we compare the single-factor graph of Figure 10 and the two metamodel plots in Figure 11, the similarities between the three are strikingly apparent. All three show the expected Blue casualties to decrease below 20 (25%) between a SensorRange of 10,500m and 12,000m. This is not affected by the inclusion or exclusion of other terms. For Experiment 2, we determine that SensorRange dominates any other single factor or interaction of factors in determining the expected quantity of Blue casualties.

The next step in our exploration is to refine the underlying computer model and reassess our input factors. By doing so, we ensure we are accurately representing an operational scenario and answering the root question—what UAS capabilities most impact the supported warfighter?

F. EXPERIMENT 3: CREDIBLE AND TACTICALLY RELEVANT MODEL

All computer-based M&S tools fall short of completely capturing the complexities of human conflict. However, this model represents our best, and what we believe to be a credible, approximation of operational results between peer-level adversaries engaged in an amphibious assault against a well-defended shoreline and the defense thereof. Along with improving the realism of the adversarial interactions and as alluded to in the Chapter II ConOps, we improve Blue-to-Blue agent interactions to more accurately reflect human dynamics in combat.

With Experiment 3, we explore the survivability, lethality, and potential for massing in our UAS systems. In addition to addressing these critical UAS capabilities, we refine cueing of CAS platforms by the UAS. When not appropriately tasked, CAS agents are now more capable of operating under their own cognizance to detect, identify, and destroy enemy forces. Further, a CAS asset that has been previously vectored towards a target now continues to prosecute the target under their own targeting power unless a higher priority target is independently classified and communicated. This modification seeks to remove confounding impacts caused by improperly modeled “dumb” aircraft not indicative of the skills and capabilities of Marine aviators. These, and sundry other refinements combine to make the following a worthy and informative model

1. Factors

In Experiment 3, we model for the first time a UAS that can be targeted by Red IADS. This is a necessary and realistic consideration as the U.S. and its potential adversaries wrestle with the challenges of counter-UAS (C-UAS) technology. While we acknowledge a UAS’s vulnerability, we also recognize its lethality by arming it with AGM-114 Hellfire missiles. Lastly, we examine the impact of multiple UASs operating simultaneously.

Table 5. Decision Factors for Experiment 3

Experiment 3 Factors				
Factor	Min	Max	Unit	Type
<i>NumUAS</i>	1	6	<i>UAS</i>	<i>Discrete</i>
<i>NumHellfire</i>	0	4	<i>Hellfire</i>	<i>Discrete</i>
OverheadSpeed	20	150	knot	Continuous
SensorRng	1000	20000	meter	Continuous
AvgTimeBetDet	5	300	second	Continuous
SurvDegrade	5	30	percent	Continuous

Further details of the Experiment 3 factors are as follows:

- *NumUAS*: We sample the number of active UASs in Experiment 3 (at the beginning of a simulation) with one to six independent UASs. The maximum of six systems is based on the full operational capability designated for current Marine Unmanned Aerial Vehicle Squadrons (VMUs) in the Marine Aviation Plan (AvPlan) (Rudder 2018). We particularly emphasize the independent quality of these systems. The benefits we see with increased numbers reflect the impact of an uncoordinated effect. This distinguishes from Major Gulosh’s recent thesis in which he explored types and techniques of “swarming” UASs (Gulosh 2018). By contrast in our model, it is possible for multiple UASs to operate in a single portion of a patrol zone and leave other areas uncovered. A coordinated effort could potentially identify other findings.

- *NumHellfire*: We use the Hellfire air-to-ground missile as a logical UAS asset—it has been successfully employed from UASs since 2001. While different Hellfire variants are available and in use, we incorporate the same missile as the AH-1Z Cobra agents. We incremented by twos from zero to four missiles to achieve a balanced airframe for launch and recovery. We do not address other potential airframe design considerations.
- *SurvDegrade*: We use this factor to capture differing degrees of aircraft stealth, or the how much survivability is degraded. All UASs in Experiment 3 start with a baseline undetectability of 100%; they cannot be seen by Red agents. While C-UAS TTPs present real challenges due to UAS’s often-small size and low radar cross-section, this is overly optimistic, particularly for larger armed UASs. We originally looked at tying a stealth penalty to being weaponized; both carrying and firing missiles typically increases aircraft visibility. However, this led to unintended factor correlation. Instead, we continue our system-agnostic approach to UAS capabilities and define a 5–30% survivability degradation to include in our DoE factorization. This means that no UAS is fully stealthy and we can assess stealth’s impact on the model independently from other factors.
- *Pclass* is omitted from Experiment 3. Following Experiment 2, we reassessed that in a reasonable tactical scenario, the probability of classifying an enemy is more a combination of other factors (i.e., enemy undetectability, range, atmospheric, etc.) than a unique capability of the UAS sensor. We opted to remove this factor to focus on those quantifiable attributes we can more reasonably control.
- *OverheadSpeed*, *SensorRange*, and *AvgTimeBetDet*: We keep these factors the same as in Experiment 2.

These three additions and one omission leave us with two discrete and four continuous decision factors for Experiment 3. We initially take a full factorial of the discrete levels giving us a very manageable, but hardly space-filling, 18 DPs. We then stack and rotate the four continuous factors three times for a total of 49 unique DPs using the NOLH template developed in the NPS Simulation Experiment & Efficient Designs Center (Sanchez 2011, SEED Center for Data Farming 2019). We cross these two sets of DPs together for a total of 882 unique DPs filling the space across the potential decision factor levels as shown in Figure 12. Finally, we run each of these 882 DPs 200 times with randomly generated (in MANA) simulation seeds to generate a total of 176,400 simulated amphibious assaults.

In the upper portion of Figure 12, we see an intuitive table quantifying the near-orthogonality of the efficiently designed experiment; each pair-wise correlation for our chosen factors is effectively equal to zero. Simultaneously, the available decision space is verifiably well-filled, as shown in the lower portion of Figure 12. We note that the rows and columns of points in subplots involving NumUAS and NumHellfire are only a reflection of the discrete nature of these two factors.

We move forward in our analysis, confident that we are thoroughly exploring our decision space.

Correlations

	numUAS	numHellfire	OverheadSpeed	SensorRng	AvgTimeBetDet	SurvDegrade
numUAS	1.0000	-0.0000	0.0000	-0.0000	-0.0000	-0.0000
numHellfire	-0.0000	1.0000	-0.0000	0.0000	0.0000	0.0000
OverheadSpeed	0.0000	-0.0000	1.0000	0.0008	0.0010	-0.0037
SensorRng	-0.0000	0.0000	0.0008	1.0000	0.0003	-0.0063
AvgTimeBetDet	-0.0000	0.0000	0.0010	0.0003	1.0000	-0.0034
SurvDegrade	-0.0000	0.0000	-0.0037	-0.0063	-0.0034	1.0000

The correlations are estimated by Row-wise method.

Univariate Simple Statistics

Column	N	DF	Mean	Std Dev	Sum	Minimum	Maximum
numUAS	176400	176,399	3.5000	1.7078	617,400	1.0000	6.0000
numHellfire	176400	176,399	2.0000	1.6330	352,800	0.0000	4.0000
OverheadSpeed	176400	176,399	85.0612	40.6707	1.5e+7	20.0000	150.000
SensorRng	176400	176,399	10500.2	5935.09	1.85e+9	1000.00	20000.0
AvgTimeBetDet	176400	176,399	152.510	92.2179	2.69e+7	5.0000	300.000
SurvDegrade	176400	176,399	17.5102	7.7463	3088800	5.0000	30.0000

Note: Statistics were calculated for each column independently without regard for missing values in other columns.

Scatterplot Matrix

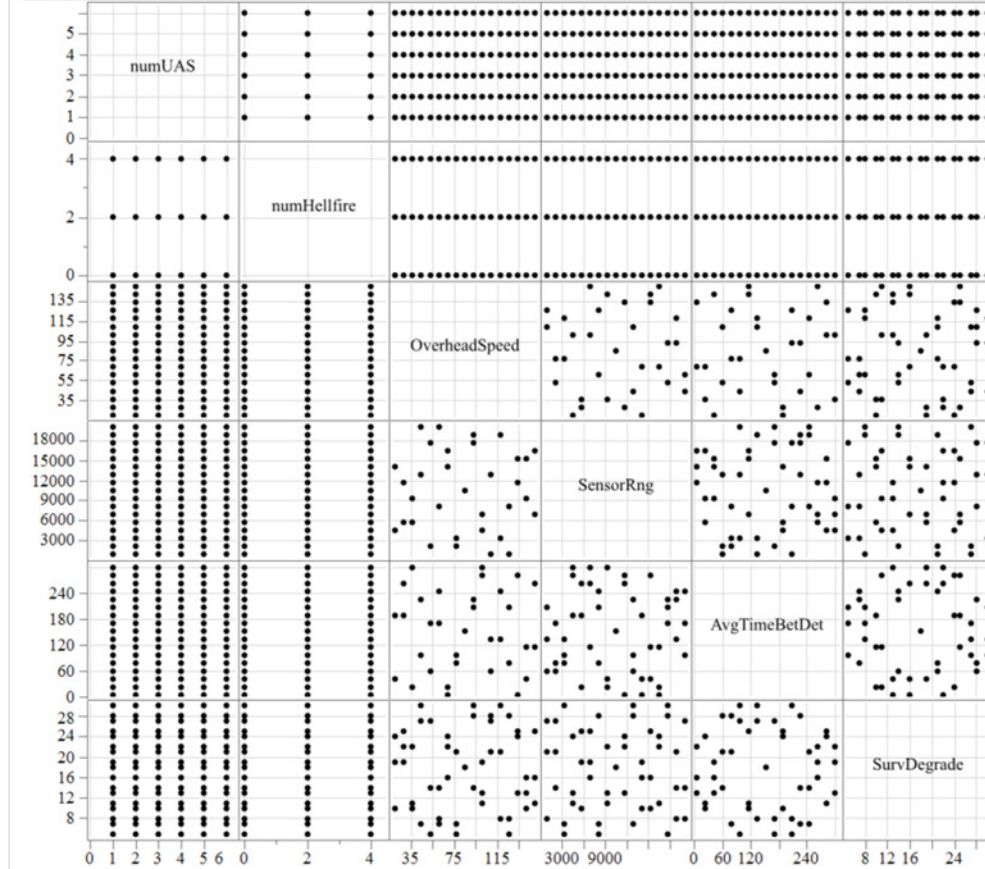


Figure 12. Correlation and space-filling behavior of NOLH for Experiment 3 decision factors.

2. Output

We begin our Experiment 3 output analysis with an examination of the five significant MoEs described in Section C of Chapter III. For this final experiment, we explore the distributions of both the MoE means and their standard deviations. These outputs are shown in Figure 13.

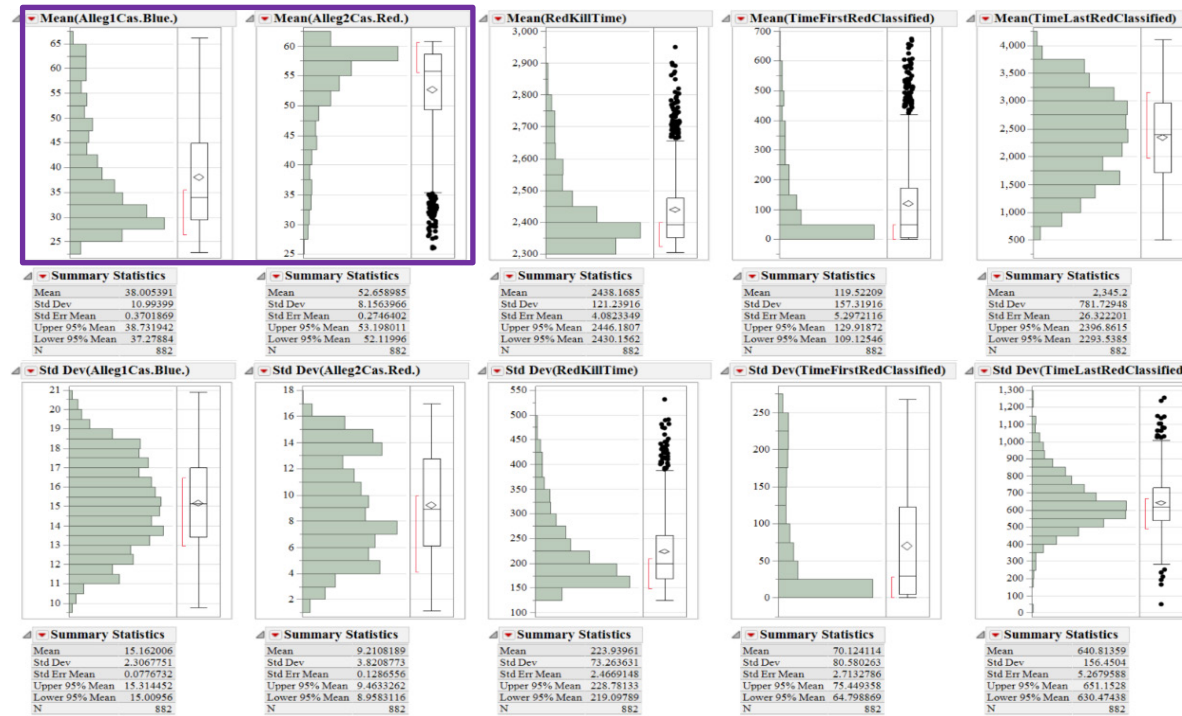


Figure 13. Experiment 3 mean (upper row) and standard deviation (bottom row) output including histograms and summary statistics for five MoEs.

We note that the histograms in the purple outlined portion indicate near-identical distributions of Blue and Red casualties as found in the Experiment 2 non-aggregated results shown in Figure 5. This continues to make sense as we still expect Blue to win (and Red to lose) most of the time.

The relationships between MoE response values are also of interest to us. In Figure 14, we show the correlation between Experiment 3 outputs. In the upper table of figures, we use blue and red numbers to indicate positive and negative correlations, respectively. This is visually evident in the near linear distribution of most of the scatterplots in the lower portion of Figure 14. Even the smallest absolute value of correlation coefficient is 0.784 (circled in green). This still represents a highly relevant correlation, in this case between TimeFirstRedClassified and TimeLastRedClassified.

For our most important MoEs, Blue and Red casualties, there is a near perfect negative correlation of -0.972 (circled in pink). All subplots exhibit essentially monotonic relationships in desirable directions; lower blue casualties are associated with better outcomes for the other MoEs (higher Red casualties but lower kill times and classification times).

	Mean(Alleg1Cas.Blue.)	Mean(Alleg2Cas.Red.)	Mean(RedKillTime)	Mean(TimeFirstRedClassified)	Mean(TimeLastRedClassified)
Mean(Alleg1Cas.Blue.)	1.0000	-0.972	0.9620	0.9243	0.8821
Mean(Alleg2Cas.Red.)	-0.972	1.0000	-0.981	-0.918	-0.836
Mean(RedKillTime)	0.9620	-0.981	1.0000	0.9380	0.8049
Mean(TimeFirstRedClassified)	0.9243	-0.918	0.9380	1.0000	0.7842
Mean(TimeLastRedClassified)	0.8821	-0.836	0.8049	0.7842	1.0000

The correlations are estimated by Row-wise method.

Column	N	DF	Mean	Std Dev	Sum	Minimum	Maximum
Mean(Alleg1Cas.Blue.)	882	881.00	38.0054	10.9940	33520.76	22.7950	66.1900
Mean(Alleg2Cas.Red.)	882	881.00	52.6590	8.1564	46445.22	25.9500	60.7650
Mean(RedKillTime)	882	881.00	2438.17	121.239	2150465	2304.71	2950.18
Mean(TimeFirstRedClassified)	882	881.00	119.522	157.319	105418.5	1.0000	674.675
Mean(TimeLastRedClassified)	882	881.00	2345.20	781.729	2068466	510.075	4098.89

Note: Statistics were calculated for each column independently without regard for missing values in other columns.

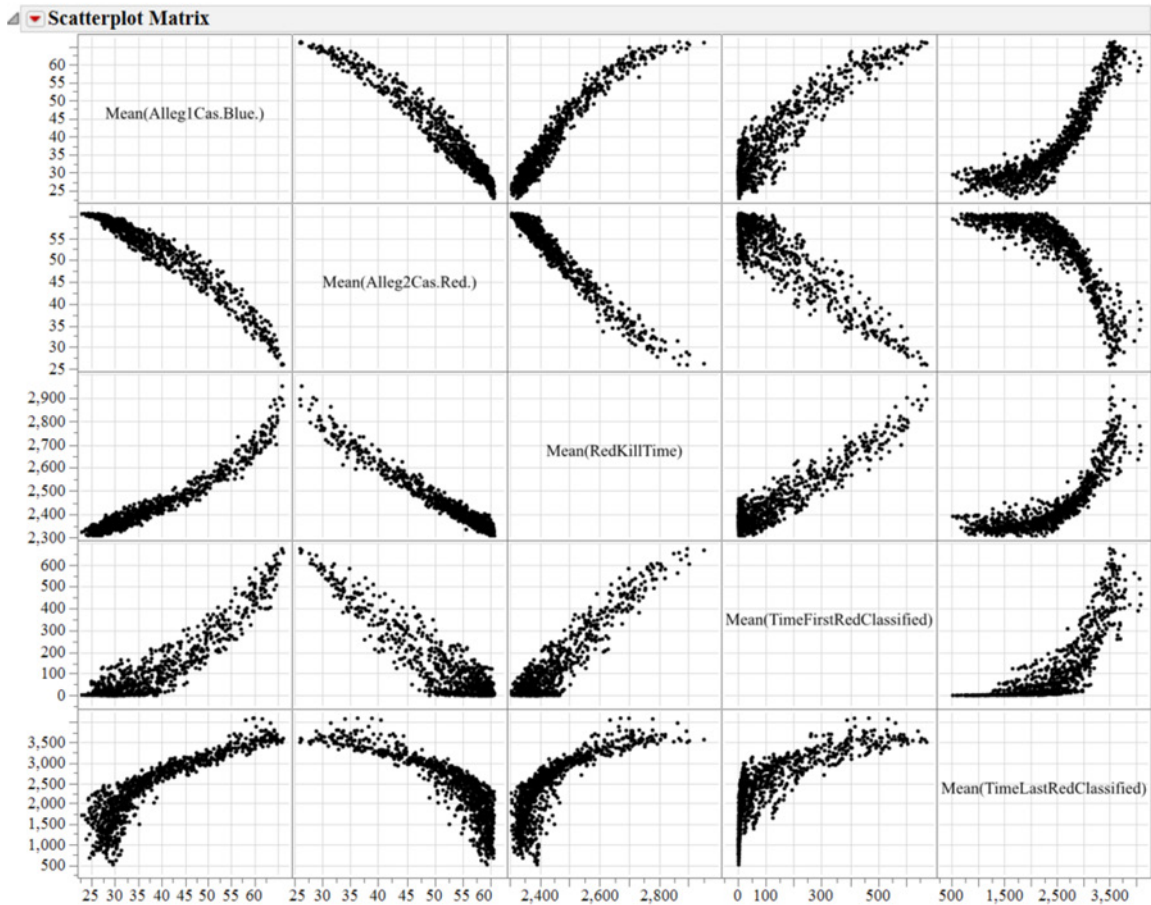


Figure 14. Experiment 3 MoE correlations and pair-wise scatterplots.

Based on the relationships exhibited between MoEs and our primary interest in the effect of UAS capabilities on the supported warfighter, we subsequently use Alleg1Cas.Blue as our sole MoE for subsequent analysis. While not perfectly analogous

with other MoEs and their effects, we deem this a suitable approximation and focuses our efforts where it matters most—saving Marine lives.

3. Robustness

Understanding the raw output of a model is helpful, but is much more so with an added understanding of the degree of robustness built into a model. As we discussed in the preceding two sections, we identify 882 unique DPs in Experiment 3 and generate a random seed for each of these DP's 200 simulations. There is innate variability built into this design because of MANA's DTS architecture, but we do not explicitly vary potential noise factors such as camouflage level, number of Red missiles per launcher, readiness of Red forces, etc.

To develop robustness in Experiment 3, we randomize the exact starting locations for Red agents within a given region. This maintains the overall structure of the operation while addressing a major shortfall of M&S. An example of this is shown in Figure 15.

While these location changes seem small at face value (the largest starting box shown is only approximately 8 NM²), we employ this principle of robust design to limit “model-isms” in which an agent wins (or loses) due to a loophole in the model configuration and not due to a genuine cause-and-effect interaction.



Figure 15. Experiment 3 starting boxes for semi-random Red SAM launcher locations.

4. Regression

We explore the results in Experiment 3 more vigorously than our previous models. We begin in a similar fashion as Experiment 2 using step-wise regression prior to fitting a model. However, we now include up to cubic and three-way interactions between factors. We do so to address the question raised in the Experiment 2 regression analysis regarding the point of negative returns on what would typically be expected to be a positive attribute (i.e., when $\text{SensorRange} > 12,000\text{m}$ and Blue casualties start increasing instead of decreasing). The resulting least squares model attributes are shown in Figure 16.

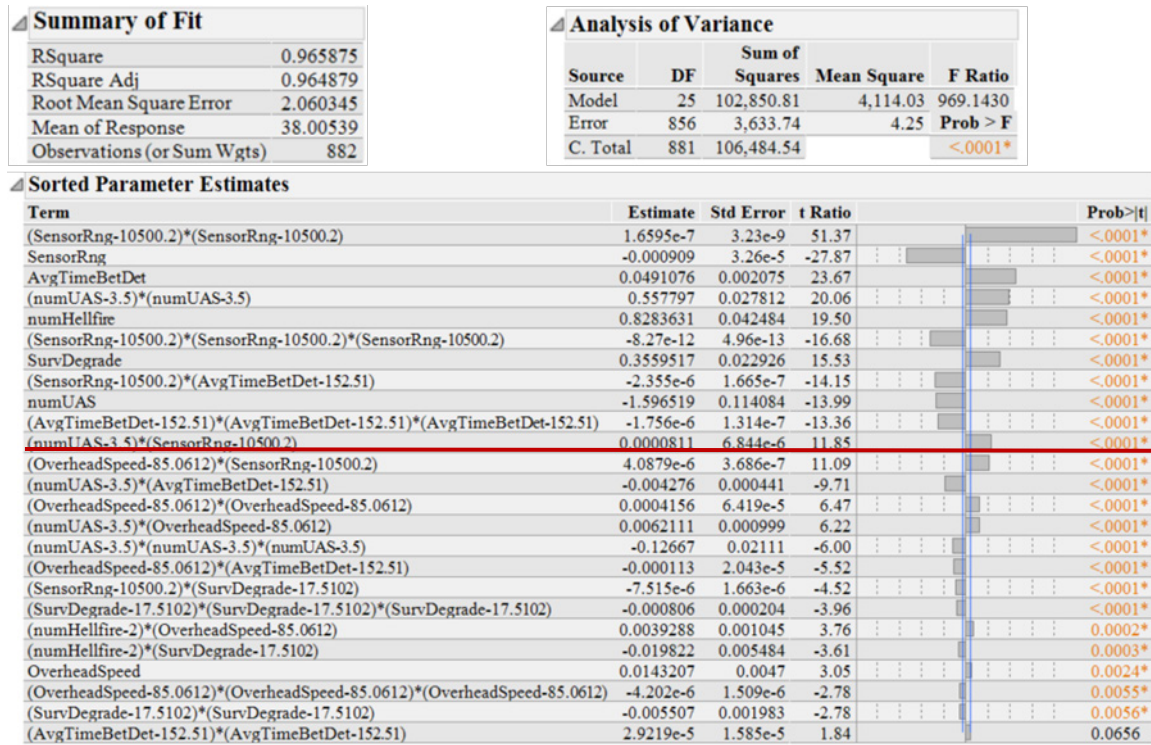


Figure 16. Experiment 3 least squares regression fit, analysis of variance, and parameter estimates of significance for expected Blue casualties.

Out of 53 possible factors and interaction terms, we use 25 and achieve an R-squared of 0.966. As shown in Figure 17, this is a very effective metamodel in predicting Blue casualties within the context of this model.

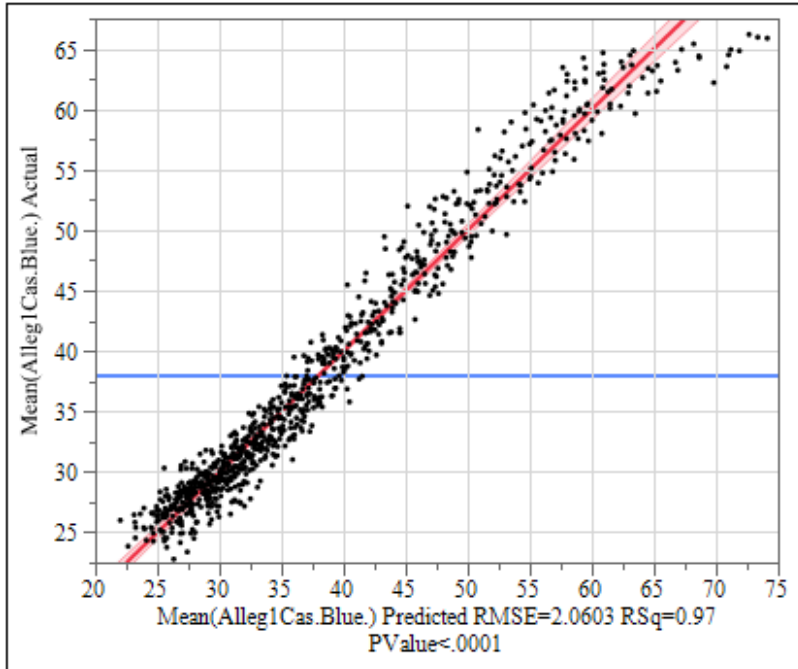


Figure 17. Experiment 3 actual (y-axis) vs. predicted (x-axis) least squares regression plot for expected Blue casualties.

Building on our reinforced confidence in this metamodel, we now explore the interactions between individual factors as shown in Figure 18. In this construct, we can visually appreciate the impact of SensorRange on the expected casualty rate. No other factor approaches the range of expected casualties as that portion outlined in green signifying the influence of SensorRange.

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob> t
(SensorRng-10500.2)*(SensorRng-10500.2)	1.5856e-7	3.201e-9	49.53	<.0001*
numUAS	-2.236203	0.048598	-46.01	<.0001*
AvgTimeBetDet	0.0249009	0.000947	26.29	<.0001*
SurvDegrade	0.2550088	0.010807	23.60	<.0001*
SensorRng	-0.000789	3.759e-5	-20.98	<.0001*
(numUAS-3.5)*(numUAS-3.5)	0.557797	0.033273	16.76	<.0001*
(SensorRng-10500.2)*(SensorRng-10500.2)*(SensorRng-10500.2)	-9.56e-12	5.76e-13	-16.60	<.0001*
numHellfire	0.8283631	0.050825	16.30	<.0001*
(SensorRng-10500.2)*(AvgTimeBetDet-152.51)	-2.48e-6	1.98e-7	-12.52	<.0001*
(OverheadSpeed-85.0612)*(SensorRng-10500.2)	4.6435e-6	4.319e-7	10.75	<.0001*
(numUAS-3.5)*(SensorRng-10500.2)	0.0000811	8.188e-6	9.90	<.0001*
(numUAS-3.5)*(AvgTimeBetDet-152.51)	-0.004276	0.000527	-8.11	<.0001*
(OverheadSpeed-85.0612)*(AvgTimeBetDet-152.51)	-0.000158	2.34e-5	-6.74	<.0001*
(numUAS-3.5)*(OverheadSpeed-85.0612)	0.0062111	0.001195	5.20	<.0001*
(numHellfire-2)*(OverheadSpeed-85.0612)	0.0039429	0.00125	3.16	0.0017*
OverheadSpeed	-0.004162	0.002068	-2.01	0.0445*
(AvgTimeBetDet-152.51)*(AvgTimeBetDet-152.51)	2.0758e-5	1.32e-5	1.57	0.1161

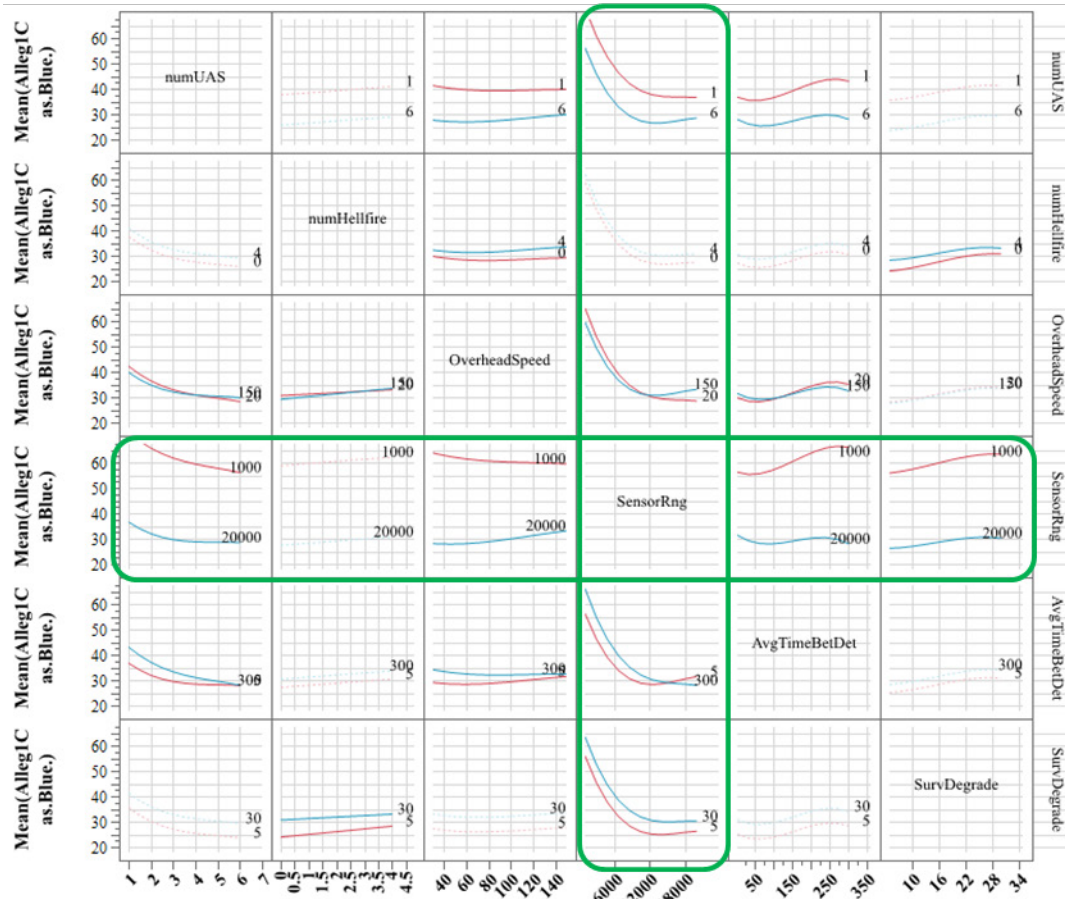


Figure 18. Experiment 3 initial regression metamodel parameter estimates and interaction profiles for expected Blue casualties.

The second-most significant term in our initial metamodel is numUAS. Subsequent terms have notably less impact, but many are still of interest. We explore these with a more focused look in our final metamodel as shown in Figure 19.

Our threshold for subsequent metamodel term selection is denoted by the red line in Figure 18. This line notes those terms with a t -ratio >15.0 . A t -ratio, the parameter estimate divided by its own standard error, is a handy tool for measuring the relative significance of a term (JMP Pro 14.3 2018).

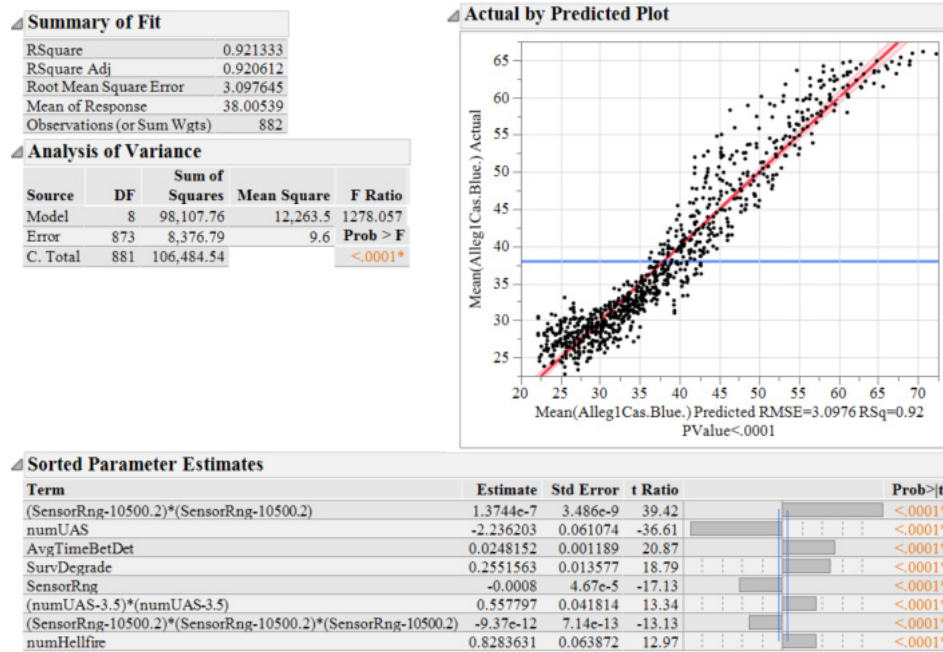
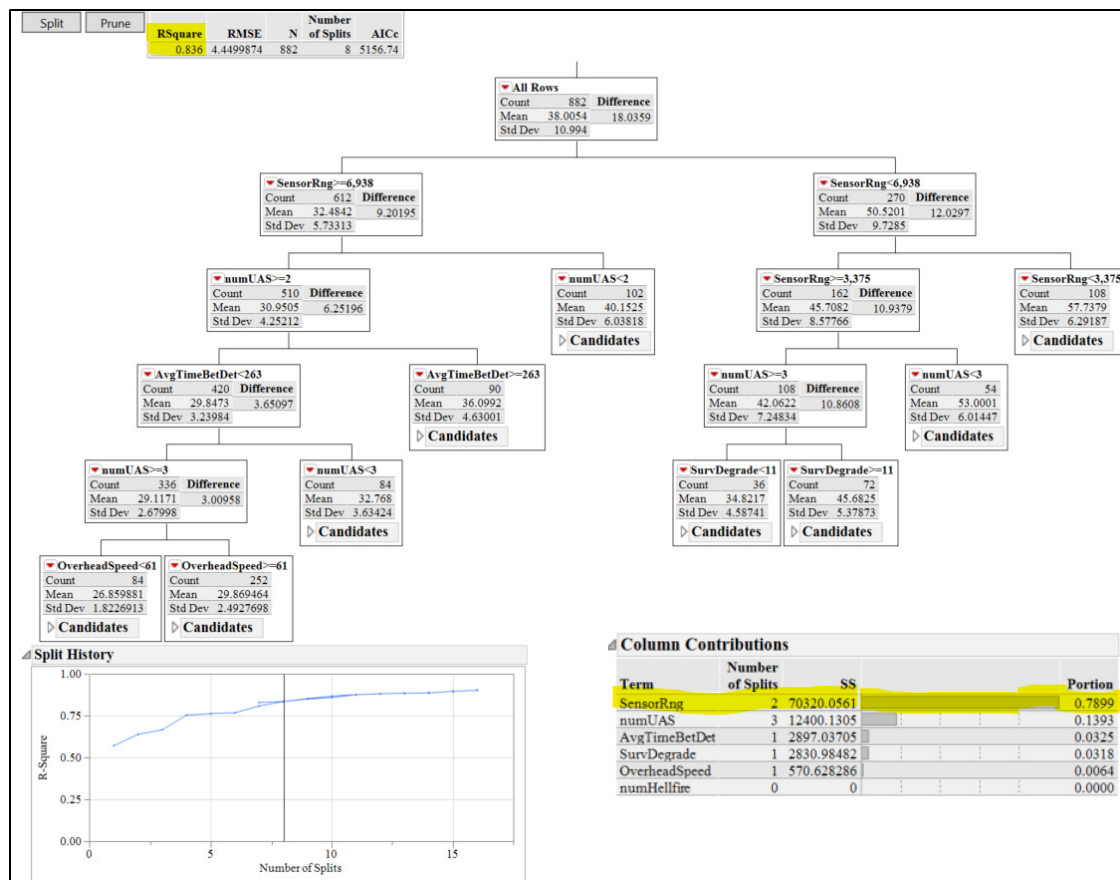


Figure 19. Experiment 3 final metamodel summary for expected Blue casualties.

Our resulting metamodel uses only eight terms and still achieves an R-squared greater than 0.92. This much tidier metamodel gives us a powerful predictive tool for expected number of Blue casualties based on only five of the original six factors.

5. Partition Tree

We continue our analysis to corroborate or disprove our regression findings by applying partition tree methodology to the same decision factors and MoE as our regression analysis. The partition tree and summary results for Blue casualties in Experiment 3 is shown in Figure 20. Even with the improvement of scenario dynamics and refinement of decision factors, we see that SensorRange is still the dominant predictive factor (shown in the bottom highlighted portion).



with split history and column contributions.

The SensorRange that partitions the results in the first split is ~7,000m—a significantly shorter range than that required by the Experiment 2 partition tree (10,500 for a comparable partition). The difference in expected Blue casualties at that sensor threshold is more than 18 Marine deaths and, as we will demonstrate in the subsequent impact analysis, indicative of larger impacts to the overall operation.

Continuing on the left (preferred) branch of the partition tree, the second split demarcates those results using only a single UAS and those with two to six. Again, there is a statistically and practically significant swing of almost ten more predicted casualties with only a single system in operation.

Based on the regression and partition tree findings, we now feel confident that SensorRange is the most powerful factor in our model. NumUAS is also still significant.

We will focus on these factors as we explore the relevance of each as they pertain to the supported warfighter.

6. Impact Analysis

All of the above findings allow us to confidently move forward in our determination of the impact to the warfighter of our chosen UAS capabilities. In other words, how does it matter to the Marine on the ground if a UAS overhead has a powerful camera?

We begin our impact analysis with a contour plot in Figure 21 showing Blue casualties as a factor of both SensorRange and numUAS. This is the raw data outputted from Experiment 3. With this simple color-coding technique, we see that with SensorRange <7,000 (the horizontal dashed line) as indicated by our partition tree, we can expect to lose more than half the Blue force every time. Similarly, even with two UAS, we never reach average Blue casualties <30.

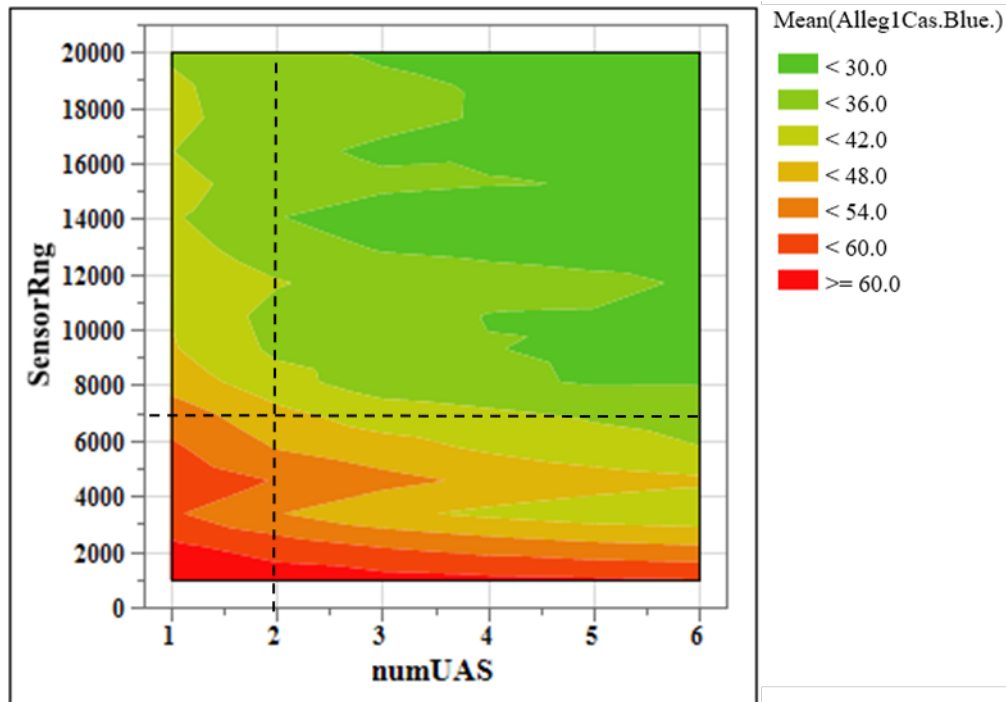
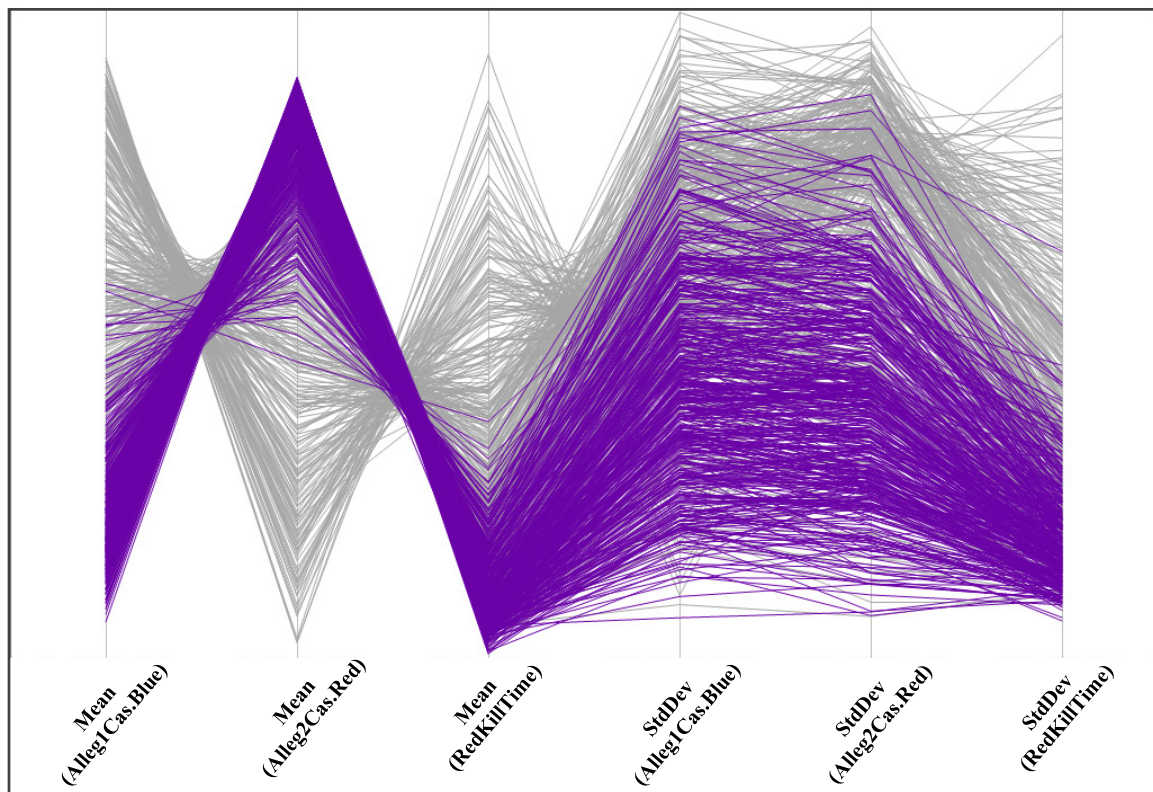


Figure 21. A Contour plot of Experiment 3 Blue casualties using sensor range and the number of UAS.

Figure 21 is a powerful argument for the impact of UAS capabilities on the individual Marine, but what does this mean for the Blue operation as a whole?

We use the parallel plot in Figure 22 to capture the relationships between $\text{SensorRange} \geq 10,500\text{m}$ (purple) and other MoEs. Each line corresponds to the results for one of the 882 DPs, average over replications. We include mean Red casualties, the mean time to kill >50% of Red forces, and the associated standard deviations for these three MoEs on the right half of the figure. RedKillTime is useful as it adds a sense of tempo to our analysis.



The purple lines depict all observations in which UAS sensor range was $\geq 10,500\text{m}$. Grey lines show all other observations.

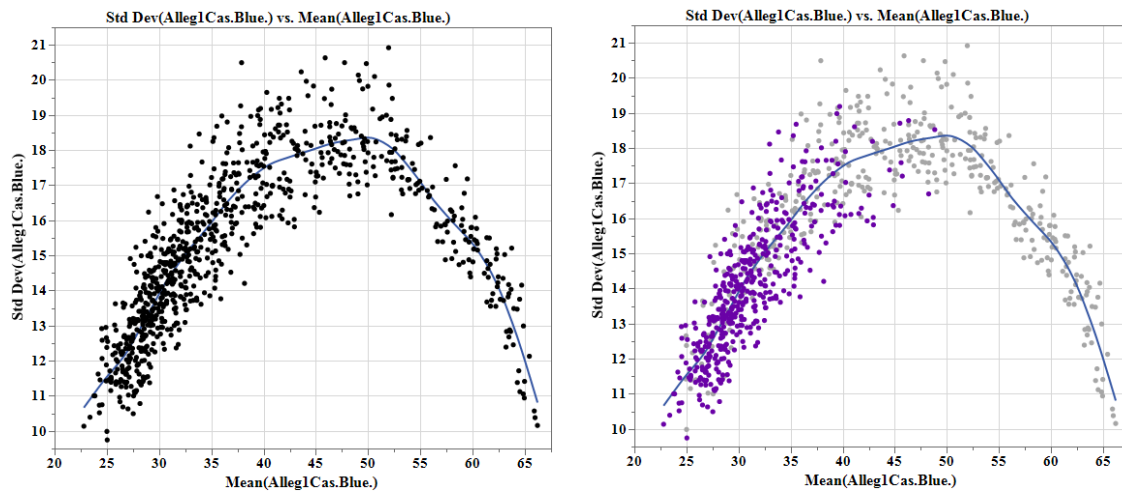
Figure 22. Parallel plot showing relationship between preferred sensor range and significant MoEs.

The parallel plot is a powerful analysis tool that normalizes results based on their low and high values in the data set. This allows us to compare the means of Blue and Red

casualties (ranging from 23 to 66 and 26 to 60, respectively), on the same graphic as the mean of RedKillTime (ranging from 2304 to 2950 secs). The standard deviations are comparably scaled.

As expected, based on the high magnitude of correlation coefficients, response means with the fewest Blue casualties are associated with the most Red casualties and take the least amount of time to accomplish. This makes logical sense as one considers the flow of conflict. There is a tipping point in battle, particularly one modeled as an all-or-nothing fight like this one, at which one side clearly dominates and will continue to dominate. This is partially due to the increasing mass ratio of forces. It also arguably ties to psychological factors, but detailed exploration of these phenomena is outside the scope of this research.

We can see in Figure 22 that, while the means of our MoEs have distinct positive or negative correlative relationships, the standard deviations are less distinct. To get a sense of what this means for our research, we look to the two plots in Figure 23.



The left plot shows all observations equally. The right plot emphasizes all observations in which the sensor range is $\geq 10,500\text{m}$.

Figure 23. Experiment 3 standard deviations vs. means of Blue casualties.

On the left half of Figure 23, we see that when there are fewer Blue casualties (the left side of the x-axis), there is less variability in our response (y-axis). This makes practical and statistical sense. On the other side of the spectrum, standard deviation also tends to be

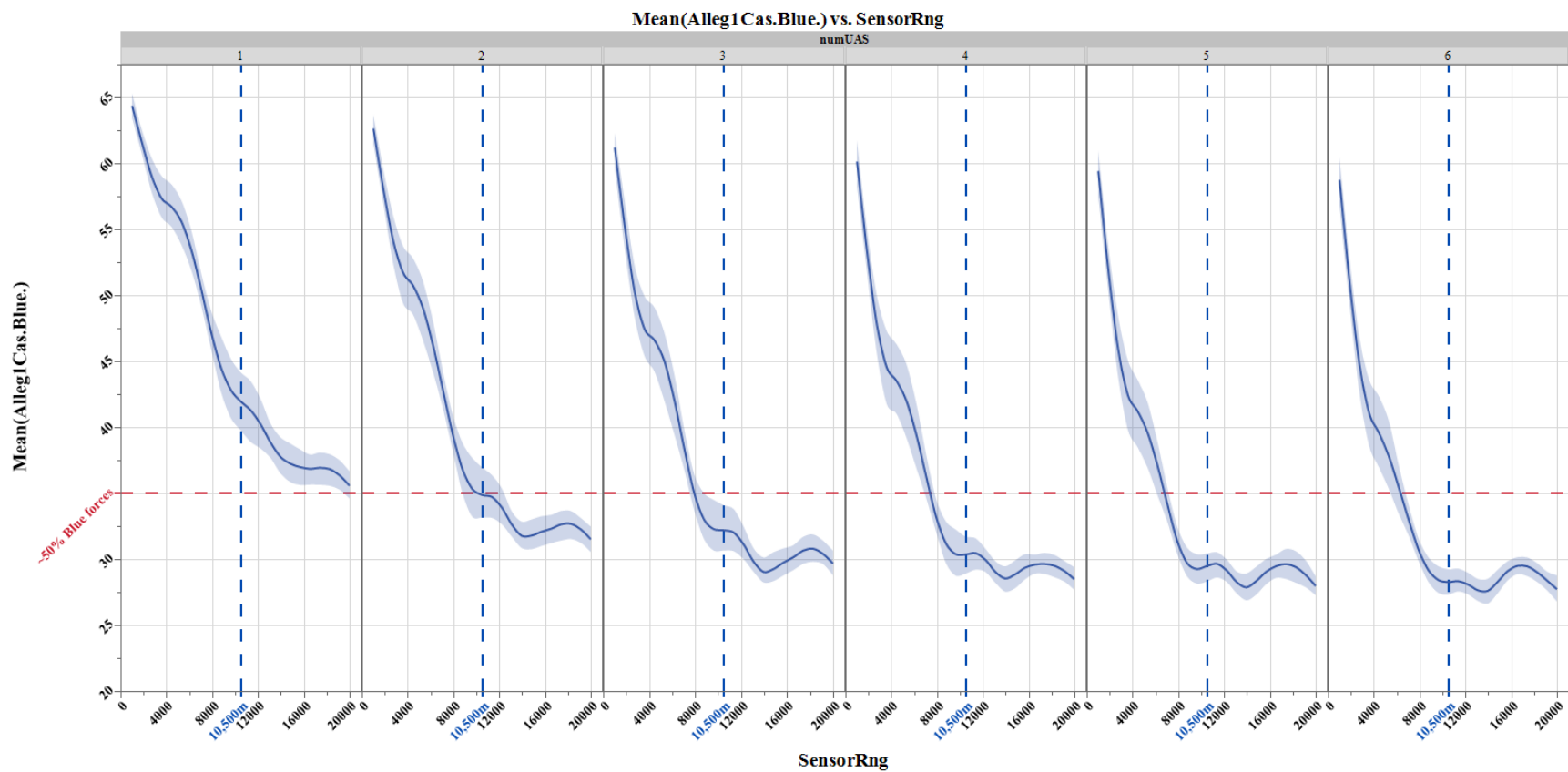
low when Blue has many casualties. These extreme response values reflect battles that go very well or very poorly; there is not a lot of variability in these instances.

The greatest variability we see in Blue casualties is in the middle ranges of the responses. This accounts for challenging battles that could end either way. The mean for these middle DPs is in the 40–50 range, but standard deviations doubled in these tough scenarios as compared to the clear-cut extremes.

The right half of Figure 23 differentiates (in purple) those responses in which SensorRange is $\geq 10,500\text{m}$. While these responses stray into the less clear-cut middle portion of the plot where variability is high, a comparison with Figure 22 confirms that this is as expected. The most noteworthy takeaway from Figures 22 and 23 is that when SensorRange is $\geq 10,500\text{m}$, there are no responses in which Blue casualties are at their worst.

We link SensorRange and numUAS together in Figure 24. Figure 24 gives us a clear snapshot of what it means for Blue forces in Experiment 3 to have increased sensor range and more UAS operating simultaneously. The overall shape in each section of the figure is similar, but the overall curve shifts down and to the left as we look left to right across the plots. Within each plot, we translate this to mean that Blue casualties decreases markedly as SensorRange increases, particularly as it increases above the 10,500m threshold. The significance of the fit line shifting left as numUAS increases is that with more functioning systems, less individual capability is required to achieve the same effect.

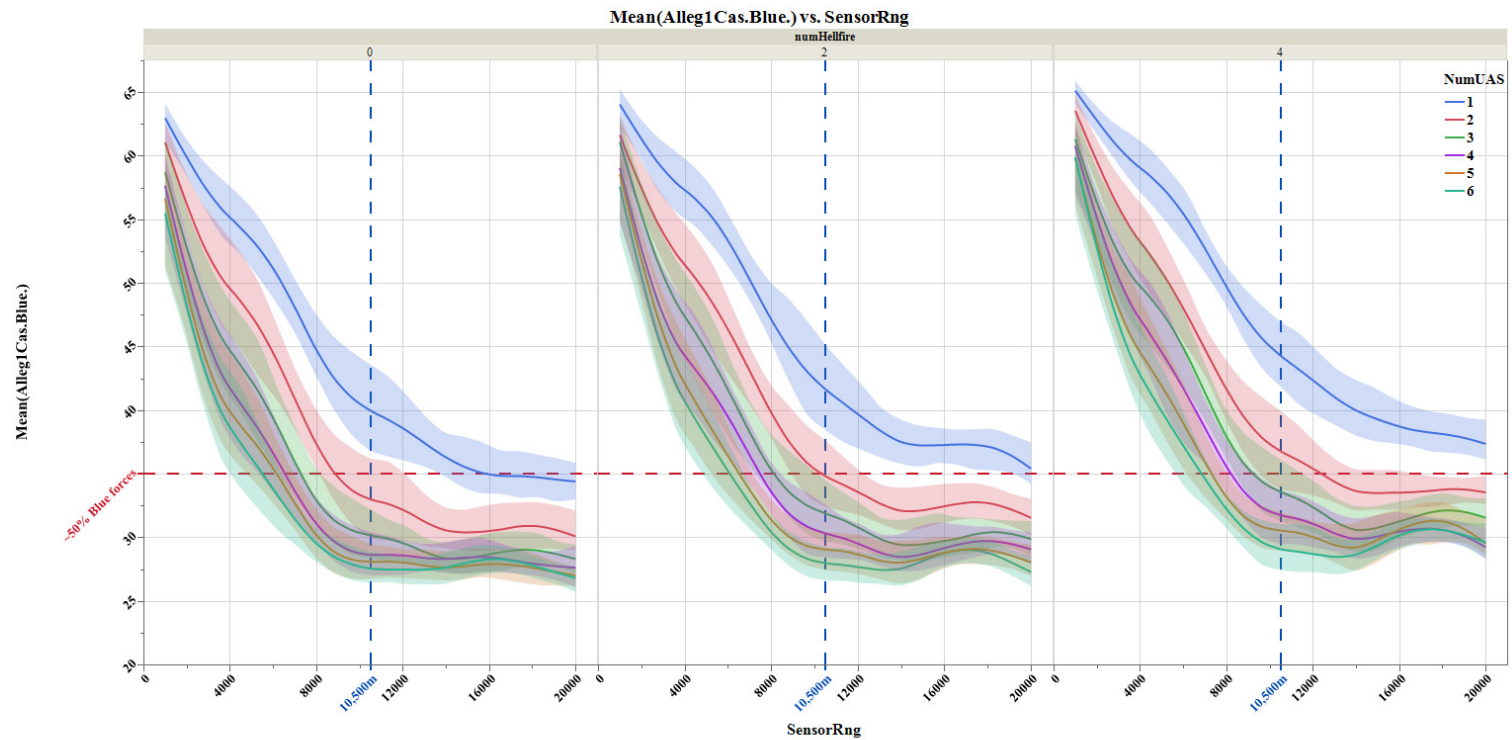
These two takeaways regarding critical UAS quantities and sensor ranges give us the information we started this research to find. These datapoints are essential for anyone exploring UAS system acquisition or TTPs. While all M&S results are predicated upon the assumptions and capabilities built into that individual model's architecture, for our analysis, these results are clear.



These are six individual plots, each of which includes the full spectrum of sensor range, showing the 95% confidence interval for each fit with one to six operational UASs. The dashed blue line in each plot shows the previously identified sensor range threshold while the horizontal red line represents approximately 50% Blue casualties.

Figure 24. Expected Blue casualties as a function of sensor range for different quantities of operational UASs.

As a final comparison for consideration in future USMC UAS acquisition and utilization, we look to Figure 25.



Each third of Figure 25 shows the same spread of sensor ranges, but with zero, two, or four Hellfire missiles included in the UASs' capabilities as we read from left to right. The shaded regions correspond to the 95% bootstrap confidence interval for each quantity of UASs used.

Figure 25. A consolidated look of Blue casualties across all sensor ranges and quantities of UASs for each UAS armament configuration.

In Figure 25, we consider all the same information as above, but also include a popular desired capability for future UASs, the ability to fire their own weapons. As with the Figure 24 plots, the same general shape of fit line is visible across all configurations in Figure 25 and, within each third of the figure, improves as expected. What is starkly and critically different is that instead of these fit lines shifting down and left as the UAS becomes more capable, the fit line actually moves up and to the right as the UASs' armament increases; this corroborates the final regression metamodel we explore in Chapter III, Section F.4, Regression.

This degradation of support by a weaponized UAS to the Marine on the ground is counter-intuitive to most common thinking and flies in the face of direction from the MOC and AvPlan. Both these guiding documents speak repeatedly about the intent and importance of well-armed future UASs, usually in the form of the multi-role MUX system. Based on this research, Marines will be better served by many UASs with powerful sensors than one or two super-UASs.

7. Discussion

Our findings in Experiment 3 paint a clear picture based on the scenario and inputs used. However, these should not be construed as universally definitive. Just as this research was built on the work Chapter I, Section C, Literature Review, there are a host of ways to build on, adapt, and refine this research.

As UAS technology and the Marine Corps' utilization of this technology continues to evolve, so too should our understanding of these evolve. We model an amphibious assault against a peer-level adversary and feel confident in our findings, but we would very likely identify different findings if we model a COIN operation in a land-locked jungle. The inclusion of altitude factors, enemy aviation agents, or an active EW threat would also drastically alter the model. This research represents a single step in understanding the interconnected relationships between Marine warfighting capability, the tools available, and the challenges we face. It also serves as a template for applying data farming methods to conduct a structured, model-based assessment of new capabilities.

IV. CONCLUSIONS AND RECOMMENDATIONS

A. CONCLUSIONS

U.S. Marines are the Nation's expeditionary force-in-readiness, the Service called when crises strike around the world. The motivation for this research is our desire to ensure Marines are equipped with and enabled by the best possible systems to continue to be. While UAS technology and the global operational environment evolve at an ever-increasing pace, it is the focus of our will, the warfighting tenacity, and the unbreakable spirit of Marines that will ensure we are feared wherever we go. This research exists to ensure that Marines have the right gear to answer our Nation's call.

We approach this challenge knowing that there are uncountable factors in determining what matters to a warfighter in combat, but that if we realistically identify the most critical, it could be of great value. We use advanced DoE and computer modeling techniques to portray an operation near synonymous with the title "Marine," an amphibious assault against a well-defended enemy shoreline. Using an increasingly focused series of experiments, we use realistic assumptions of current and developing technologies to model the impacts of differing UAS capabilities on the survivability of supported Marines.

Over the course of almost 180,000 simulated amphibious assaults, we determine that increasing UAS sensor range and increasing the quantity of UASs employed in an operation is more significant in keeping Marines alive and accomplishing their mission than any other explored factors. We determine that a UAS with a sensor range capable of detecting and identifying enemies at a range of 10,500m or more is impactful in increasing the expected survival rate of Marines the UAS exists to support. We also find that when more than one UAS is used simultaneously in an operation, the expected number of Marine casualties is significantly less.

The critical threshold values we identify for SensorRange and numUAS are specific to this research. The fundamental takeaway of this research is clear however; employing multiple UASs with high-quality sensors can directly translate to operational success for Marine expeditionary forces.

B. RECOMMENDATIONS

1. Marine Corps

As we move forward and continue to refine the Marine Corps' role in the scope of great power competition, we must remember the Commandant's direction in the MOC, "to leverage the full capabilities of the MEF to support Naval maneuver and Combined/Joint operations, reinvigorate our emphasis on maneuver warfare, and integrate information warfare into our combined arms approach" (Neller 2017). While the MOC, and the AvPlan derived from it, emphasize some UAS capabilities this research finds to be nonessential, there does not need to be a contradiction. Future UAS decision-making should focus on the supported warfighter; their success is what allows us, as a Corps, to achieve what the nation expects of its expeditionary force in readiness: We determine the following as critical steps to achieve the best possible support to those Marines.

Explore beyond the bounds of the newest, most impressive piece of gear available from industry. The Marine Corps is famously known for doing more with less. There is a balance to be found in equipping our Marines with the best possible gear while still maintaining the resilient mindset that allows Marines to overcome no matter the situation.

Continue to expand the use of M&S experiments to inform and enhance the Marine Corps manned-unmanned team concept. There will likely not be a single solution, such as the MUX, that fills all requirements or desired roles.

Build upon this type of research to focus acquisition strategies and employment doctrine, not on what makes the Marine Corps *appear* to be a more capable force, but on what best enables individual Marines in the accomplishment of their assigned tasks. It is at that level that the Marine Corps has always distinguished itself and where we should continue to focus our efforts.

Continue to explicitly refine and focus the Marine Corps' role in the execution of our support to Naval operations and the Joint fight. This clarity of intent allows research such as this to better identify impactful capabilities and TTPs for all Marines and Marine missions.

2. Future Research

In this thesis, we develop the most realistic and operationally credible M&S tool we were able within time and resource constraints, but there is always room for improvement. The following activities would expand and generalize our findings.

Assess the robustness of this model by incorporating additional factors into the data farming experiment. This could be done by varying some of the Red or Blue characteristics that were fixed for this study or exploring the relationship between step size and the results of the model as-is. While we believe the time step used is valid, independent corroboration would either reinforce or refine our findings, or potentially uncover any errors we may have incorporated inadvertently.

Update this model to explore in more detail the effects of altitude and ground speed on sensor efficacy. As so many of our findings are based on sensor range, determining more refined relationships between these controllable factors would only enhance any subsequent recommendations.

Blend this work with swarm concepts, such as modeling coordinated ISR efforts for multiple UASs. Assigning specific overlapping sectors or incorporating different UAS platforms across phases of an operation may illuminate new relationships and significant findings.

Expand the range and accuracy of decision factors and unit capabilities to ensure there is not a critical threshold we missed in this work. While factor ranges were selected based on existing systems and reasonable assumptions of future technology, there may be an unexplored tipping point for one or more factors that would alter these findings.

Model the JSF agents as more-capable agents in a similar scenario. F-35 advocates would likely assert that we modeled these developing assets in an overly conservative manner. The future Marine Corps will almost assuredly continue to incorporate both JSFs and UASs. To best do so, both should be understood and modeled as realistically as possible.

C. SUMMARY

Marine warfighting doctrine is built on the concepts of integrated fire and maneuver in which all components of a MAGTF coordinate efforts to achieve unity of effort. Typically, this translates to the ACE providing fires, ISR, and mobility to the GCE as it accomplishes our assigned mission.

In this study, we determined that multiple UASs with long-range sensors are more effective at supporting this concept than other configurations. Multiple UASs, each able to detect and identify enemies at long ranges and operating simultaneously, best ensures Marine survival and facilitates MAGTF mission accomplishment in a challenging expeditionary environment.

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