A THREAT-BASED LEAST-COST PATH DECISION SUPPORT MODEL FOR NATIONAL SECURITY RESOURCE ALLOCATION ALONG THE US-MEXICO BORDER

by

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DEDICATION

I dedicate this thesis to my family for their unwavering support, my country for the opportunity to contribute and my God for his blessings.

ACKNOWLEDGMENTS

I will be forever grateful to my mentor, Denise Bleakly, whose inspiration and support has revealed the wonders of geographic information science. To my family, for their sacrifice in indulging my pursuit of knowledge; and my employer, whose trust and investment has made this pursuit possible.

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LIST OF ABBREVIATIONS

ATV	All-Terrain Vehicle
BPA	Border Patrol Agent
CBP	Customs and Border Protection
DEM	Digital Elevation Model
DEPO	Design and Evaluation Process Outline
EASI	Estimate of Adversary Sequence Interruption
GEOINT	Geospatial Intelligence
GIS	Geographic Information System
IBC	Illegal Border Crosser(s)
KDE	Kernel Density Estimate
LCP	Least Cost Path
MRLC	Multi-Resolution Land Characteristics Consortium
OBP	Office of the Border Patrol
NED	National Elevation Dataset
NHD	National Hydrography Dataset
NLCD	National Land Cover Dataset
PPS	Physical Protection System
SME	Subject-Matter Expert
UAV	Unmanned Aerial Vehicle
USBP	United States Border patrol
USGS	United States Geological Survey
UTM	Universal Transverse Mercator

ABSTRACT

The U.S. Office of the Border Patrol defends the nation at its borders from unauthorized entry and terrorist incursion through the strategic application of detection, delay and response resources in variable terrain. Compounding their task, the expansive geography of the border region, along with a constrained budget, necessitate the allocation of resources to areas of greatest concern based upon a perceived threat that varies both spatially and temporally. The purpose of this research is to demonstrate a flexible geospatial decision support model that incorporates human and geographic variables identified through intelligence collection to define a threat and predict human route selection along a path of adversary least cost. Leveraging historical research into the characteristics and motivational factors of illegal border crossers, this research models a hypothetical terrorist threat to predict a route from a location near the U.S.-Mexico border to a predetermined location within the U.S. The model utilizes cost-weighted rasters representing postulated threat-based factors contributing to human route selection. The results of the model are intended to serve as a demonstration-of-concept to aid in defense resource allocation along the U.S.-Mexico border. It is anticipated that the results of this research will demonstrate a novel geospatial approach toward resource allocation through the synergy of intelligence information and spatial analysis techniques to yield likely transnational adversary routes.

CHAPTER ONE: INTRODUCTION

Since September 11, 2001, the United States federal government has struggled to shore up security along the porous US-Mexico/Canada national borders in an effort to protect the citizenry and national interests against transnational criminal and terrorist activities (Kalacska 2009). The U.S. Border Patrol is charged with the daunting task of securing the vast regions between ports of entry, which are often remote, rugged and variable in ownership, terrain, environment and weather (Williams 2009). The aforementioned challenges have served as enablers to drug couriers, weapon smugglers, foreign terrorists, fugitives and a plethora of other criminal activities that threaten our national security. An approach to accomplish the USBP mission suggests the application of contemporary fixed-site physical security theory, which necessitates a means of detecting, delaying and responding to unauthorized entry, which in turn requires the systematic application of technology, infrastructure and personnel (Garcia 2008). This research proposes the use of the Least-Cost Path (LCP) methodology to aid the United States Border Patrol (USBP) with the tactical allocation of resources (technology, infrastructure and personnel) along the U.S.-Mexico border region by demonstrating a proof-of-concept methodology for predicting adversary paths of least resistance and threat avoidance.

Background

According to the U.S. Customs and Border Protection (CBP) agency website, the CBP mission is to serve as guardians to our nation's borders against terrorists and their weapons of terror. The CBP Snapshot (U.S. Customs and Border Protection 2014) states that, on any given day, the CBP maintains employment of 21,650 CBP officers, 20,979 Border Patrol agents, 766 Air Interdiction agents, 116 Aviation Enforcement officers, 343 Marine Interdiction agents, more than 1,500 canine teams and 250 horse patrols. In that day's work, they identify approximately 137 people who pose national security concerns, apprehend 1,153 persons between ports of entry and arrest 22 wanted criminals at our nation's ports of entry. Research of available data by the START Consortium (Smarick and LaFre 2012,) has identified 221 terrorism-related border crossing events by 264 border crossers at 22 ports of entry with associations to at least 12 known terrorist organizations and the demographics of which are outlined in Table 1.

Table 1 Demographics of Known Terrorism-Related Border Crossers

DEMOGRAPHICS OF BORDER CROSSERS INDICTED ON TERRORISM CHARGES
• Mean age at time of crossing = 31 years old
• 86.6% of crossers were male
• Average (mode) highest level of education = high-school diploma (33%)
• 82% were married at time of crossing
• 11% known to have been previously arrested in U.S.
• 11.1% known to have been previously arrested abroad

Source: National Consortium for the Study of Terrorism and Response to Terrorism (Smarick and LaFre 2012)

The data suggest that the threat posed by transnational terrorist organizations is real and given the limited resources, variable terrain and variable interdiction-potential along the 5,525 mi. U.S.-Canada, 1,989 mi. U.S.-Mexico and 95,000 mi. maritime borders, the CBP mission is formidable.

With an increasing annual budget since 1990, the latest CBP figures report approximately $3.5B allocated to the Border Patrol program whose function is to detect, apprehend and deter terrorists attempting illegal entry into the U.S. Even with this sizable budget, the variable geographic expanse of the border makes it impossible for the OBP to patrol and monitor the entire border, thereby posing the question of how human and technological resources are to be effectively deployed (Predd et al. 2012). In 2012, the Border Patrol published the 2012-2016

Border Patrol Strategic Plan which outlined their strategy for transitioning from a resource-based approach to a risk-based approach to border security (Schroeder 2014). This new approach required the implementation of standardized risk assessment methodologies, increased interagency cooperation and a flexible method to adapt to the threat in its many forms. National border security strategy can be approached through the implementation of contemporary physical protection system (PPS) methodologies where a balance is achieved between system objectives, resource availability and a means of assessing system performance. Figure 1 demonstrates an example of a systematic approach toward the design and evaluation process of a physical protection system, from objective determination to system design and analysis (Garcia 2008, 370).

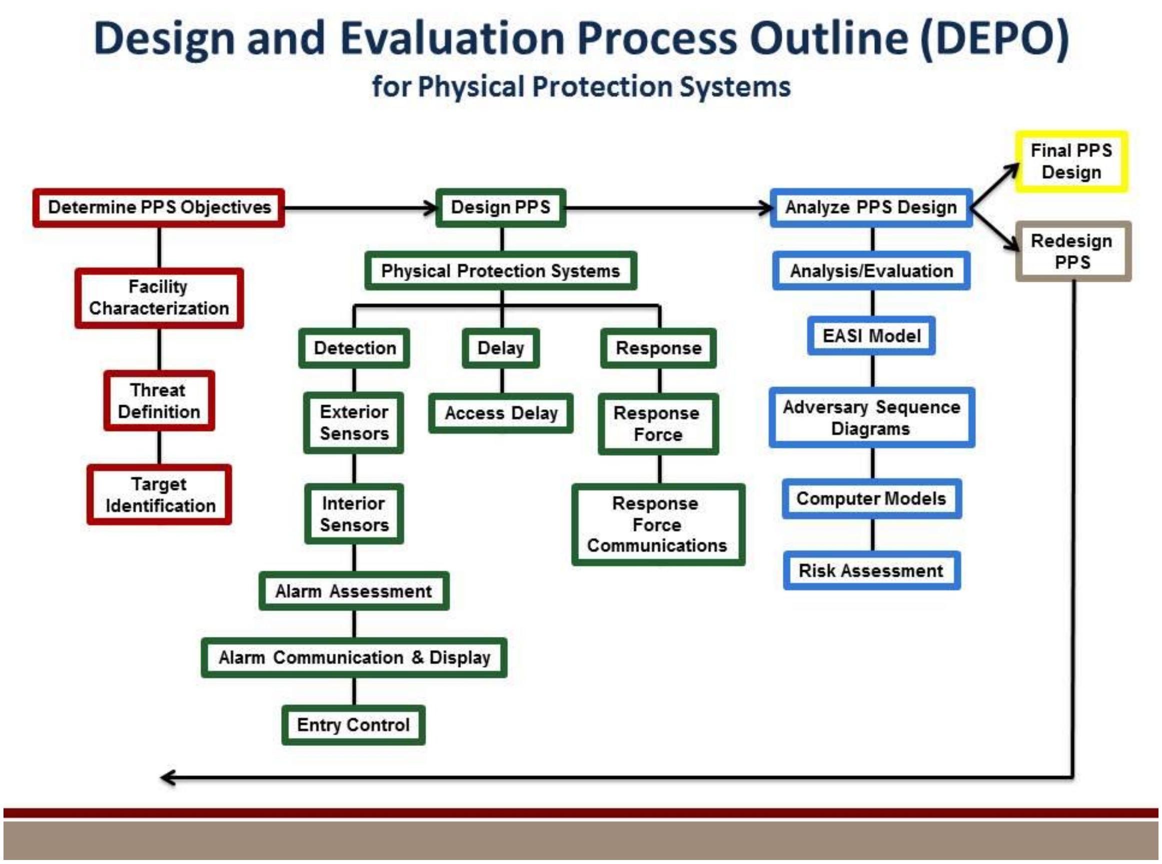

Figure 1 Design and Evaluation Process Outline (DEPO) for Physical Protection Systems (PPS) *(Garcia 2008)*

The aforementioned process, developed by Sandia National Laboratories, provides a means of determining PPS objectives through the characterization of the threat and the environments they operate in. With this process in mind, physical security should be designed with clear objectives aimed at designing a system to effectively address a specific threat in physical and human geographic space.

For this research, the system objective is postulated to be the design of an integrated security system aimed at mitigating the threat posed by a highly-skilled terrorist who is attempting dismounted entry into the U.S. from Mexico, while minimizing detection potential and energy expenditure. From the determination of a threat-parameterized likely path, resources can be geographically allocated through a repeatable, data-driven methodology, which maximizes its effectiveness in those areas deemed most vulnerable.

CHAPTER TWO: RELATED WORK

Research into the driving factors of illegal transnational migration have exposed a multitude of human motivations, either pushing or pulling them through geographic space (Gathmann 2008), but few have explored the factors that contribute to route selection under these circumstances. Failed attempts at surreptitious entry have prompted interactions with law enforcement, who have opportunities to collect valuable intelligence into the motivation and contributing/inhibiting factors to illegal border crosser (IBC) migration. When exploited and analyzed spatiotemporally, imagery and geospatial information evolve into geospatial intelligence (GEOINT), which characterizes natural and human geographic features and activities upon the Earth (National Geospatial-Intelligence Agency). The military have long relied upon this type of intelligence, along with other complementary forms, to visualize spatiotemporal patterns and base decisions (Camez Meillon 2008). The following research examples demonstrate the type of information that, when geographically referenced and processed in a geographic information system (GIS), can generate GEOINT in support of resource allocation.

Research Correlating Geography to Apprehensions

Rossmo et al. (2008) investigated the geographic enablers and inhibitors to IBCs in an effort to determine the features contributing to cross-border movement and enhance border security through resource allocation optimization. Their findings suggest that IBCs adapt to natural geographic and physical security changes in their environment by identifying gaps in the security system and exploiting them in their favor. To address this problem, the authors conducted a GIS analysis, which investigated geographic and human patterns to illegal migration based upon the volume of interdictions made by the USBP within the Border Patrol's Del Rio

Sector along the Texas-Mexico border. Their approach explored human features (transportation networks, legitimate ports of entry, urban development and population density) and geographic features (terrain, hydrography, vegetation, soil, temperature, precipitation and natural region) as independent variables, while geocoded land border crossing locations served as the dependent variable. Exploration of the apprehension data within the spatial and temporal study area provided a threat profile of the typical IBC as being 1) male (90.9%), 2) adult (89.7%), 3) and single (64.6%). The most active months for illegal border crossings independent of motivation was the span between January to May while the months of January, May and September showed increased criminally motivated crossings by post apprehension determination and suggested an unresolved cyclic temporal pattern. The authors identified that the majority of illegal migration occurs between Thursday and Sunday with two peak times of day, the first being between 10:00 am and 2:00 pm, and the second between 8:00 pm and 10:00 pm. Spatial analysis of the data identified the presence of spatial clustering of IBC activity, especially with those associated with criminal activity. Figure 2 depicts the relative distribution of all illegal apprehensions using graduated symbology, while Figure 3 depicts only those apprehensions associated with criminal intent. Figure 4 depicts a 3D isometric perspective of the study area topography overlaid by the spatial occurrence and magnitude of apprehensions geocoded by mile marker.

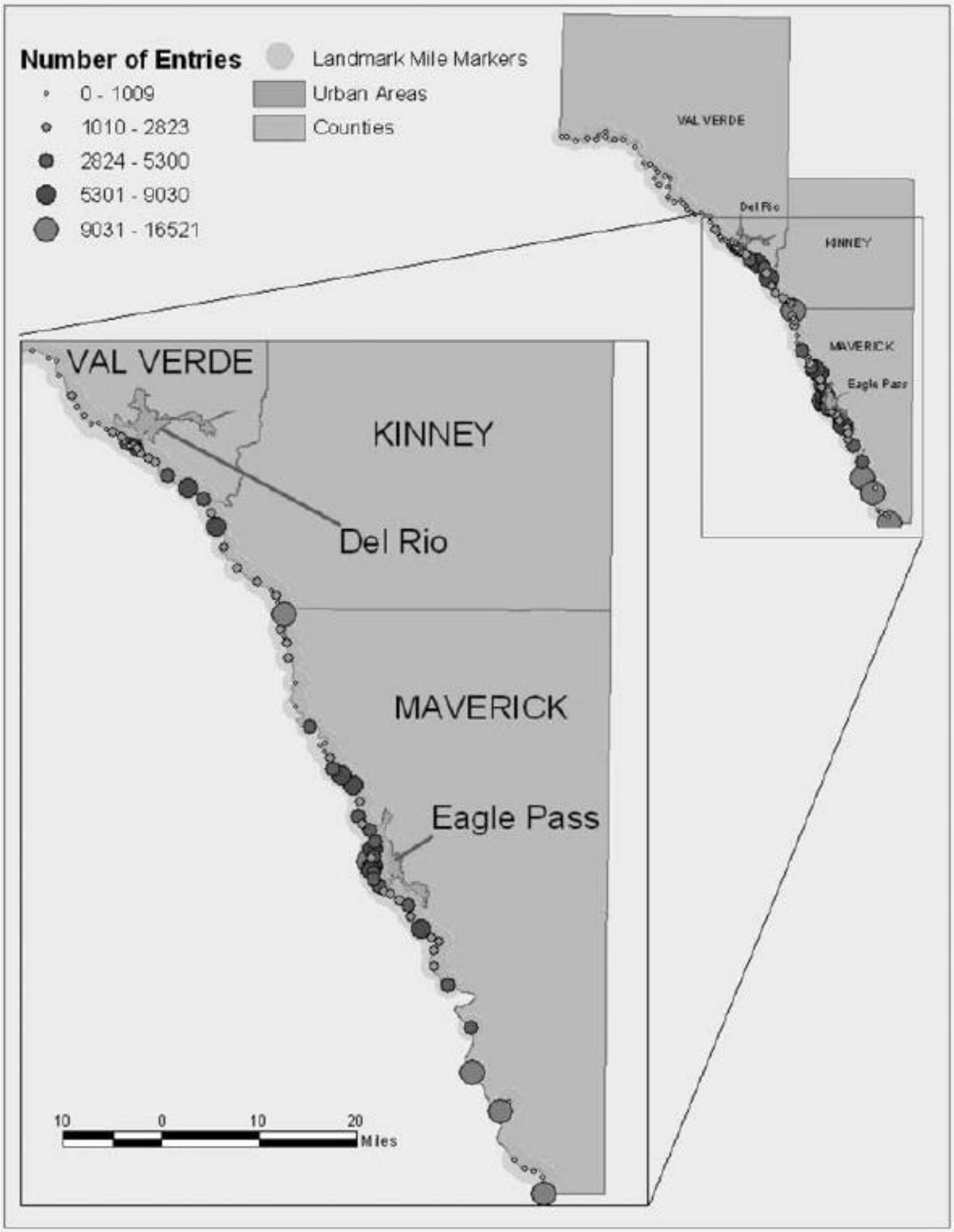

Figure 2 Map of all illegal entries in the study area (from Rossmo et al. 2008)

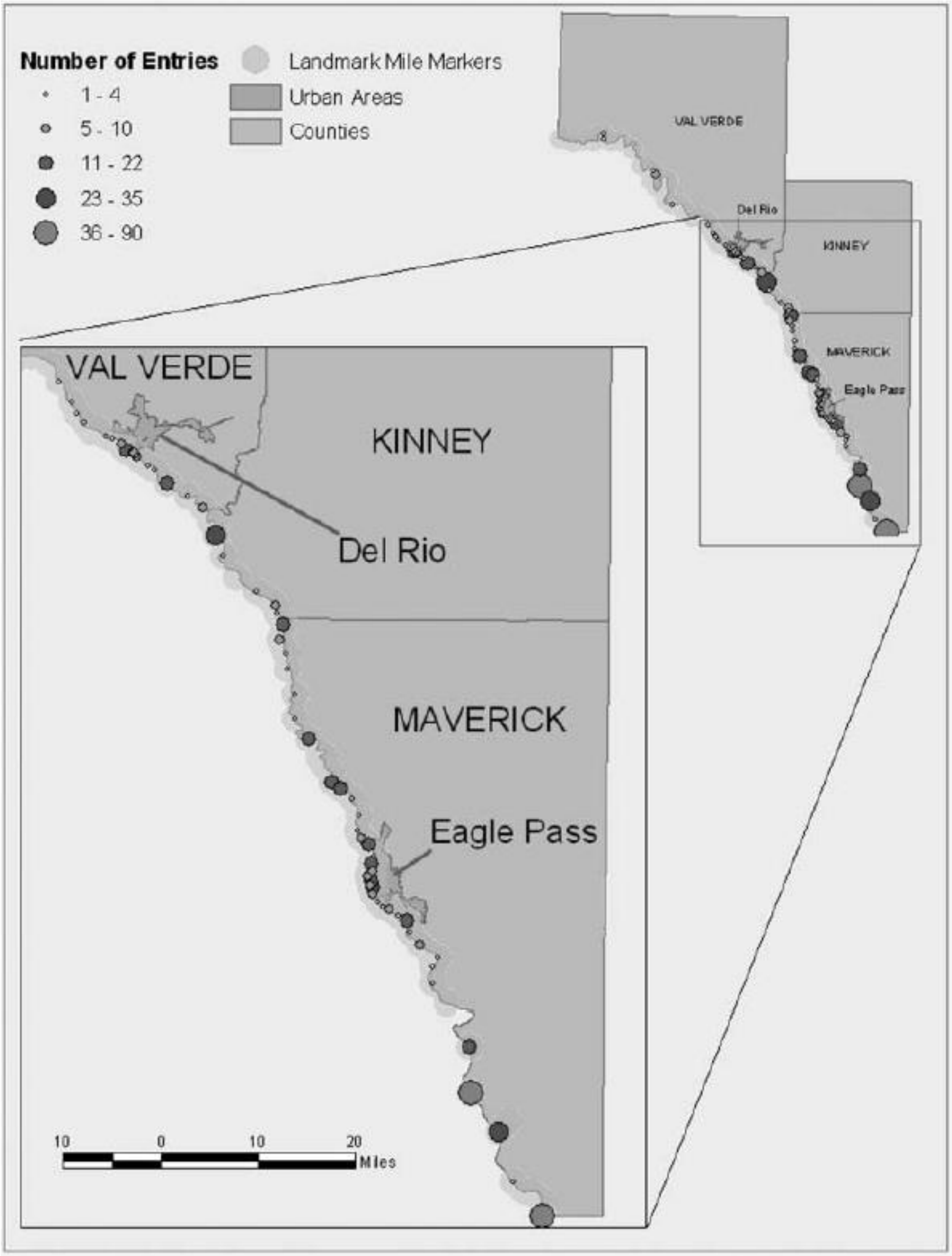

Figure 3 Map of criminal entries in the study area (from Rossmo et al. 2008)

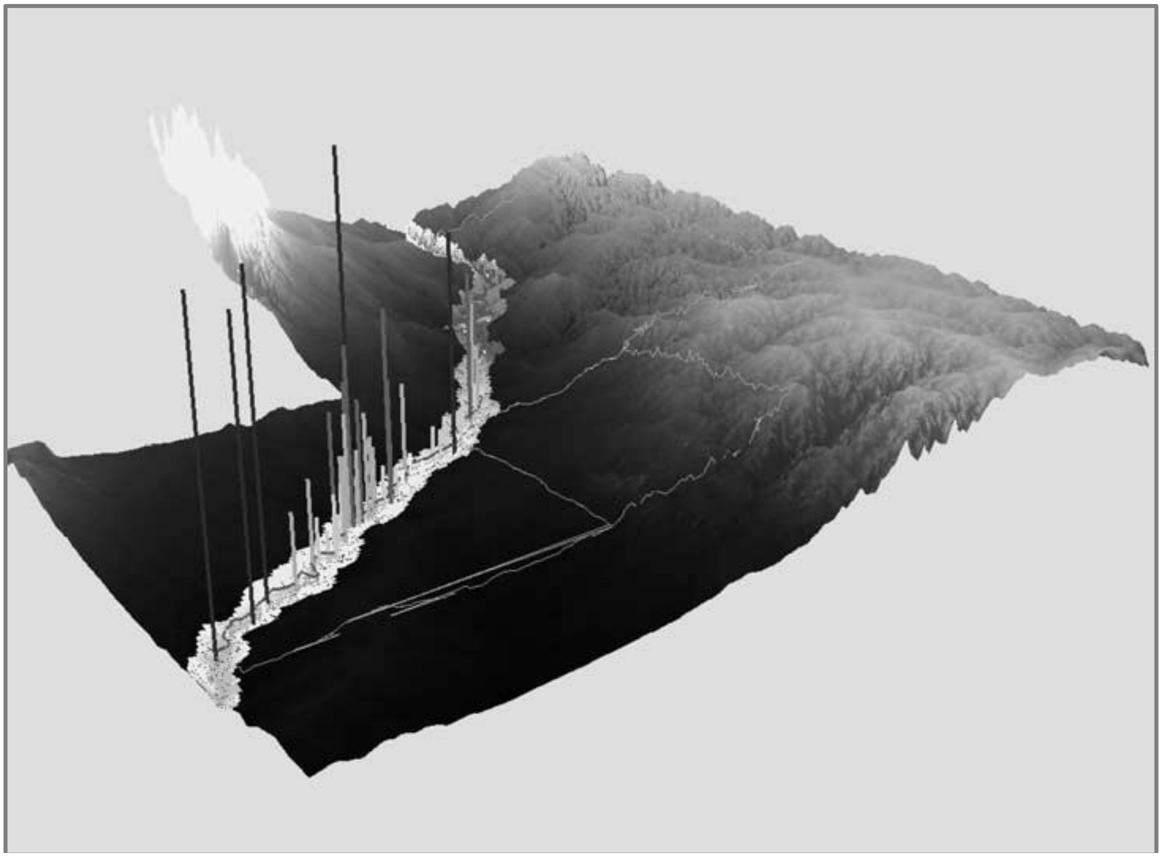

Figure 4 Magnitude of illegal border crossings and the physical topography (from Rossmo et al. 2008)

Pearson correlation coefficients (r) were used to explore statistical relationships between IBC spatial occurrence and the aforementioned independent variables which identified IBC geographic preference factors by travel segment. Those segments were identified as:

- Origin (in Mexico)
- Waiting location (in Mexico near the border)
- Staging area in Mexico
- Staging (south bank of the Rio Grande)
- River crossing
- Landing point (north bank of the Rio Grande)
- Intermittent destination (in Texas), and

- Final destination (in the U.S.)

Each segment contained different, but correlated, contributing factors to IBC selection along their route toward migration into the U.S. Proximity of Mexican urban areas to the border proved significant in the IBC selection process as did proximity to natural bridges over barriers like the Rio Grande, while well patrolled man-made bridges served as a deterrent. Other hydrologic features like streams and small rivers demonstrated a correlation based upon the risk associated with those features. For example, turbulent and fast flowing streams increased risk, while intermittent streams served as an attractive walking path. Similarly, correlation was observed with proximity to other features like railroad spur lines and rural highways although patterns for the criminally disposed cases suggested some aversion to features like railroad main lines and paved county roads. Tables 2 and 3 demonstrate the results of the Pearson's correlation measurements determining the strength of each respective variable's association to migration.

Table 2 Correlations for all IBC entries – Del Rio Sector, Texas

Variable	*r*	*P*
Distance to Closest Large Flowing River	0.503	0.000
Distance to Closest Railroad Spur Line	-0.467	0.000
Distance to Closest Flowing Streams and Small Rivers	0.417	0.000
Distance to Closest Intermittent Stream	-0.394	0.000
Distance to Closest Mexico Urban Area	-0.367	0.000
Distance to Closest Rio Grande Natural Bridge	-0.345	0.000
Distance to Closest Urban Area	-0.259	0.006
Distance to Closest Rural Highway	-0.244	0.010
Distance to Closest City Street	-0.238	0.012
Distance to Closest Medium Flowing River	0.213	0.025

Source: (Rossmo et al. 2008)

Table 3 Correlations for criminal disposition IBC entries – Del Rio Sector, Texas

Variable	*r*	*P*
Distance to Closest Large Flowing River	0.379	0.000
Distance to Closest Flowing Streams and Small Rivers	0.372	0.000
Distance to Closest Railroad Main Line	0.361	0.000
Distance to Closest Medium Flowing River	0.276	0.003
Distance to Closest Intermittent Stream	-0.274	0.004
Distance to Closest Paved County Road	0.263	0.005
Distance to Closest Railroad Spur Line	-0.225	0.018
Distance to Closest Mexico Urban Area	-0.202	0.034

Source: (Rossmo et al. 2008)

In addition, the Border Patrol subject matter experts (SMEs) indicated that the presence of key geographic features like vegetation and arroyos served IBCs as a means of concealment from visual detection, while the latter provides natural pathways to ascend the riverbank on the north side. Similarly, elevated positions south of the border provide IBCs with observation points to monitor patrol movement in the U.S. and plan their movement across the border during periods of reduced OBP presence. To investigate this factor further, Rossmo et al. compared the result of a viewshed analysis with apprehension locations, where they found positive correlation suggesting that IBCs tend to minimize visual detection potential during migration.

The work pioneered by Rossmo et al. demonstrates that valuable intelligence can be gleaned from independent observations, investigated for statistical correlation among variables and used as a tool to counter illegal migration through directed countermeasure implementation. It is also of specific relevance to this research to note that geographic features had significant influence on route selection by threat type and the importance of this variable in route forecasting. Consideration should be given to the fact, however, that this study represents results from unsuccessful crossing attempts while those that were successful go unrepresented in the observations. In order to effectively mitigate the IBCs successfully entering the U.S., we must first gain an understanding of the factors that make them successful at exploiting the porous and most vulnerable areas along the border.

Survey-Based Intelligence for Threat Profiling

In their technical report, *Reasons and Resolve to Cross the Line: A Post-Apprehension Survey of Unauthorized Immigrants along the U.S.-Mexico Border*, (Grimes et al. 2013,) reported on a 2012 initiative by the Center for Border Security and Immigration (BORDERS) to interview 1,000 detainees to ascertain IBC characteristics, border crossing attempts (past and present) and their reasons for crossing. The survey consisted of 38 questions administered to apprehended IBC suspects during the summer of 2012 in the Tucson Sector of the U.S. Border Patrol. The findings of the survey that are specifically applicable to the development of a notional threat profile for this research are identified in Table 4.

Table 4 Summary of Research-Applicable Interview Responses (n=1,000) and Applicability to This Research

VARIABLE	RESPONSES		POSTULATED APPLICABILITY
GENDER	Male: 94%	Female: 6%	Physical Ability
AGE (years)	Majority: 20-29 (57%) Average: 29 Range: 18-57		Experience and Physical Ability
RELATIVES IN U.S.	Sibling: 23% Children: 9%	Spouse: 8% Parent: 5%	Potential Aid in Crossing, Escape and/or Safe-house Destination
REASONS FOR CROSSING	Seek Work: 65% Reunite w/Family: 28% Reunite w/Friends: 21%	Return to Job: 51% Study: 13% Other: 8%	Self-Disclosed Motivation
CROSSING LOCATIONS	Altar-Sasabe: 33% Agua Prieta-Douglas: 18% Sonoyta-Lukeville: 6%	Nogales-Nogales: 20% Naco-Naco: 9% Mexicali-Calexico: 3%	Demonstrated Preference in Crossing from a Near-Border Staging Location in Mexico to a Near-Border Destination in the U.S.
CROSSING METHODS	More than 2/3 Used Coyote or Guide to Cross		Demonstrated Value in Knowledge and/or Experience in Route/Path Selection
INFORMATION & AWARENESS	Fewer than 1/3 Had Accurate Information About Crossing		Potential Sampling Bias – Apprehension may be Indication of Poor IBC Intelligence
CROSSED IN GROUPS	Crossed in Group: 78% (1/3 w/family members in group)		Mobility of the Group Limited to Least Mobile IBC
WHO SELECTED CROSSING LOCATION	Coyote: 50% With Friend: 14% Family: 4%	Self: 18% Group: 5% Other or NR: 8%	Coyote/Guide Presumed to Have Experience and/or Intelligence Regarding the Threat Environment
CONSIDER CROSSING IN CA OR TX	Yes: 19% No: 80% NR: 1%		Experience Gained through Apprehension may Provide Insight into System Performance Resulting in Updated Threat Assessment

Source: Data adapted from (Grimes et al. 2013)

The work of Grimes et al. demonstrates the tactical intelligence that can be obtained through post-apprehension surveys and applied toward understanding the spatiotemporal factors driving IBC route selection by threat type. For example, interpretation of the survey results facilitates the characterization of the most likely encountered threat in this Sector: an illegal immigrant seeking employment in the US. Given the adapted statistics in Table 4, it can be postulated that the threat is likely a male in his twenties with relatives in the US, traveling in a group, motivated by economic gain and aided by an experienced guide and/or provided with best-route information acquired through successful past crossing attempts. Similar motivation-based threat profiles can be created to characterize an array of threats along with the factors associated with their likely route selection into the US.

Leveraging the power of GIS, exploration of the spatiotemporal variables driving illegal migration can facilitate the development of a multi-factor decision support model to identify likely IBC routes based upon threat type and their impedance potential. The results from this analysis can serve as a basis for the integrated and geo-specific application of detection, delay and response countermeasures.

Theoretical Perspective on LCP

Least-cost path (LCP) analysis is ubiquitous in many geoscience-based disciplines: from anticipating the spread of phenomena like wildfires and insect infestation (Mitchell 2012) to archaeological investigation of ancient routes (Herzog 2010, Herzog 2012, 26, Pingel 2010, 137-148) and autonomous vehicle route selection (Stahl 2005). In its basic form, LCP analysis involves the multiplication of costs represented by a base cost raster such as distance, and an expenditure cost raster, such as slope, where pixels within the respective rasters act as interconnected nodes forming a network. Through the application of shortest-path algorithms in a GIS, a least-cost path can be calculated from the network (Pingel 2010).

For example, a hiker may be interested in traversing mountainous terrain from a parking lot to an observation point at the top of a peak. Assuming this hypothetical hiker intends to conserve time, energy, distance traveled or other factors, she may consider the costs associated with her route selection based upon criteria that contribute to perceived cost of an infinite number of traversal possibilities. For the sake of argument, imagine that she considers the following impedance factors, in descending order of cost, to arrive at her final route selection: slope, distance, barriers (natural or manmade) and vegetation, in order to arrive at her destination before sunset and with enough energy to explore the peak for a geocache. Her decision-making process may include aspects of her experiences, abilities, fears, needs and anticipation and are weighted in terms of personal priority (Vilar et al. 2013): to arrive safely at the peak before sunset. She may then construct a mental visualization of her intended route that avoids steep slopes, minimizes distance travelled, avoids known barriers to her objective and avoids vegetation that hinders mobility bounded by her physical limits.

Exploring this scenario further, assume she never arrived and the local search and rescue have been called to search for her based upon knowledge of the aforementioned factors using a GIS. The modeling of movement can be approached as cost in the form of energy, time, money or distance associated with traversal across a surface where features on the surface contribute to movement impedance (Mitchell 2012). Applying this approach an analyst may acquire the best available data from which to construct a physical and human geographic model of the search area. This would likely include digital raster representations of elevation, vegetation and barriers, which are then reclassified into their relative cost surfaces and overlaid to create an overall cost surface from which to predict her likely route, given her origin and known destination.

ArcGIS 10.2.2, the GIS of choice for this demonstration-of-concept, offers a set of tools capable of forecasting a least-cost path through the calculation of the minimum accumulative travel cost across a surface. This is accomplished by incorporating impedance factors and compensating for horizontal and vertical factors that influence the total cost of moving from an origin to a predetermined destination on a cell-by-cell basis. By linking these tools in a process flow diagram type interface, the source data is prepared for processing by subsequent tools and accumulated into a pair of rasters required to calculate a path of least resistance from an origin to a destination. Figure 5 is a conceptualization of this process in its basic form.

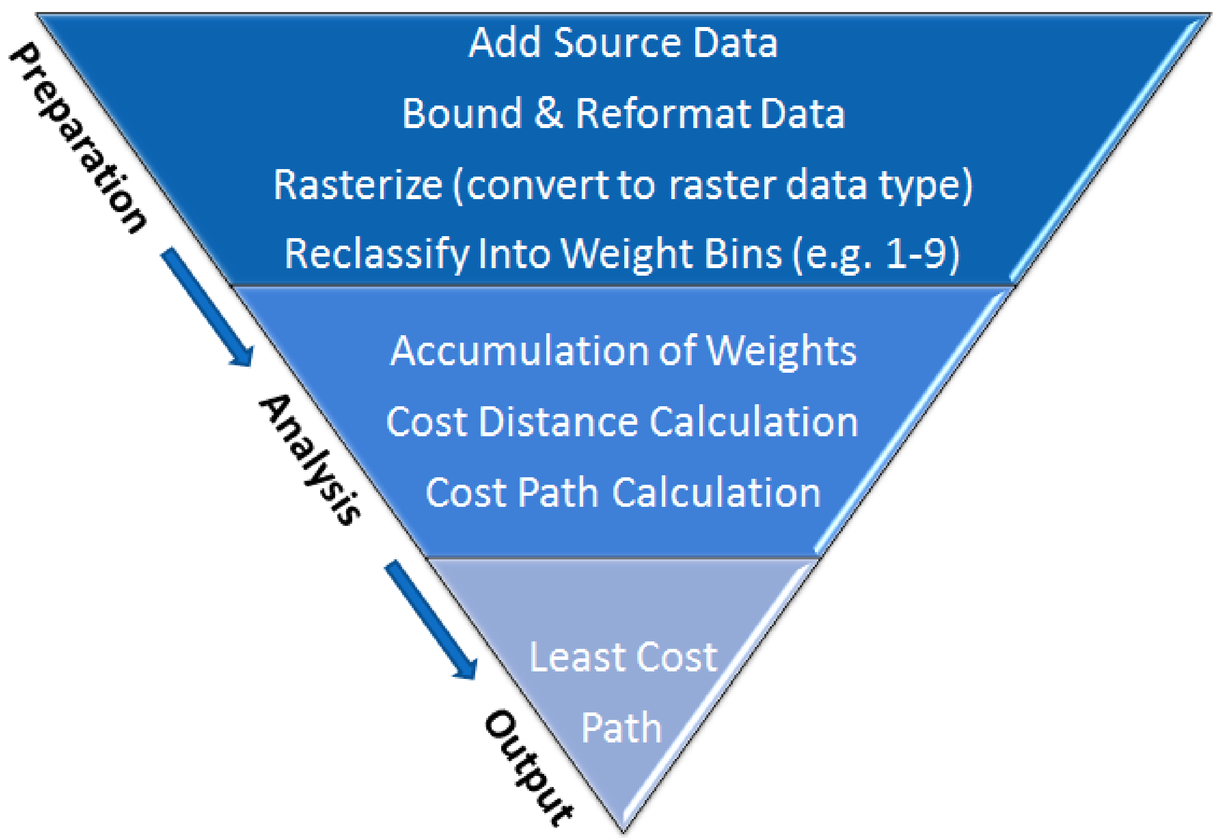

Figure 5 Least Cost Path Process Conceptualization in Basic Form

This process can be modeled using the Cost Distance tool to perform a cost-weighted distance analysis, which results in cost-distance and cost-direction or backlink rasters. It is from these rasters that the least-cost path is determined. Figure 6 depicts the conceptual analysis workflow demonstrating the reclassification and accumulation of impedance factors to generate a raster representing all costs, the derived rasters for LCP calculation and finally the LCP.

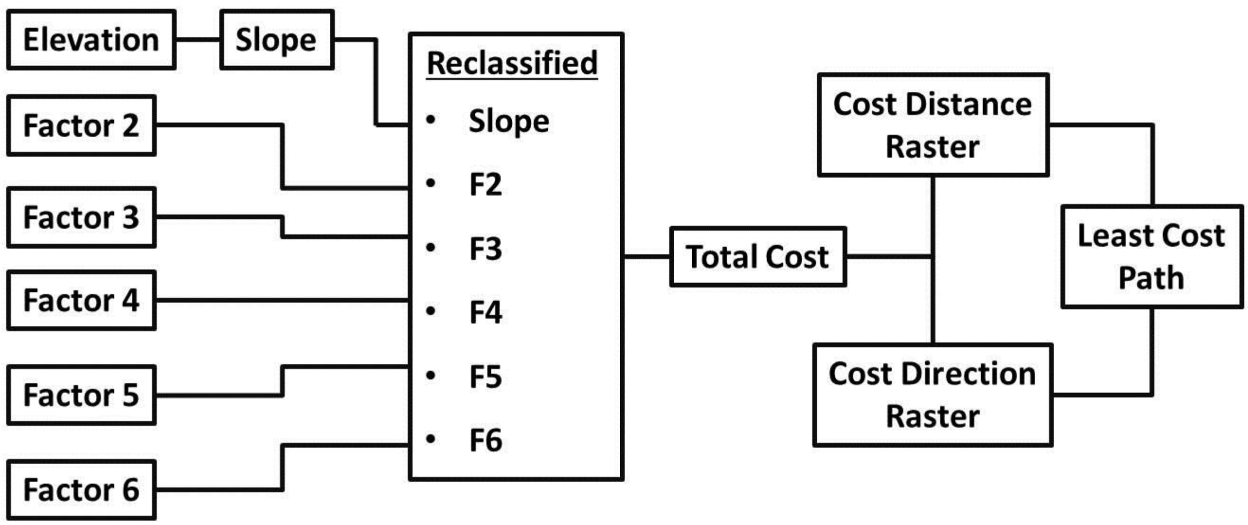

Figure 6 LCP Analysis Workflow Diagram

Research suggests that there are different approaches to predicting route selection to include the identification of the shortest and/or fastest path (Kang, Jha, and Hwong 2011, Tracy et al. 2007), optimized route selection along predetermined stops in a network (Golledge 1995, Blaser and Ginchansky 2012, Hochmair 2007, Winter 2001, Langford 2010) or the least costly path (LaRue and Nielsen 2008, Herzog 2012, Tracy et al. 2007). Each approach has its own strengths and weaknesses that presuppose data availability and/or a comprehensive understanding of the traveler, their environment and their motivations. This demonstration-of-concept implements the least cost path method which takes advantage of publicly available spatial datasets and leverages human factors data from which a threat profile can be created.

CHAPTER THREE: A SPATIAL EXPERIMENT

The Office of Border Patrol's San Diego Sector serves as the focus for this demonstration-of-concept. In its entirety, the Sector covers over 56,000 square miles of California's coast from its 60+ mile border with Mexico in the south to Oregon in the north. The San Diego Sector is comprised of varied terrain consisting of coastal beaches, rugged mountains, high desert vegetation, farmland, forests and urban areas. Historically, the Sector was one of the most porous to illegal immigration in the nation, comprising more than 40% of the national average in the early 1990s, and recording a record number of apprehensions in 1986 at over 628,000, according to the CBP. On October 1, 1994, the Executive Office for Immigration Review, U.S. Attorney for the Southern District of California and the former Immigration and Naturalization Service initiated Operation Gatekeeper, which directed resources and adapted strategies to stem the flow of illegal migrants into the U.S. in this region. The CBP asserts in their San Diego Sector webpage that the evolution of resource allocation and adaptive strategies have been credited for a marked decrease in illegal entries in the sector since 1969, with a record low of 42,447 apprehensions by FY 2011.

In response to the increased security at the US-Mexico border, IBCs have had to adapt to the new environment by either exploiting vulnerabilities in protection or attempting to cross at a less secure regions along the border (Gathmann 2008, Predd et al. 2012, Roberts et al. 2010). In a seemingly perpetual chess match of move and counter-move, the threat has resorted to less-traditional methods to gain entry into the US, employing aerial and marine insertion methods, as well as subterranean tunnel networks, to avoid detection and subsequent apprehension. Through intelligence collection and interagency cooperation, the CBP has kept abreast of the adapting adversary strategies and has adopted directed countermeasures to ensure that the national security resources are allocated efficiently and responsibly.

In an attempt to automate and standardize the resource allocation geographically, a spatial experiment was devised to aid decision makers through subject-matter expert selection of contributing factors associated with illegal migration to determine the most likely path of an IBC. In a weighted layers situation such as this, informed experts anonymously assign weights to each variable and the results are averaged to distill final weighting in the forecast model (Esri - Virtual Campus 2014). It is anticipated that the decision makers in this case are intelligence informed and field experienced experts responsible for resource allocation for their respective area of responsibility along the US-Mexico border.

This spatial experiment leverages Esri's ArcGIS 10.2.2 with the Spatial Analyst extension enabled to serve as our analysis toolset of choice. The objective was to identify the least-cost path (LCP) leveraging intelligence about the traveler to determine the likely path they would use to travel between two points, given costs associated with traversal in any particular direction. The development of the analysis environment began by bounding the spatial extent to the California-Mexico border, approximately 11 km northward into the U.S. Customs and Border Protection's San Diego Sector as depicted in Figures 7 and 8.

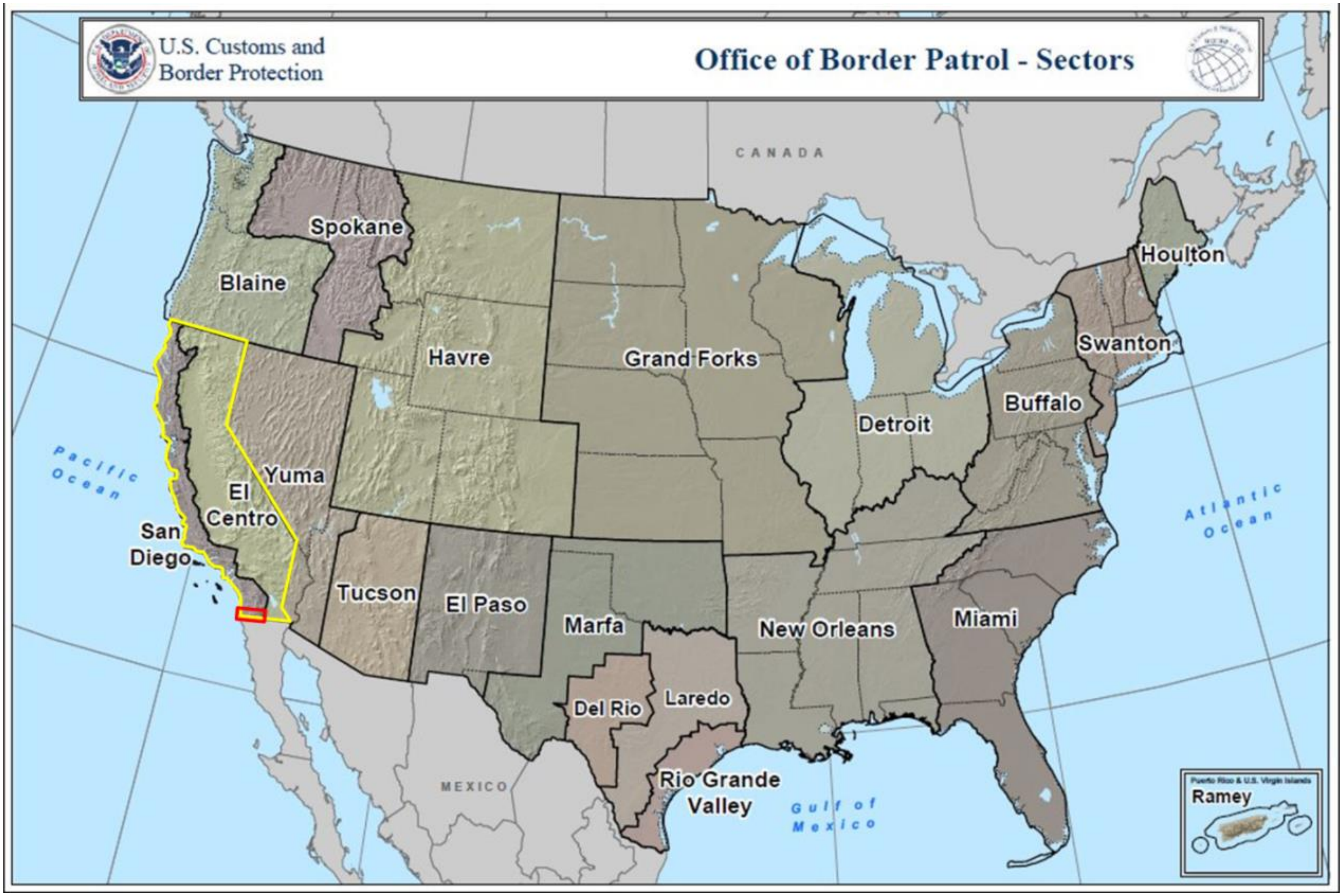

Figure 7 Map of the Office of Border Patrol Sectors, Sectors of Interest: San Diego and El Centro (yellow) and the Study Area (red). Map Courtesy: US Customs and Border Protection via the [Migration Policy Institute]

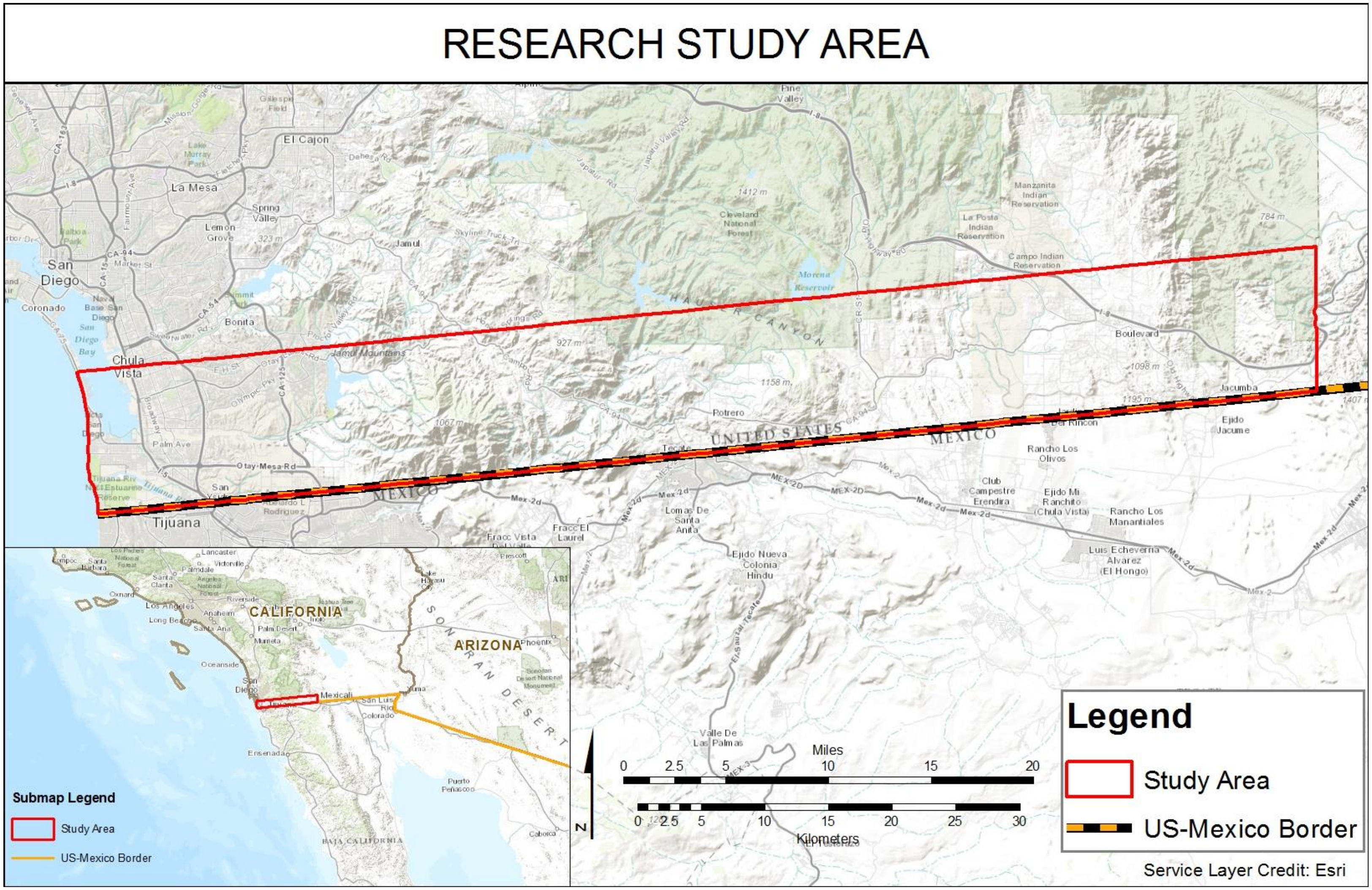

Figure 8 Map of the study area composed of the OBP San Diego Sector from the US-Mexico Border to a Parallel Boundary Approximately 7 Miles (11 km) North of the US-Mexico Border

Although there are many options for illegal border crossers to enter the U.S. such as by boat, airplane, land vehicles or pack animals, this experiment focused on dismounted threats. Data used for these studies were a reapplication from their intended purpose; however, it was sufficient to develop a rudimentary IBC threat profile for this demonstration-of-concept. Drawing from notional open source intelligence data presented in the Rossmo, 2008 and Grimes, 2012 studies, we assumed that our model IBC would have the characteristics listed in Table 5.

Table 5 Notional IBC Threat Characteristics

IBC THREAT = HIGH	IBC ATTRIBUTE
Gender	Male
Age (years)	29
Insider Collusion	Yes (aided by family, friends or associates residing in the U.S.)
Reason for Crossing	Import Controlled Substance (Man-portable, 10 lb. (4.5 kg.))
Mobility	High Dismounted Mobility (rate of travel unimpeded for distances < 10 mi. (16 km.))
Crossing Location	Mobile to any Border Location in Mexico to Nearest U.S. Primary Road (IBC Assumed to Operate Undetected in Mexico. IBC Assumes First Reliable Detection Occurs when Border is Crossed.) Latitude: 32.56631569°N, Longitude: 116.76290501°W
Information & Awareness	Experienced IBC Aided by Map, Compass, Mobile Phone and Google Earth Imagery Reconnaissance
Crossing Method & Destination	Dismounted from Border to Awaiting Colluders Near U.S. Primary Road Latitude: 32.65808813° N, Longitude: 116.80925748° W

These characteristics served as an example distillation of a detailed notional threat profile from which to determine motivation and weigh the effect of impedance factors for this specific type of threat. For this example, we assumed that intelligence had determined that the most likely border crossing location is approximately 3.7 miles (6 km) west of the Tecate-Tijuana municipality boundary at the US-Mexico border. Similarly, intelligence predicted that the IBC would rendezvous with colluders on Campo Rd. approximately 6.9 miles (11.1 km) Euclidean distance northward into the US at the following geographic coordinates: Latitude: 32.65808813°N, Longitude: 116.80925748°W. Given the aforementioned origin and destination locations and threat profile, georeferenced data representing the human and geographic features affecting route selection were identified and prepared for use in the model.

Input Data

For this research demonstration-of-concept, the following impedance factors were considered for LCP determination and formed the basis for the generation of the cost surface:

- Slope
- Land Cover
- Hydrographic Obstacles
- Population Density by Census Block
- Visibility from Presumed Border Patrol Route
- Proximity to OBP Headquarters, Stations and Substations

Data for this study was of variable spatial and temporal resolution and represented the best, publically available information for a demonstration-of-concept. For clarification, spatial resolution pertains to the ground area covered by a single cell while temporal resolution pertains to the frequency of data collection in a certain area, effectively representing a picture in time. It is assumed that limited distribution equivalents of these data are available to the OBP and should be used in a real-world application.

Data Preparation

The data required some preparation prior to analysis. The research was executed using the Universal Transverse Mercator (UTM) projection as the study area lies completely within Zone 11 and this projection preserves areal calculations and minimizes distortion. All data was re-projected from their native coordinate systems to the UTM projection prior to analysis and clipped to the study extent boundary. A brief comment about the error common to this type of analysis is appropriate. Overlay analyses such as this are often prone to error due to issues of data quality, scale, and compatibility, coregistration to a common coordinate system, and false assumptions about the data and their relationships (O'Sullivan and Unwin 2010). To address the inherent uncertainty in the results, it is recommended that the analyst perform sensitivity analyses to thoroughly explore the variability in output and effectively communicate implications to decision makers.

Slope

The digital elevation model (DEM) used for this research was acquired from the National Elevation Dataset (NED), which originated by the (U.S. Geological Survey (USGS), EROS Data Center 2007,) and consisted of tiled 1/9 arc-second (approximately 3m spatial resolution) pixels. The data was processed in ArcGIS 10.2.2 to derive the slope categories outlined in Table 6, while Figure 9 depicts a map of the result of the slope calculation. It is important to note, however, that the relative slope-weight should accurately describe cost in terms of a function which, in a GIS, can be represented as a line on a graph (Mitchell 2012) or a table of category-cost pairs. In a real-world application of the model, the slope-weight function will likely differ from a simple linear relationship. In most cases, the cost of uphill and downhill movement is not equivalent. For example, the cost of uphill movement at a 45 degree slope may be more costly than movement downhill at a -45 degree slope and should be reflected in the slope-weight pairing or graph. It should be noted that the slope-weigh functions described in this research are notional and are not intended to represent actual performance data.

Table 6 Slope Cost Value Classification

SLOPE CATEGORY	COST VALUE
No Data	No Data
70° - 80°	9
60° - 70°	8
50° - 60°	7
40° - 50°	6
30° - 40°	5
20° - 30°	4
10° - 20°	3
5° - 10°	2
0° - 5°	1

The DEM served as the main factor for slope classification for route prediction and subsequent cost layers classified and overlaid upon the DEM to further refine trafficability, threat and avoidance areas across a continuous surface.

For example, a rational person may be expected to minimize traversal over steep slopes in order to preserve energy where possible, unless a barrier or threat exists along that path that diminishes the cumulative benefit of taking that route. Examples of barriers include lakes and ravines, while threats include areas of increased detection due to casual observation and hostile indigenous populations.

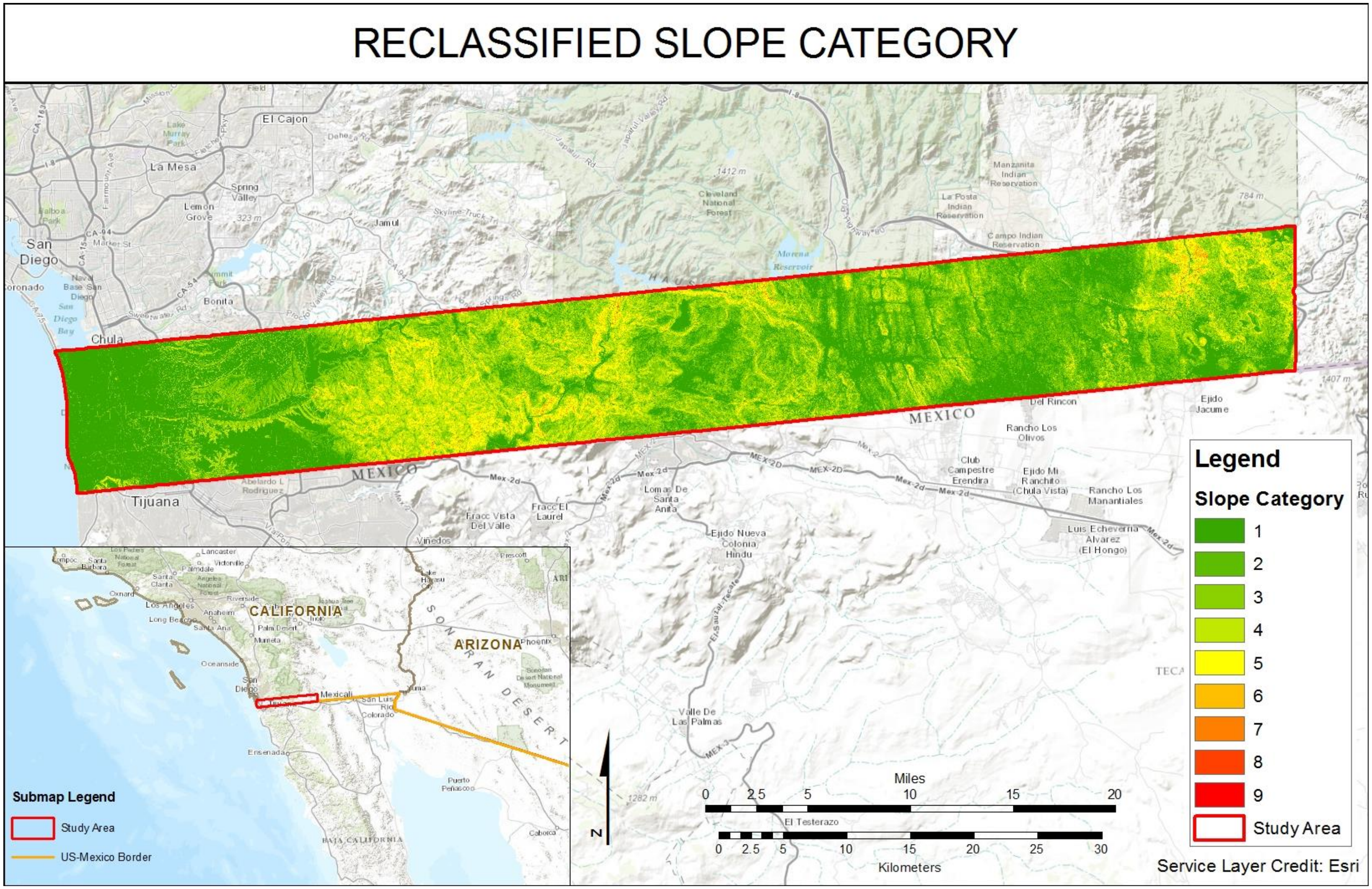

Figure 9 Map of a Reclassified Slope Surface Generated from a 3m Resolution Digital Elevation Model (DEM) from the National Elevation Dataset (NED)

Slope values were reclassified on a cell-by-cell basis, in this case, into nine bins representing a range of slope values, which correlated to an increased level of impedance to the dismounted IBC. For example, a slope category of one represented a cell of less impedance that a cell with a larger value.

Land Cover

The data representing land cover was acquired from the National Land Cover Data Set (NLCD) originated by the Multi-Resolution Land Characteristics (MRLC) Consortium, and was led by the ((USGS) U.S. Geological Survey 2013). The data was converted from their native vector data type to a categorized raster data type. Table 7 represents the factors and their relative notional cost values considered for inclusion in this research. Figure 10 depicts the spatial extent and occurrence of land cover categories within the study area.

Table 7 Land-Cover Cost Value Classification

LAND-COVER CATEGORY	COST VALUE
No Data	No Data
Hardwood Woodlands	1
Urban	8
Herbaceous	2
Shrub	3
Water	Restricted
Conifer Forest	1
Barren/Other	5
Agriculture	3
Desert Shrub	6
Wetland	9
Conifer Woodland	2

Land-cover categories were reclassified in a similar process to slope reclassification except that the newly assigned cost value represented the anticipated level of impedance by land cover type versus a range of values. The *restricted* cost value for water assumed that the water feature it represented provided an impedance value so great that it should be ignored as a viable traversal surface. Other trafficable hydrographic features such as rivers and streams are addressed separately in the next section.

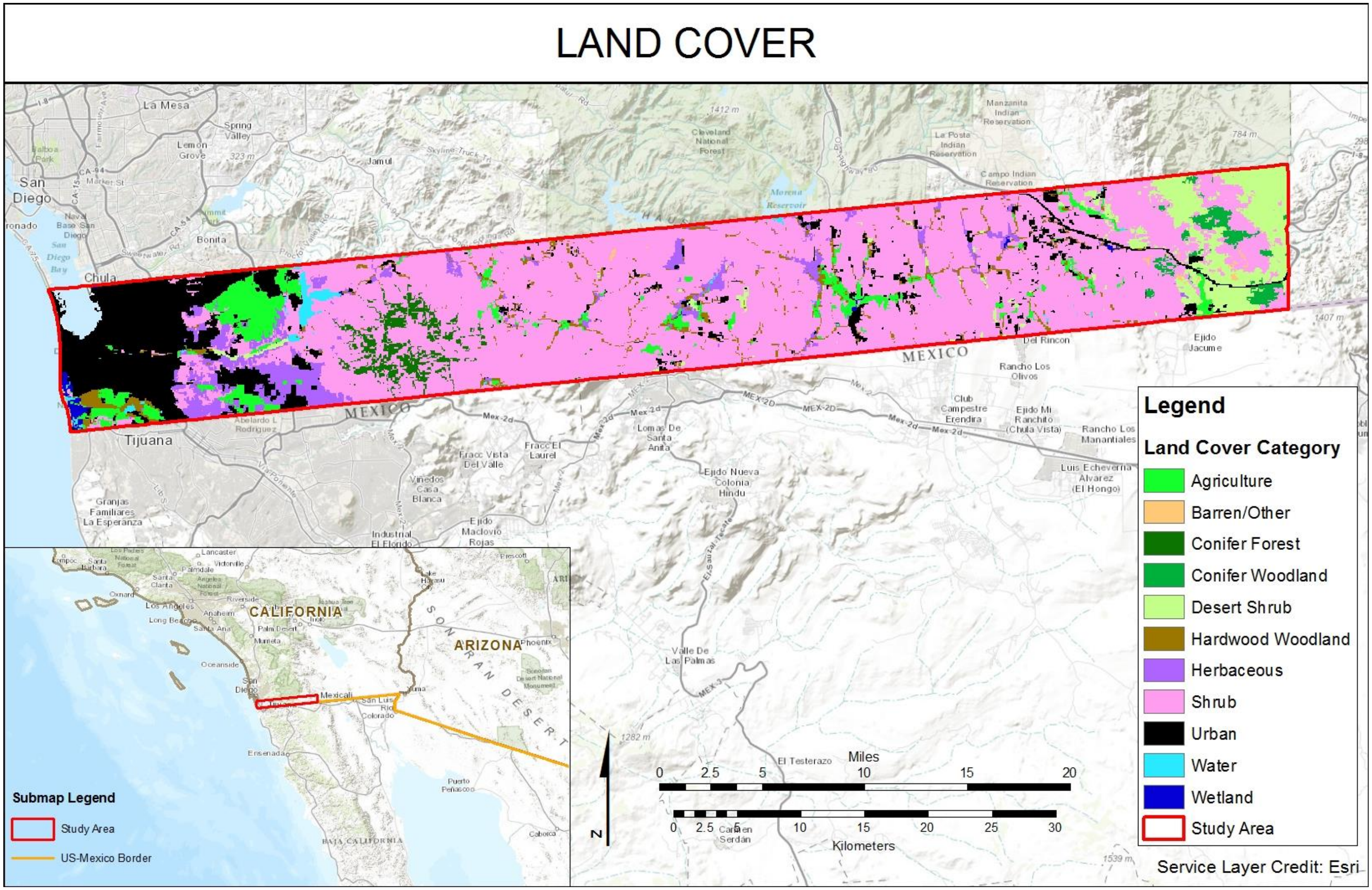

Figure 10 Map of the Land Cover Classification within the Study Area

Hydrographic Obstacles

The data representing hydrographic features such as rivers, streams, lakes, etc. and was acquired from the National Hydrography Dataset (NHD) published by the (U.S. Geological Survey (USGS) 2014). The linear features were buffered to a distance of 10 meters to generate generalized areal features, and converted from their native vector data type to a categorized raster data type. Table 8 represents the factors and their relative notional cost values considered for inclusion in this research. Figure 11 depicts the spatial extent and occurrence of hydrographic categories within the study area.

Table 8 Hydrography Cost Value Classification

HYDROGRAPHY CATEGORY	COST VALUE
Lake/Pond	9
Reservoir	9
Swamp/Marsh	9
Estuary	8
Connector	1
Canal/Ditch	7
Underground Conduit	1
Pipeline	1
Stream/River	9
Artificial Path	9
Coastline	1

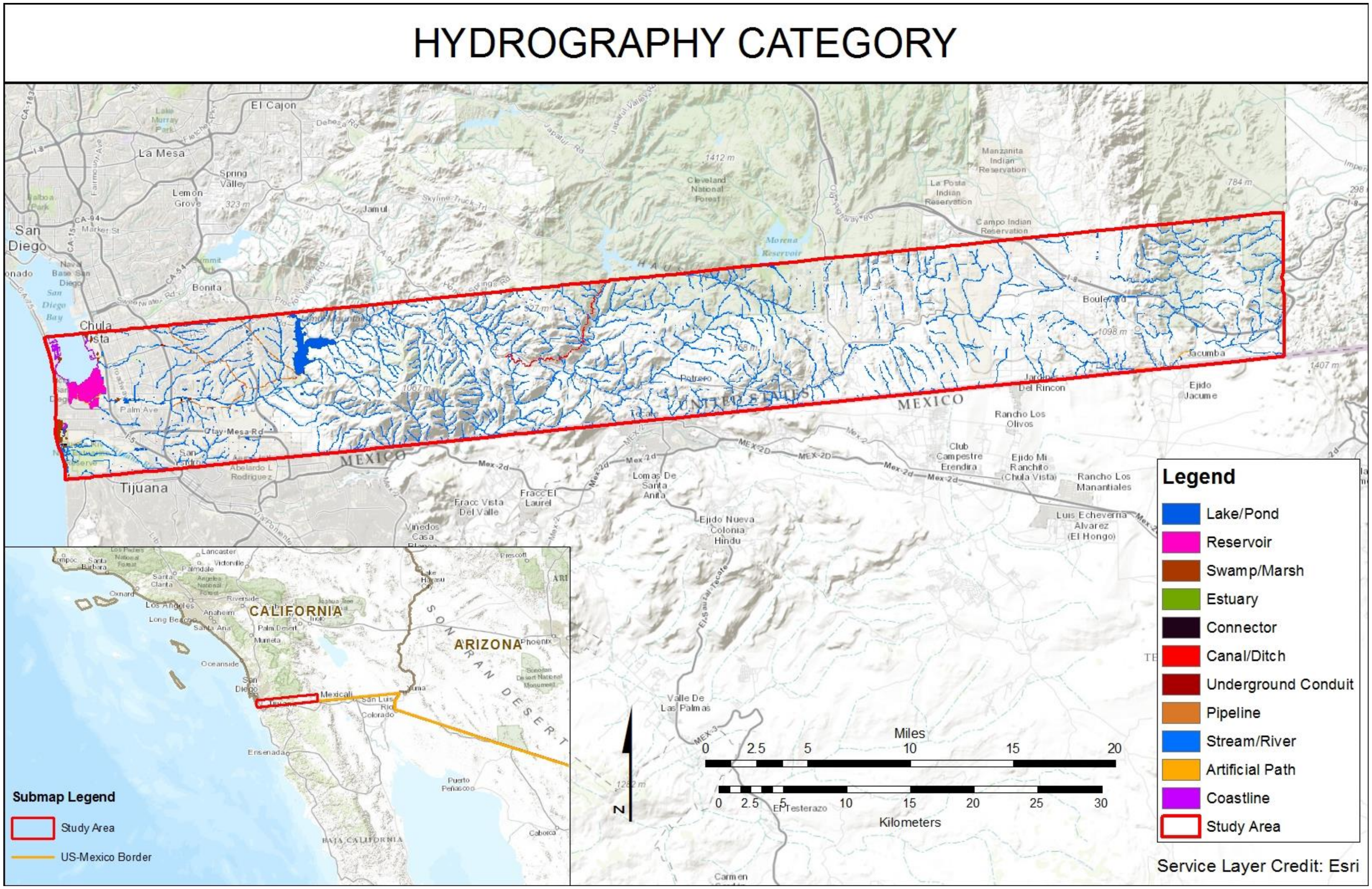

Figure 11 Map of Hydrographic Features Serving as Obstacles

Population Density

The data from which population density was derived originated from ArcGIS Online (Esri 2013) as a layer package file featuring the U.S. census block centroids, which represent the 2010 population by census block. Through the application of the Kernel Density (Spatial Analyst) tool, the point data was used to calculate a smooth surface representing the magnitude of population per square mile by applying a kernel function within a search radius conducive to achieving a raster surface of sufficient detail to affect route selection. Table 9 represents the relative population-to-cost assignments from the derived raster surface and Figure 12 depicts the results of the kernel density estimation. Population ranges were reclassified into nine bins with an increasing cost value correlated to an increase in population and increased risk of detection by casual observation.

Table 9 Population Threat Cost Value Classification

POPULATION THREAT CATEGORY	COST VALUE
POP > 8000/ Square Mile	9
POP 7000 – 8000 / Square Mile	8
POP 6000 - 7000/ Square Mile	7
POP 5000 - 6000 Square Mile	6
POP 4000 - 5000 Square Mile	5
POP 3000 – 4000 / Square Mile	4
POP 2000 – 3000 / Square Mile	3
POP 100 - 2000/ Square Mile	2
POP < 100/ Square Mile	1

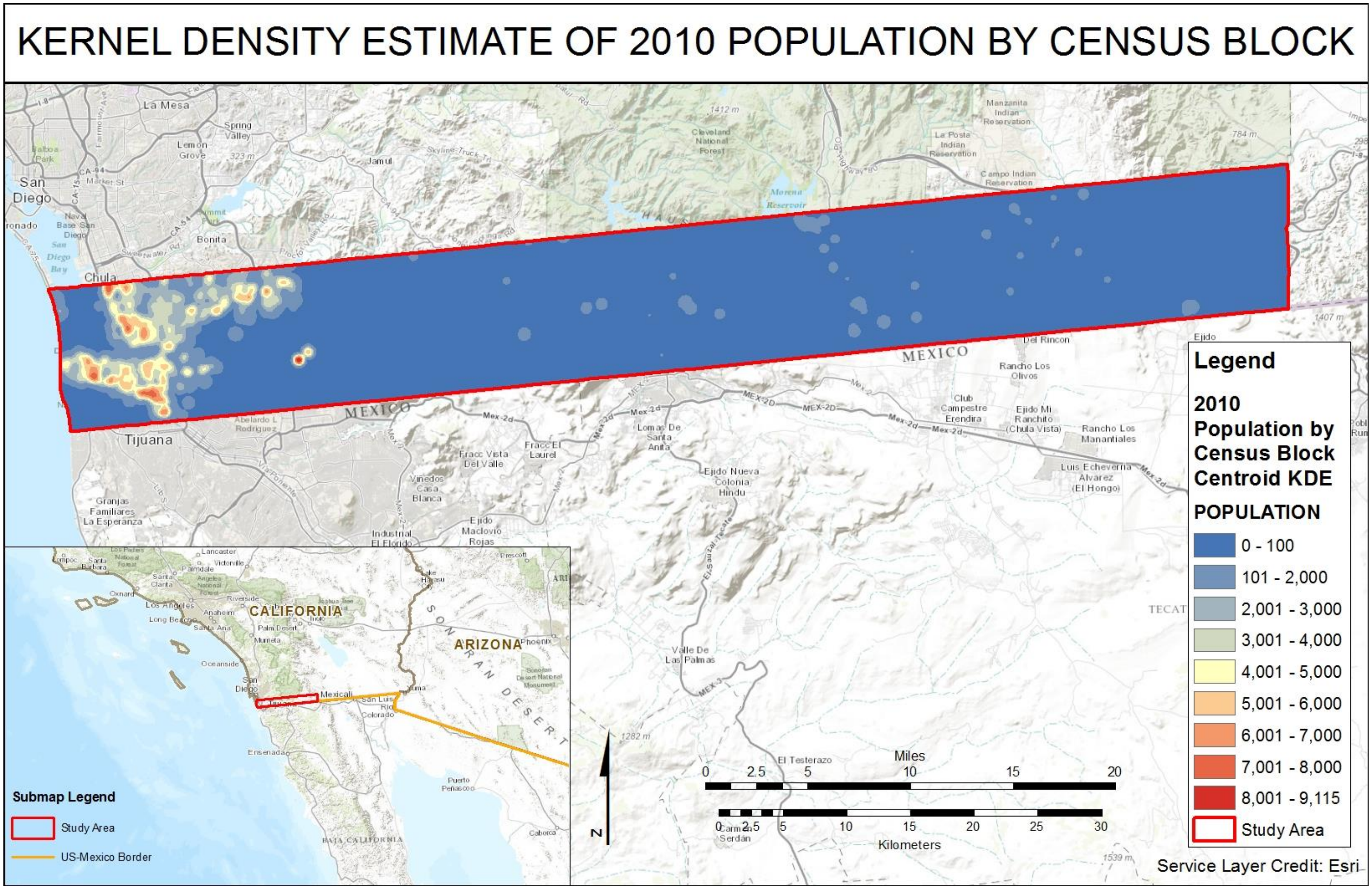

Figure 12 Map of a Kernel Density Estimation of Household Population Derived from Household Centroid Points Published by the U.S. Census in 2010

Border Patrol Route Visibility

The data representing the U.S. Border Patrol route visibility was generated by digitizing a notional patrol route through the study area and performing a visibility analysis to predict areas of visibility and non-visibility. The result was reclassified according to the parameters outlined in Table 10 while Figure 13 depicts the results of the visibility analysis.

Table 10 Visibility/Cost Value Classification

VISIBILITY	COST VALUE
No Data	No Data
Visible	9
Not Visible	1

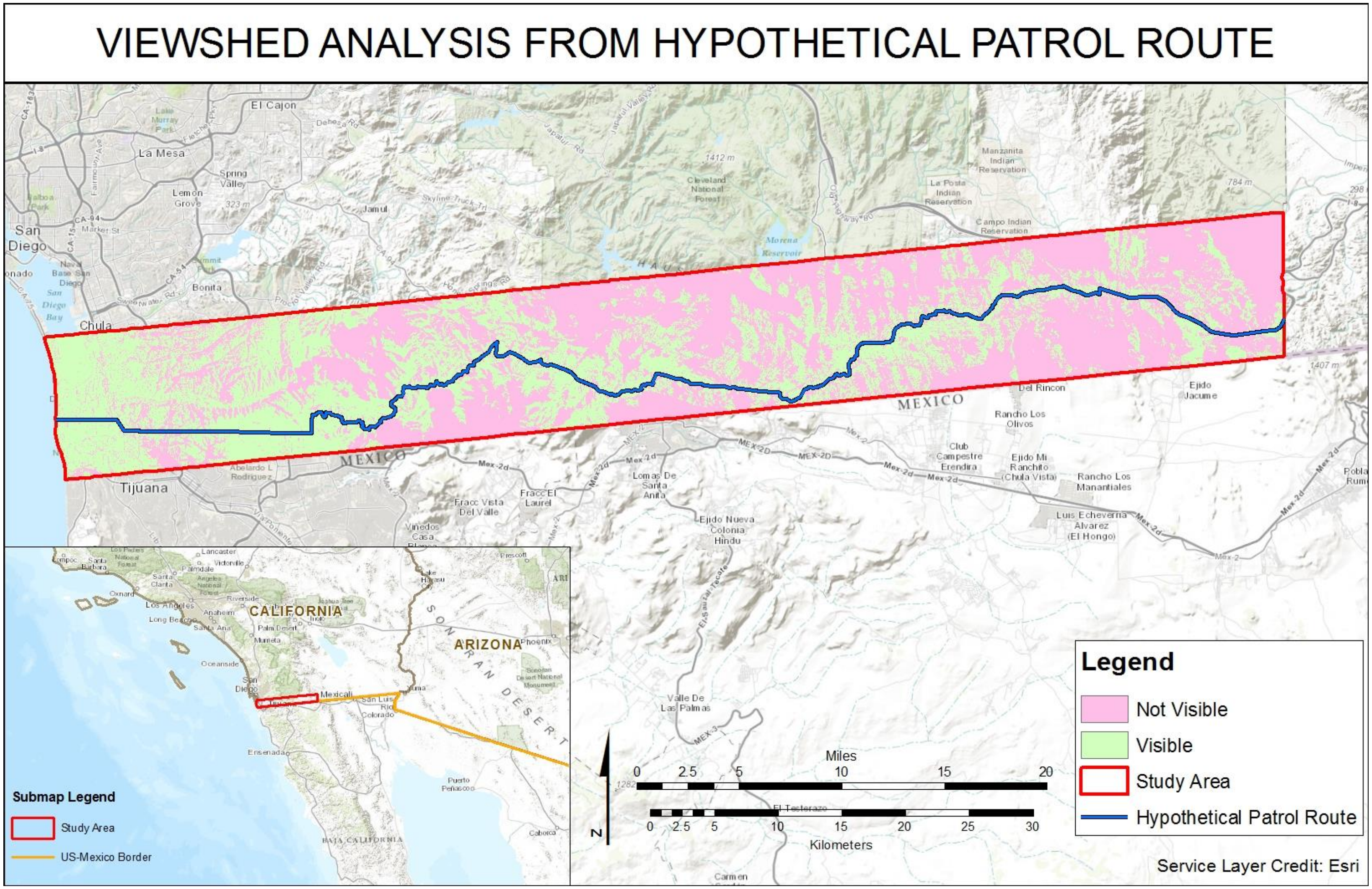

Figure 13 Map of the Result of a Viewshed Analysis Predicting Intervisibility from a Notional Border Patrol Route

Conceptually similar to the premise that the IBC would tend to avoid highly populated areas posing an increased threat of detection, the result of the viewshed analysis represented areas of increased detection potential by patrols along a predetermined route. Cells of non-visibility were reclassified to a low impedance value of one, while cells of visibility from the patrol route were assigned a high impedance value of nine. It is important to note that the viewshed analysis was performed upon a DEM representing a bare earth model that excludes objects, such as buildings and vegetation, which may yield significantly different results in some cases.

Border Patrol Stations

The data representing the U.S. Border Patrol Station was digitized from an ArcGIS map layer representing OBP headquarters (Anonymous), stations and substations and buffered at a 2 km radius to define a theoretical IBC threat avoidance area. The feature class was converted to a raster data type and reclassified to identify areas within and outside the 2 km buffer area. Table 11 represents the relative cost of the presence/absence of an OBP station buffered at a radius of 2 km. Figure 14 depicts the 2 km buffer distance around OBP stations within the study area. Again, similar to the population density and viewshed factors, OBP station proximity represented areas of increased detection potential within 2 km of OBP headquarters, stations and/or substations. The 2 km threat avoidance area used in this study was notional and should be replaced with performance values for each station in a real-world application.

Table 11 Station/Cost Value Classification

OBP STATIONS	COST VALUE
No Data	No Data
In 2 km Buffer	9
Outside 2 km Buffer	1

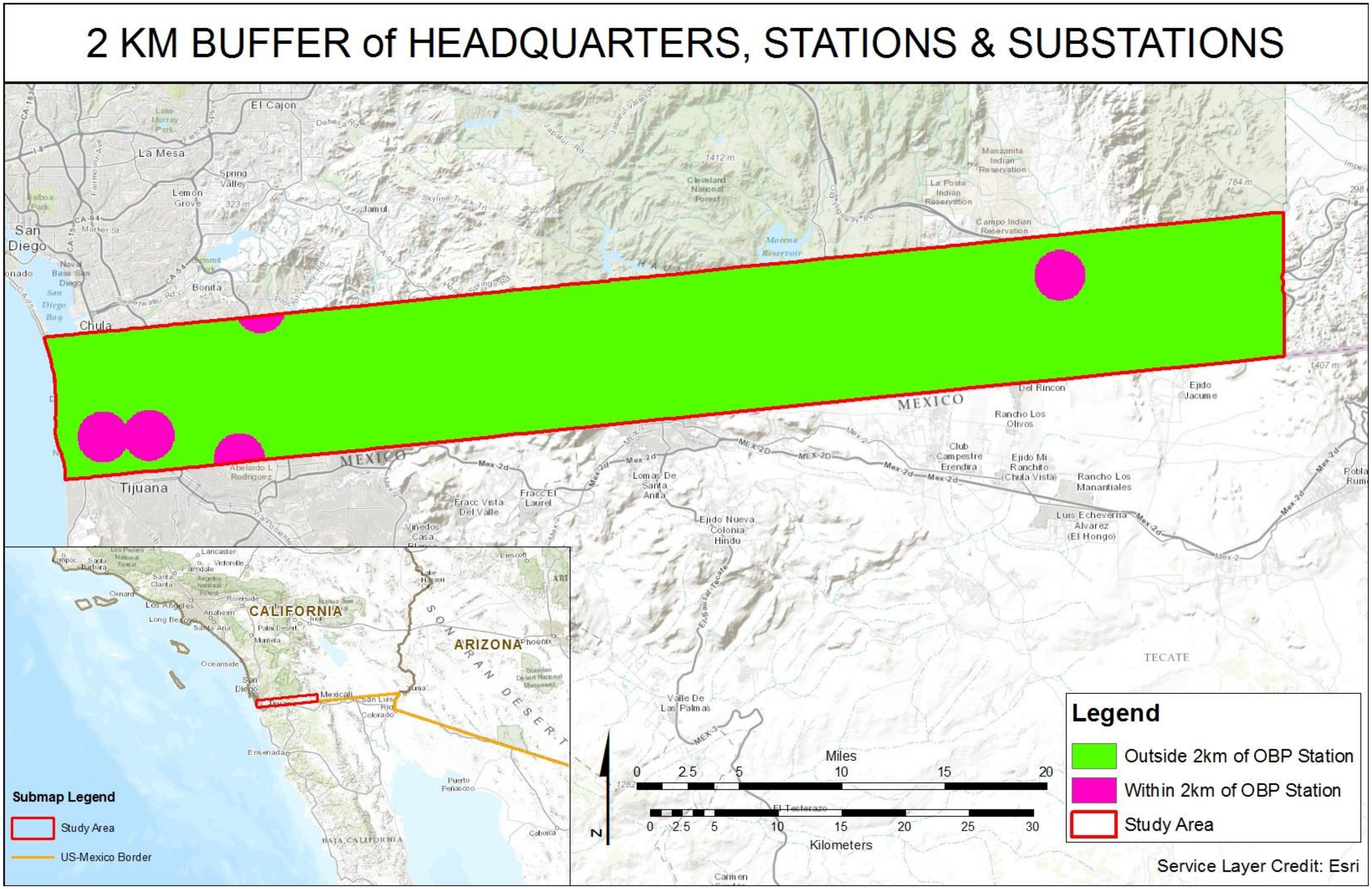

Figure 14 Map of a 2 km Buffer around OBP Headquarters, Stations and Substations within the Study Area

Methodology

This section describes the proposed creation of the spatial decision support model for calculating the least-cost path from any destination along the California-Mexico border to any location inside the U.S. given a cost surface developed from notional weighted cost criteria. The process involved the creation of the example ArcGIS 10.2.2 model depicted in Figure 19, which began with a slope calculation from the DEM raster using the Slope Spatial Analyst tool. The slope was then reclassified using the Reclassify Spatial Analyst tool to change the values of the raster to a ratio scale; its product is depicted in Figure 9. Next, the Weighted Overlay Spatial Analyst tool was used to overlay multiple rasters and assign the expected influence according to its importance using a common measurement, which results in the cost surface depicted in Figure 18.

The Cost Distance Spatial Analyst tool was then run to determine the least accumulative cost distance on a cell-by-cell basis by proximity to the nearest source over the cost surface. The Cost Distance operation resulted in a cost distance raster and a backlink raster depicted in Figures 20 and 21 respectively. The Cost Path Spatial Analyst tool was then run to calculate the path of least-cost from an origin to a destination in the form of a raster. Finally, the Raster to Polyline Conversion tool was run to convert the aforementioned cost path from raster to polyline form. The final product was a polyline depicting the LCP from the predetermined origin to the destination as shown in Figure 22. Figure 15 demonstrates the process of arriving at the accumulative least cost path representing the predicted terrorist route.

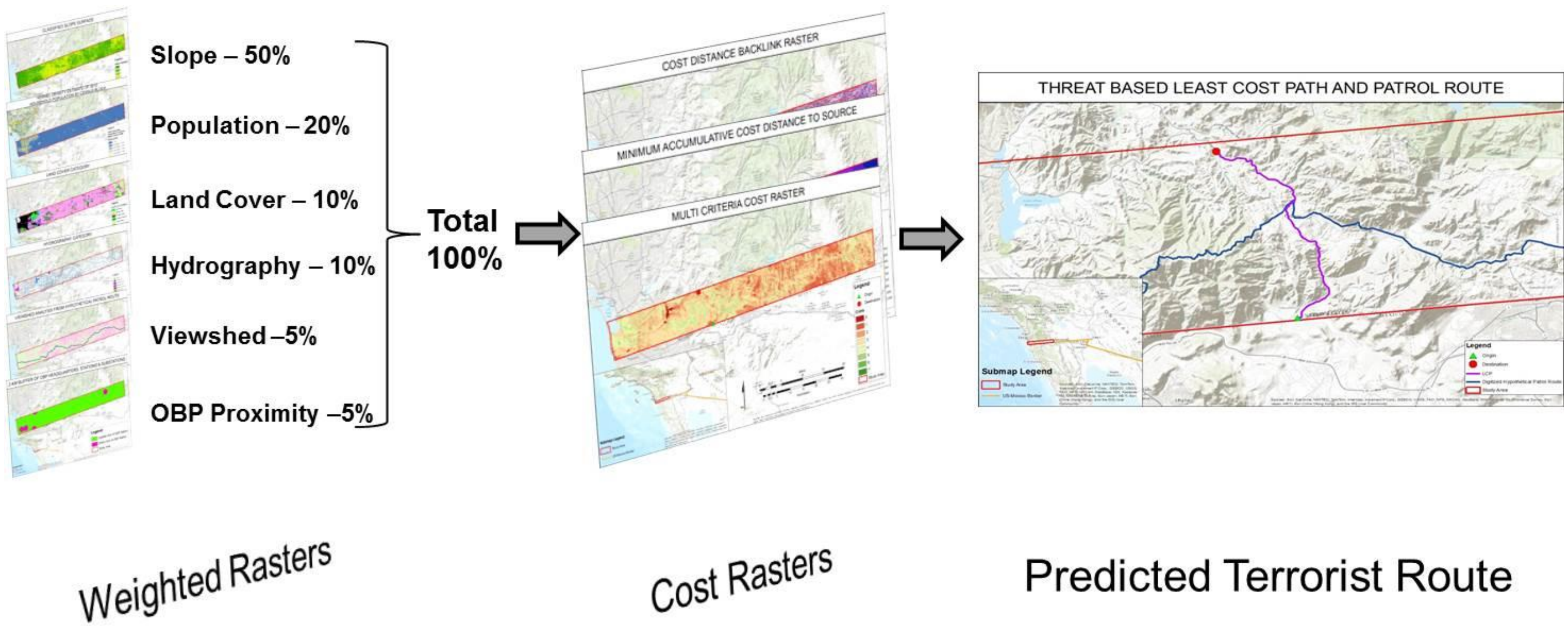

Figure 15 ArcGIS Raster Fusion Example

Integration of Subject-Matter Expertise in this Decision Support Model

The integration of distilled and averaged subject-matter expert (SME) opinion provided a mechanism to arrive at a representative response. In this application, SMEs would assign weights to each layer based upon their interpretation of available data, analyses and opinion derived from current intelligence of the threat and its perceptions regarding impedance from origin to destination. Figure 16 depicts a hypothetical assignment of averaged weights by their level of influence in the analysis.

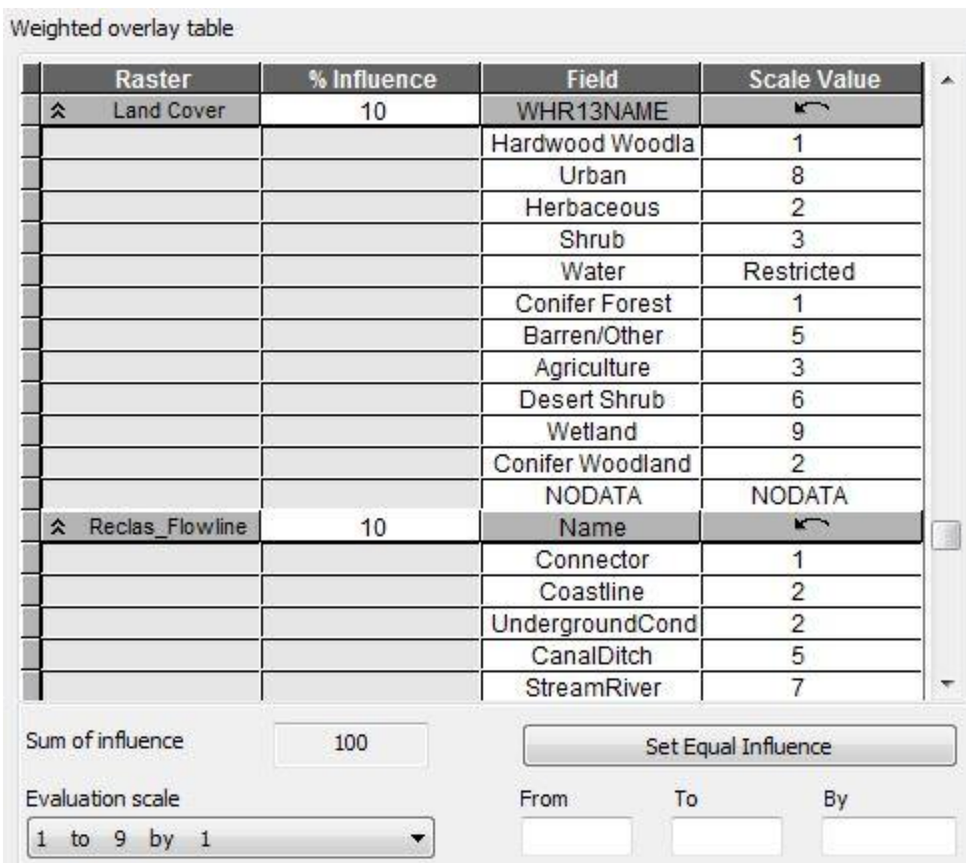

Figure 16 Example of a Weighted Overlay Table Set as a Model Parameter Facilitating Subject-Matter Expertise Input

The Weighted Overlay Table was set as a variable model parameter within the model that, when reached in the process, opened to facilitate the input from the average response values obtained from SMEs. The raster column indicated the factor being considered in the analysis and

% influence was modifiable to the relative influence that factor contributed to the analysis. The higher the percentage value, the more importance was placed upon that factor in the analysis. For example, the weighting depicted in Figure 17 suggests that the SMEs had determined that slope was the most influential factor in this analysis at 50 percent, followed by population at 20 percent, land cover and hydrography at 10 percent respectively, etc. In versions of the analysis that experimented with exclusion of one or more of these factors necessitated re-weighting to achieve a 100 percent total.

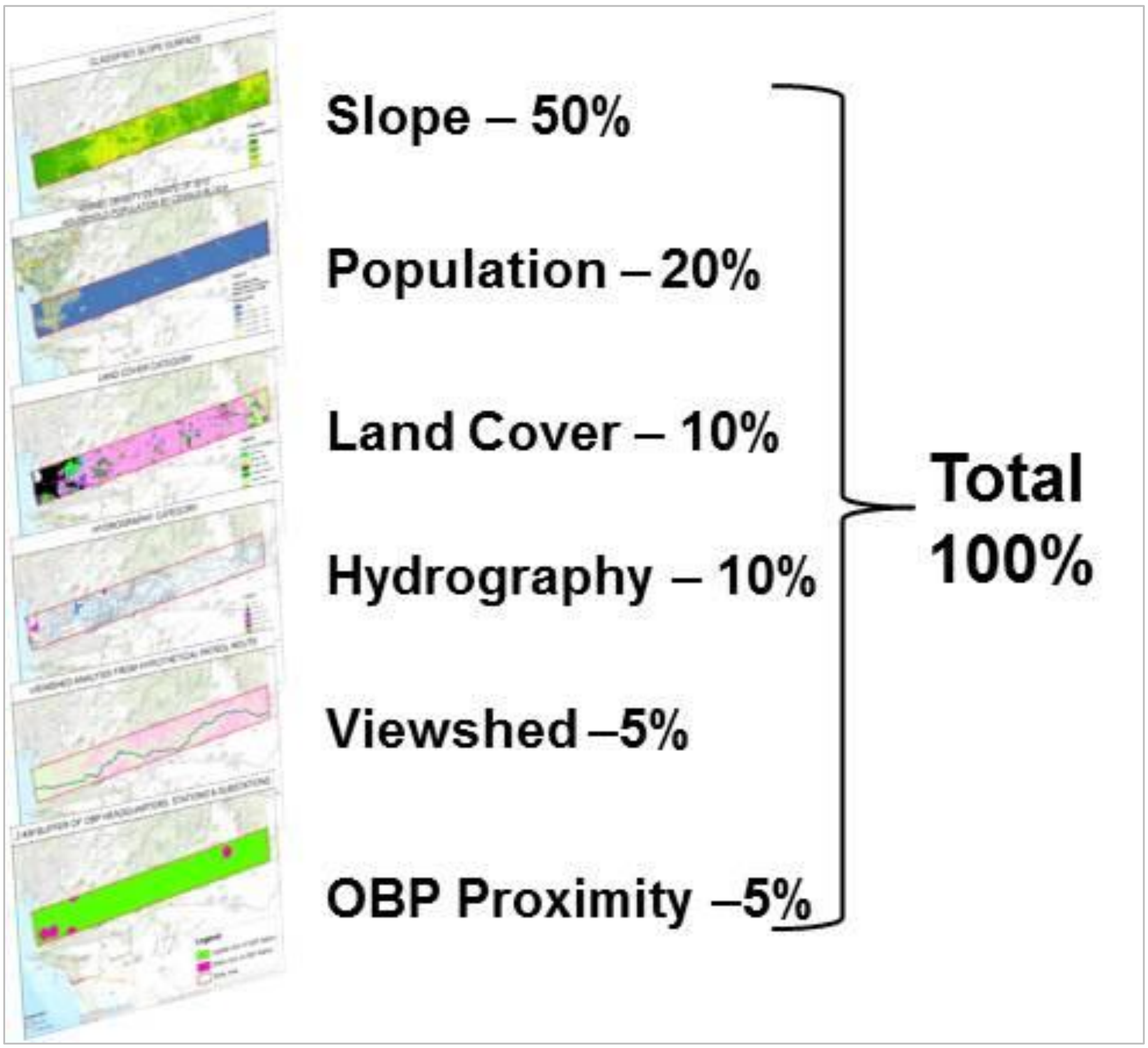

Figure 17 A Weighted Layers Example in the Decision Support Model Facilitating Subject-Matter Expertise Integration in Decision-Making

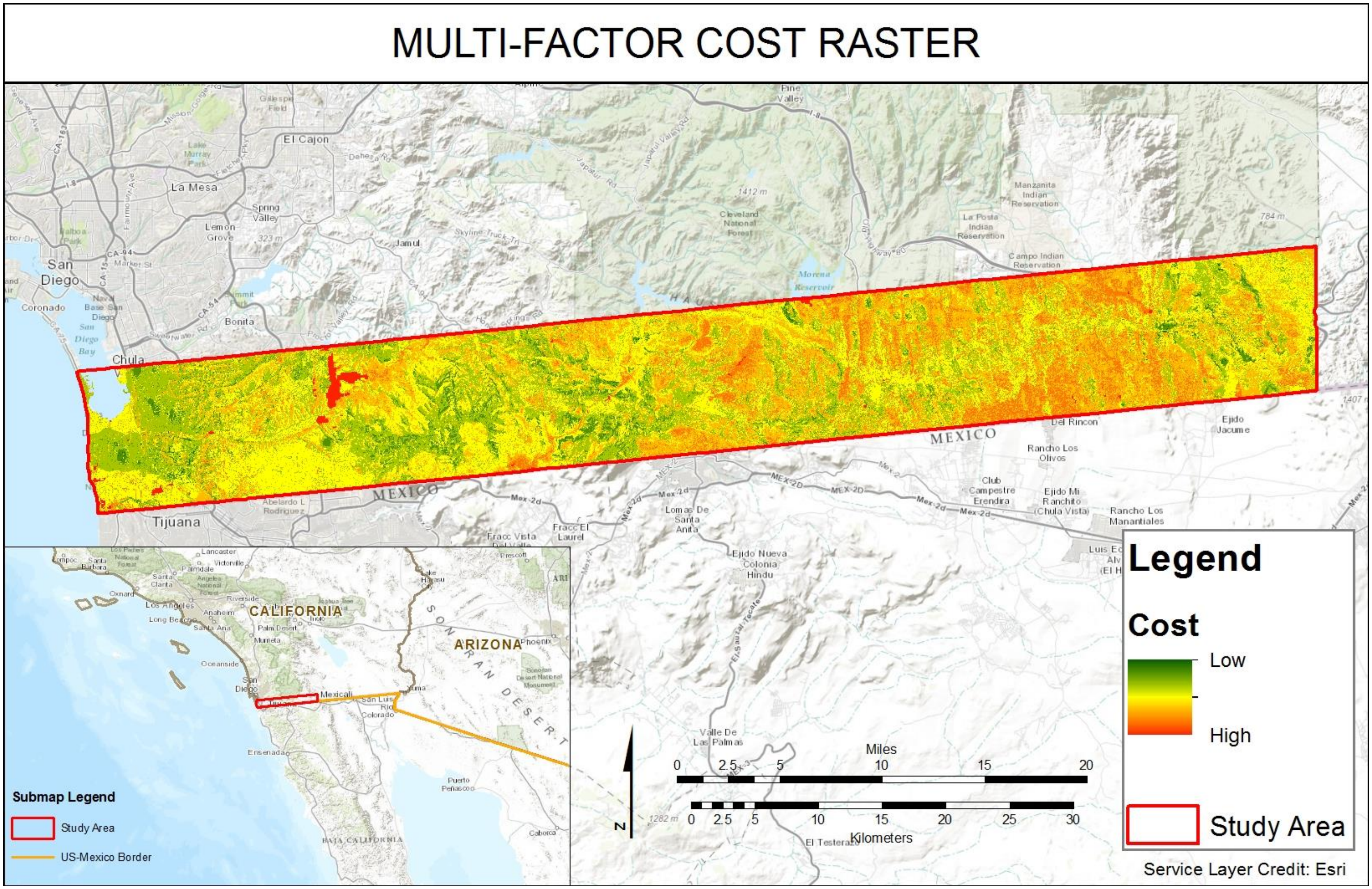

Figure 18 Map Depicting the Multi-Factor Cost Raster

The cost raster depicted in Figure 18 represents the cell-by-cell assignment of cost as determined by the combination of the reclassified weighted layers depicted in Figure 17, and was used to assign the level of traversal impedance through each cell.

The geoprocessing model depicted in Figure 19 is a sequential linkage of data and geoprocessing tools available in ArcGIS 10.2.2 through an application called ModelBuilder. Deceptively similar to the process workflows depicted in Figures 5 & 6, the geoprocessing model is a type of visual programming language that facilitates the creation of a computer program without having to be proficient with traditional programming languages. The orange rectangular elements in the model are geoprocessing tools, green ovals are derived data from the tools and the blue ovals are input data which may or may not have been derived. Once complete, the model can be modified and reused for subsequent analyses and shared with other ArcGIS users. If implemented as a standard analysis tool, the geoprocessing model can be used by analysts and decision-makers to standardize adversary route prediction among all sectors while allowing flexibility to adapt to threat, geographic and data differences within each OBP Sector.

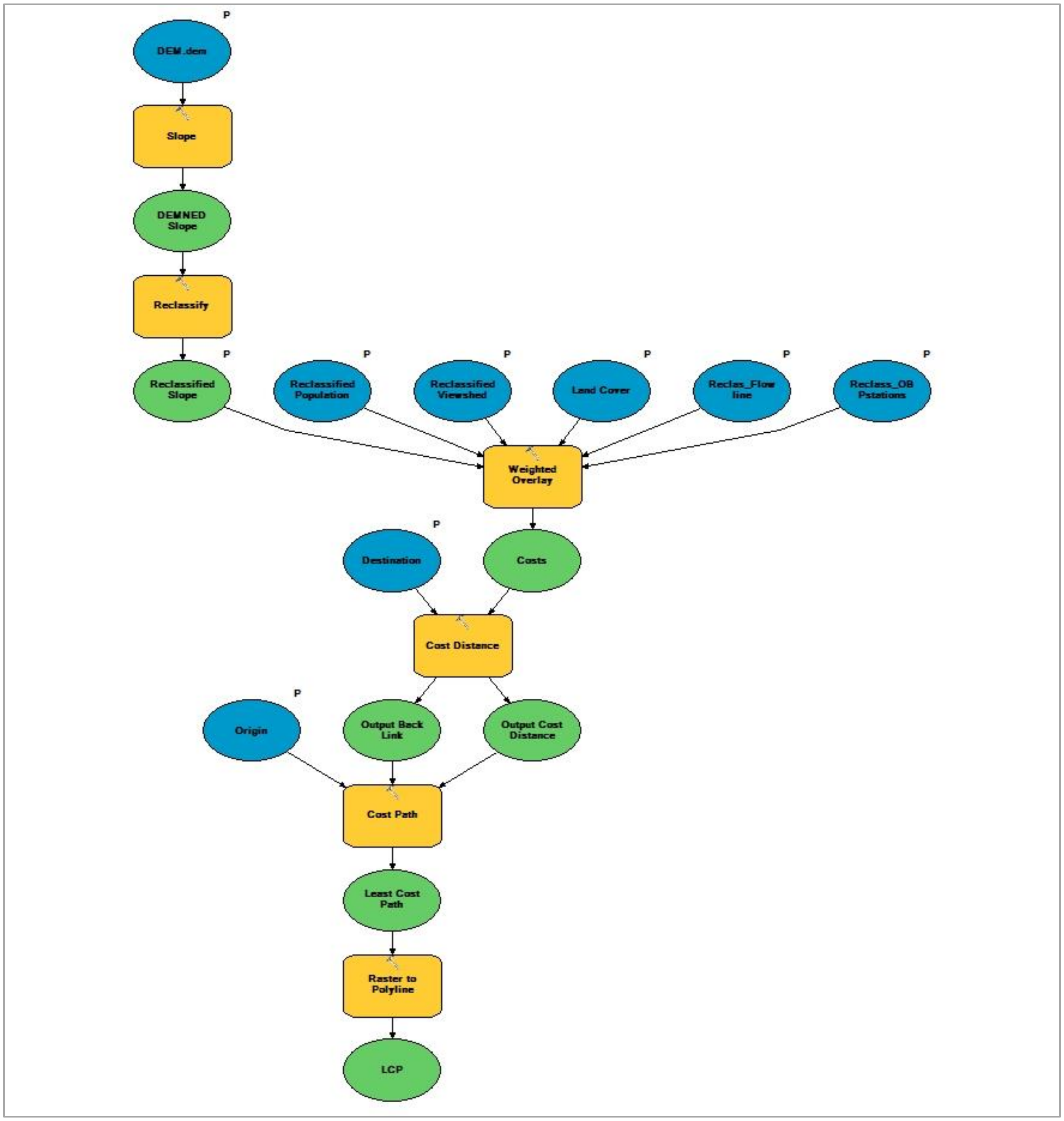

Figure 19 ArcGIS Least Cost Path Model & Workflow Diagram

In order to calculate the least-cost path (LCP), two derived rasters were required: the cost-weighted distance raster and the backlink raster depicted in Figures 20 and 21 respectively. The cost distance raster depicts the least accumulative cost of moving from cell-to-cell toward the source/destination over the cost surface.

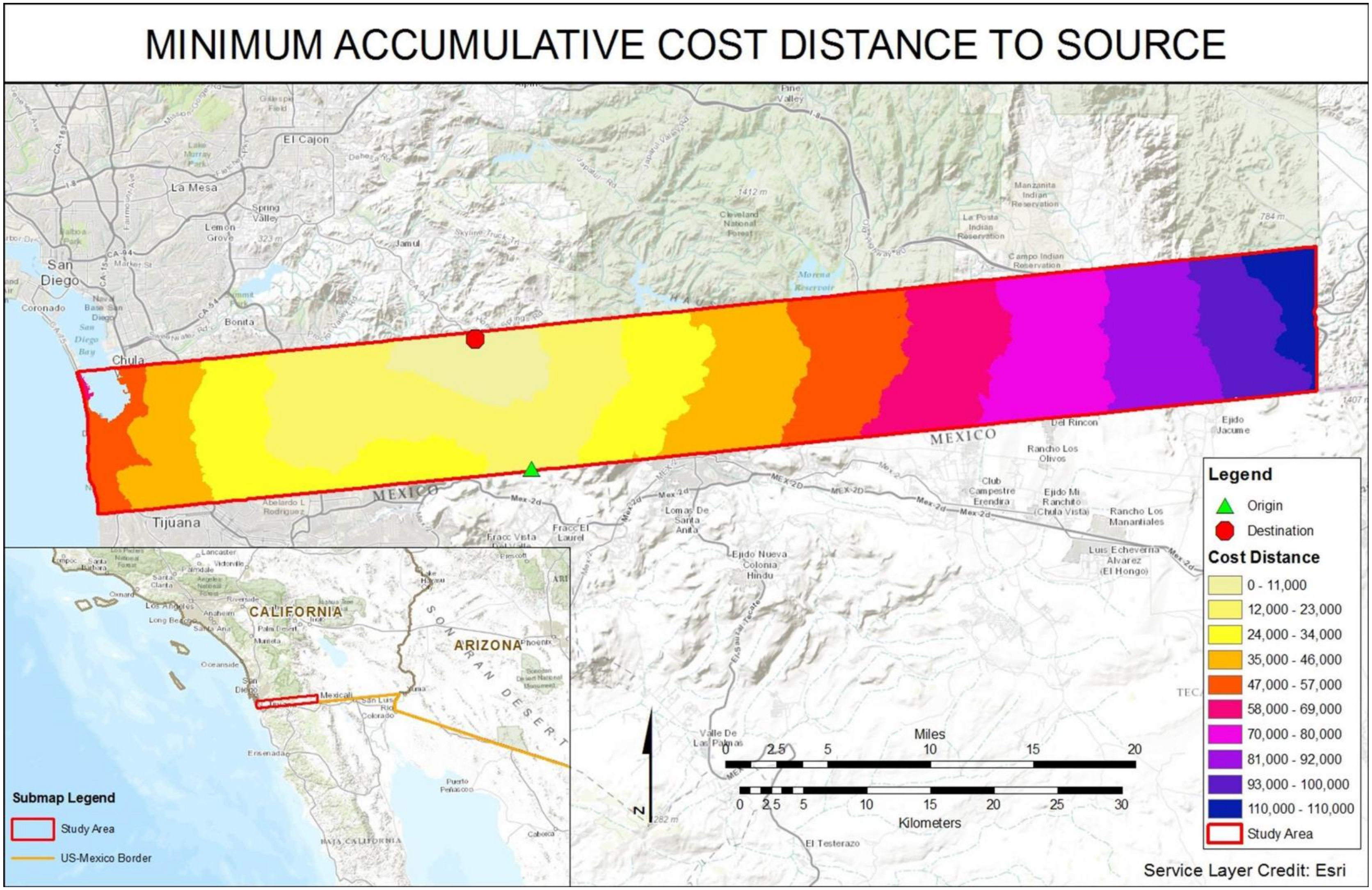

Figure 20 Map Depicting the Result of a Cost-Distance Calculation from the Cost Surface Raster

Figure 21 is a map depicting the backlink raster, which specifies the direction of travel, on a cell-by-cell basis to the source/destination, of accumulative least cost. Cell values range from zero (destination) to eight and identify the neighboring cell by direction (Right, Lower-Right, Down, Lower-Left, Left, Upper-Left, Up & Upper-Right) of accumulative least cost.

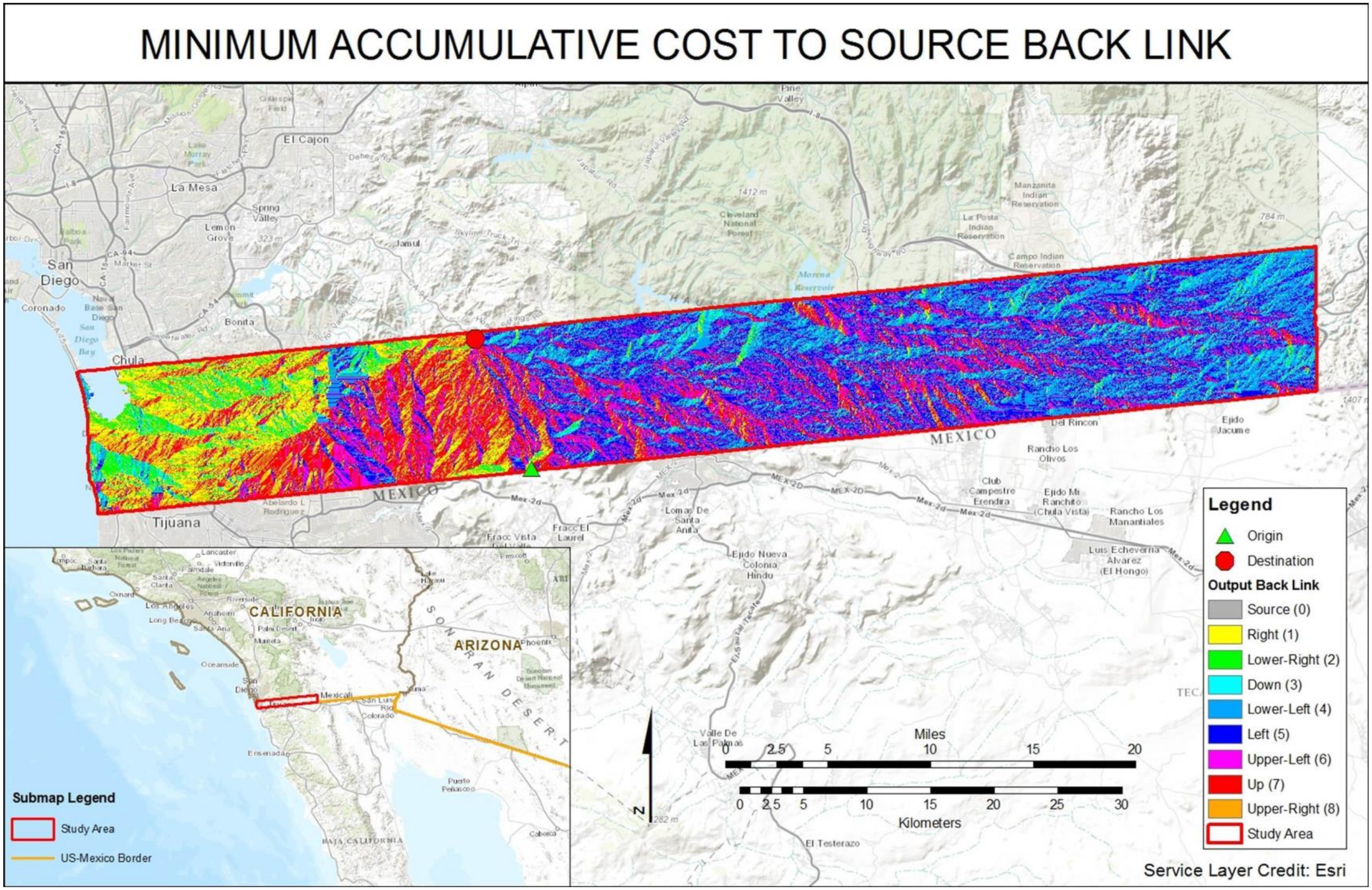

Figure 21 Map Depicting the Result of a Backlink Calculation

CHAPTER FOUR: RESULTS

Results

This section describes the results of the LCP model. Figure 22 depicts the resultant least cost path from origin to destination. Visual inspection of the 2D and 3D perspectives suggested that the generated least cost paths successfully yielded reasonable paths given the factors considered and their geographic coincidence. Figure 23 depicts a 3D isometric perspective of the least cost paths considering the same origin and destination but different factors and weights outlined in Table 12.

In an attempt to assess the forecast performance of the model, notional threat characteristics were identified to help bound the analysis in terms of motivation and impedance potential. The resultant notional threat profile outlined the IBC threat as being a lone male, approximately 29 years old and being aided by associates inside the U.S. The presumed adversary intent was to import a 10lb. man-portable controlled substance from a likely entry location at the border (indicated by the green flag in Figure 23) to a predetermined location inside the US to rally with waiting colluders (indicated by the red flag in Figure 23). The geoprocessing model was run using the factors outlined in Table 12, adjusting the weighting as factors were added or removed, but keeping slope as the highest contributing factor at 50% influence or higher. The resultant 6 paths are depicted in Figure 23. For reference, the black dotted line represents the notional patrol route from which the viewshed was generated. The blue path considers only slope, green adds population, pink adds the patrol route viewshed, purple adds land cover, and red adds hydrography. Note that paths 5 & 6 are essentially the same due to the lack of OBP stations in this area.

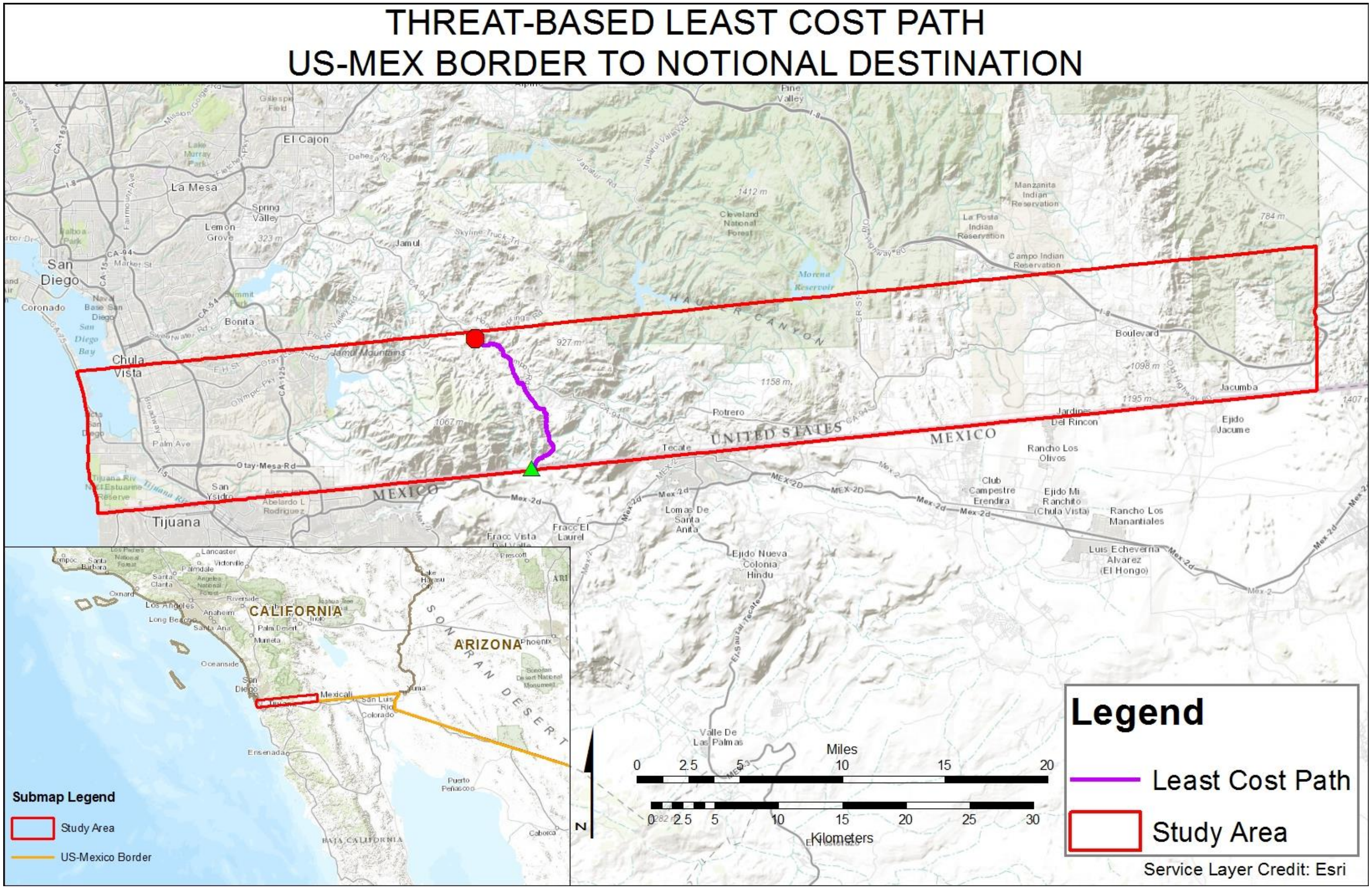

Figure 22 Results of the LCP Model. The Red Line Indicated the LCP from Origin to Destination

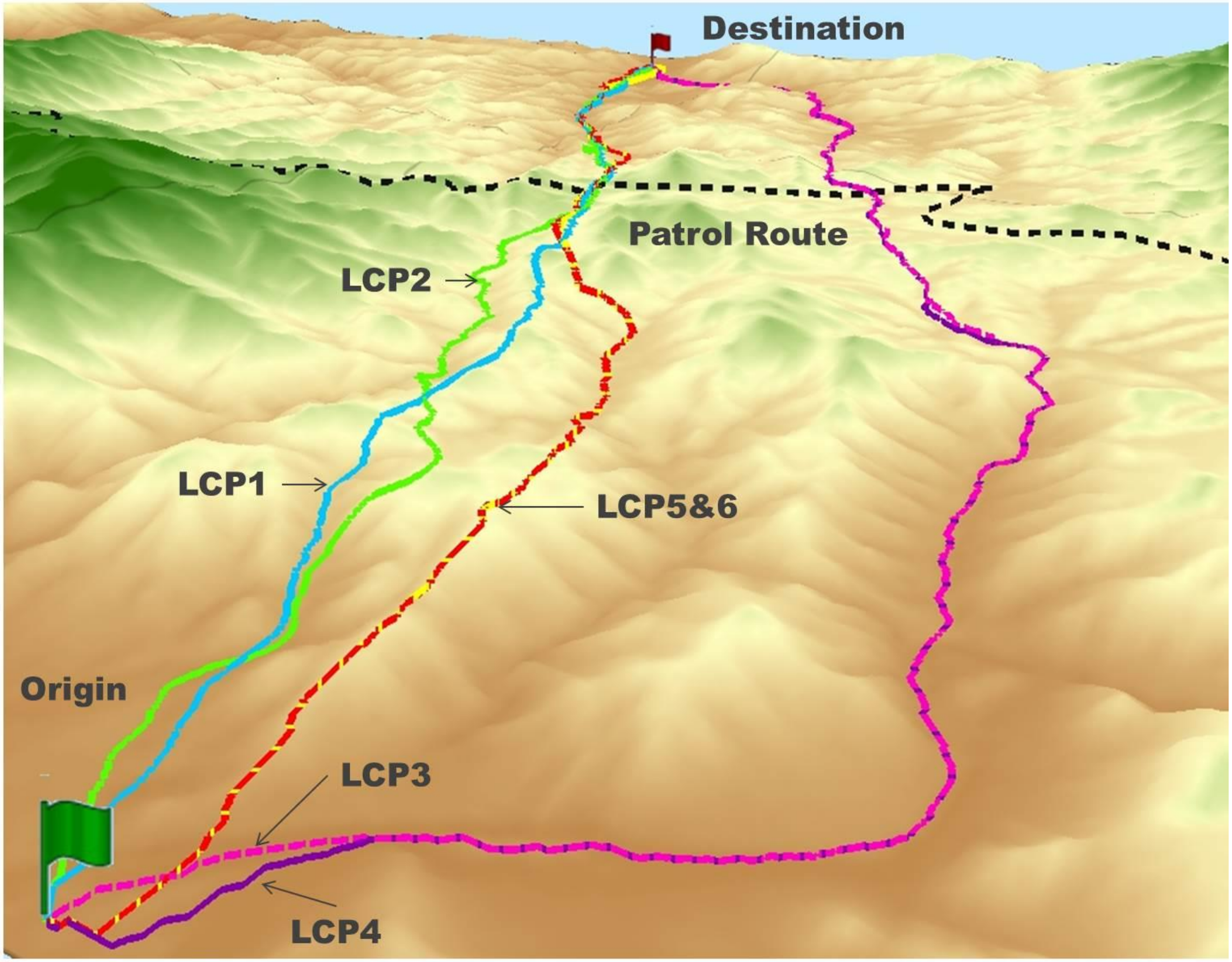

Figure 23 3D Isometric Perspective of Six Least Cost Paths. LCPs 5 and 6 Are Coincident Due to the Lack of OBP Station Proximity in this Area

Table 12 Six Factor/Route Pairings Visualized in Figure 23

Factor	Slope	Population	Viewshed	Land Cover	Hydrography	OBP Station Proximity
LCP1 / Blue	X					
LCP2 / Green	X	X				
LCP3 / Pink	X	X	X			
LCP4 / Purple	X	X	X	X		
LCP5 / Red	X	X	X	X	X	
LCP6 / Yellow	X	X	X	X	X	X

The results from a least cost path decision support model can provide valuable situational awareness to decision makers by drawing attention to the geographic areas most likely to be exploited by threats in their many forms. Once likely paths and/or corridors of illegal migration are identified, resources can be directed to mitigate the threats through the tactical application of:

1) **Detection & Assessment Technologies:** Unmanned Aerial Vehicles (UAVs), Sensors & Cameras

2) **Delay Mechanisms:** Personnel & vehicle barriers installed after point of reliable detection and of sufficient impedance to serve as a deterrence and/or increase the likelihood of interdiction by responders

3) **Response Enablers:** Less restrictive patrol routes, All-Terrain Vehicles (ATVs), increased agent presence in areas of suspected porosity

As demonstrated, mapping these paths has the potential to provide decision makers with a rapid visualization of exploitable vulnerabilities within their area of responsibility and can serve as a basis for directed resource allocation. The relevance of these findings are dependent upon a few key assumptions which the stakeholders should be made aware of.

- The factors accurately represent the enablers and inhibitors to movement for a particular threat profile.
- The staging and destination locations are accurate.
- The data are of sufficient spatial and temporal resolution for the analysis.

It is important to emphasize here, however, that the output from the model is one of many potential solutions to an inherently wicked problem. To paraphrase (Rittel and Webber 1973), a wicked problem is one that cannot be easily defined, require judgements on problem definition abstraction, have solutions that range between better and worse – not right or wrong, and have no objective measurement of success (Rittel and Webber 1973). In the context of this research, the development of the LCP model itself can be viewed as a manifestation of stakeholder compromise; from the determination of physical protection system objectives and threat definition to the ultimate design and evaluation of the conceptual or realized system.

CHAPTER FIVE: CONCLUSIONS

Conclusion

The objective of this research was to explore the use of LCP methodology to aid the USBP with the tactical application of resources along the U.S.-Mexico border region by demonstrating a proof-of-concept for predicting adversary paths of least resistance and threat avoidance. The success of the decision support model demonstrated in this study is heavily dependent upon the identification and interpretation of many factors that are not easily quantified for empirical analyses. For example, in this research, weighting prioritization had significant influence upon the resultant LCPs. As such, it is reasonable to suggest that subject-matter experts be well informed with regard to current intelligence in their Sector.

Many assumptions about the nature and motivation of the perceived threat required for LCP analyses in this domain are subject to human interpretation of natural and manmade physical factors as well as ideological motivators contributing to adversary route selection. Results may be expected to vary from real-world observations in cases that deviate from one or more variables that were identified as key factors in route prediction. For example, access to potable water may be of greater importance to route selection as opposed to OBP station proximity; thereby decreasing confidence in results for a particular threat profile. Similarly, the geographic coincidence of factors determines whether or not a factor deemed important is accounted for in the scenario being run. An example of this situation is depicted in Figure 23 where there were no OBP stations in this particular area to affect path planning and resulting in coincident paths.

A retrospective view of this research identifies how the use of the LCP model can help decision-makers consider the who, what, when, where, why and how of the problem more holistically. The *who* reminds them what they are trying to defend against, while the *what* helps narrow down the likely motivations of the threat. The *when* prompts consideration of the seasonal and/or social impedance factors that change frequently. The *where* helps to isolate the areas of greatest vulnerability, or conversely, areas where the highest return on investment can be expected. The *why* helps to describe the push/pull effects that influence adversary movement through space, while the *how* accounts for the various modes of travel that can be employed by the threat; each with its own trafficability properties.

By integrating objective input into a historically subjective decision-making process, we arrive at a new and more comprehensive understanding of the problem from which stakeholders can base their decisions. To the greatest extent possible, every effort should be made to ensure that the analysis is driven by data while noting influence by subjective factors such as those imposed by subject-matter expert opinion.

Implications

The findings of this research have demonstrated that the synthesis of geospatial data, GEOINT and subject-matter expertise, when fused in a decision-support model, can yield valuable information to decision makers to enhance security between ports-of-entry through directed resource allocation. If adopted as a decision support model to resource allocation, the proposed method may serve the national interest by:

1) Providing an auditable methodology to geographic resource allocation
2) Facilitating an engineered threat-based border security system between ports of entry
3) Implementing a flexible model capable of adaptation to contributing factors

Future research

Through this investigation, several opportunities for future research were exposed. First, a comparative analysis can be conducted which explores the spatial coincidence of LCP model output and real-world apprehension statistics by geographic location. Conversely, known IBC routes determined by groundtruthing and/or derived from remotely sensed imagery can be used to gauge forecast accuracy by OBP Sector. Second, the incorporation of actual IBC characteristics by threat type, as determined by intelligence, can yield a more predictive model than those used in this notional example. In any future research or real-world application of this methodology, it is recommended that a comprehensive exploration of uncertainty and result variability through sensitivity analyses be undertaken to ensure that the results are meaningful.

In the myriad of potential research directions spawned from this investigation, three common variables emerge as key to the success of a LCP decision support model.

1) Clear Objectives – Identification and communication of the model objectives to all stakeholders is critical to the identification of model parameters and agreed measurement standards. Failure to do so increases the risk of potentially answering the wrong question.
2) Data – It is unreasonable to expect the result of computer operations to be accurate if the data input is substandard, outdated or incomplete. Real-world application of this model will likely necessitate access to data that is restricted on the basis of its potential to adversely affect national security if disclosed to the public. Additionally, data uncertainty and error should be investigated thoroughly through sensitivity analyses to ensure that the results are meaningful in the context of stakeholder objectives.
3) Stakeholder Input and Subject-Matter Expertise – Commonly conceptualized as a homogeneous boundary at some scales, the nation’s border is heterogeneous at the scales

investigated here. As such, the consideration of stakeholder interests and subject-matter expertise is critical to ensure that the unique geographic and social characteristics of border regions are considered.

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