A Spatial and Temporal Exploration of How Satellite Communication Devices Impact Mountain Search and Rescue Missions in California's Sierra Nevada Mountain Range

by

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A Thesis Presented to the
FACULTY OF THE USC DORNSIFE COLLEGE OF LETTERS, ARTS AND SCIENCES
UNIVERSITY OF SOUTHERN CALIFORNIA
In Partial Fulfillment of the
Requirements for the Degree
MASTER OF SCIENCE
(GEOGRAPHIC INFORMATION SCIENCE AND TECHNOLOGY)

August 2023

To my husband, Martin Doerr, for his endless support

Acknowledgements

This paper would have been challenging without the guidance and support I received from the University faculty. I would like to thank the members of my thesis committee, Dr. An-Min Wu and Dr. Diana Ter-Ghazaryan, for encouraging meaningful and accessible research; my thesis advisor, Dr. Elisabeth Sedano, for her support that made this paper possible; and Dr. Vanessa Osborne, for her editing prowess. I am grateful to LtCol Ryan Sealy, Mike Myers, and Danny Conley at the Air Force Rescue Coordination Center for preparing and sending data on personal locator beacon activations. I am likewise indebted to Lovell Hopper, Meg Wilson, Eric Howard, and Monty Bell at the California Office of Emergency Services, who connected me with a statewide Search and Rescue dataset and humored my flood of questions related to the data. I would be remiss if I failed to mention Doug Samp, the search and rescue program manager for the United States Coast Guard (USCG) Pacific Area, and LCDR Zach “Texican” Geyer, a USCG helicopter pilot responsible for coordinating aviation resources during an emergency incident, for their support, encouragement, brainstorming, and connection to USCG resources. I also could not have arrived at the starting line of this project if it were not for the backing by CAPT Jose “Pepe” Arana and CDR Tom “Dirty” McCurdy, who supported my continuing education while active duty. Thank you, everyone, for your time and consideration.

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Abbreviations

AFRCC	Air Force Rescue Coordination Center
ART	Alpine Rescue Team
BLM	Bureau of Land Management
CALOES	California Office of Emergency Services
CCG	Canadian Coast Guard
CDFW	California Department of Fish and Wildlife
DEM	Digital elevation model
ELT	Emergency locator transmitter
EPIRB	Emergency position-indicating radio beacon
ESDA	Exploratory spatial data analysis
FOIA	Freedom of Information Act
FS	Forest Service
GIS	Geographic information system
HEMS	Helicopter-based emergency medical services
IAMSAR	International Aeronautical and Maritime Search and Rescue Manual
ICAO	International Civil Aviation Organization
IERCC	International Emergency Response Coordination Center
IMO	International Maritime Organization
INSARAG	International Search and Rescue Advisory Group
IR	Infrared
ISRID	International Search and Rescue Incident Database
JMT	John Muir trail

KDE	Kernel density estimation
MODIS	Moderate Resolution Imaging Spectrometer
MRA	Mountain Rescue Association
NAPSG	National Alliance for Public Safety GIS
NPS	National Park Service
NSS	National SAR Supplement to the IAMSAR Manual
NVD	Night vision device
OHV	Off-highway vehicle
PLB	Personal locator beacon
RCC	Rescue Coordination Center
SAR	Search and rescue
SASH	Spatial association of scalable hexagons
SEND	Satellite emergency notification device
SSI	Spatial Sciences Institute
STC	Space-time cube
USC	University of Southern California
USCG	US Coast Guard
USDA	US Department of Agriculture

Abstract

Mountain search and rescue (SAR) incidents are high risk events that consume time and money, often placing the lives of rescuers and subjects alike in precarious situations. The increasing accessibility of satellite communication (sat-comm) devices for outdoor recreation may change when and where mountain rescue teams are tasked, and California's SAR agencies need to understand the implications of emerging sat-comm device usage on SAR requirements to mitigate future risks caused by resource and training shortfalls. To date, no academic studies have conducted a holistic assessment of SAR incidents in the Sierra Nevada mountains or considered the impacts of sat-comm device usage on the SAR caseload. Such a knowledge gap impairs the ability of federal, state, and local agencies to anticipate costs and adequately train rescue teams to respond to mountain SAR incidents. This research explores the spatial and temporal patterns of historical mountain SAR incidents in the Sierra Nevada wilderness areas to understand how sat-comm devices impact SAR services in one of the most visited mountain regions in the continental United States. The results of this study suggest sat-comm devices are replacing traditional methods of notification that alert authorities to an emergency. Incidents where the subject communicates using a sat-comm device occur at sites of historical SAR activity where traditional methods of communication are dominant, as well as at new – and more isolated – locations. A lack of confidence in data quality, however, means this study primarily serves to demonstrate spatial and spatiotemporal analysis methods that SAR agencies may adopt to explore historical mountain SAR incidents at a regional scale.

Chapter 1 Introduction

Nature cares little for the boundaries built by humans to define dominion and stewardship. People who venture into the wild and encounter emergency situations likewise request aid irrespective of jurisdictional lines. Administrative boundaries continue to blur thanks to technological advances in portable satellite communication (sat-comm) devices. Sat-comm devices have near-global coverage areas, and they enable users to call for help anytime, anywhere. More traditional methods of calling for help have limited capabilities compared to sat-comm devices: cellular network antennas do not provide universal coverage; and word-of-mouth relay of an accident is limited by human mobility. In theory, increased accessibility to rescue services could mean an increased level of demand without a matching increase in supply. Furthermore, should sat-comm devices enable connectivity to communications infrastructure in areas that previously lacked access to human or cellular services, then the spatial distribution of emergencies might broaden in addition to increasing numbers of requests for rescue services.

Activating a sat-comm device sets in motion search and rescue (SAR) efforts that are ultimately executed by the emergency response agency with jurisdiction over the activation site. Private and public organizations who monitor sat-comm device activations and coordinate the response often maintain separate SAR incident datasets that adhere to different reporting requirements. Similarly, the local SAR agencies who execute the response to all SAR incidents within their jurisdiction, regardless of the method of notification, frequently keep records that are not held to a state or national standard. This isolation of SAR incident records contributes to a general lack of awareness of how trends play out across a geographic region. Emergency response agencies would benefit from an analysis of cross-jurisdictional datasets in order to improve their SAR response and determine to what extent new technologies like sat-comm devices alter the SAR landscape. The optimal datasets for research therefore lie with state-, regional-, national-, or international-scale agencies responsible for collecting and standardizing records.

The intent of this research is to take two, cross-jurisdictional datasets and examine how the spatial and temporal patterns of mountain SAR incidents originating with a sat-comm device activation compare with the traditional means of distress notification (e.g., in-person notification, cell phone, etc.) over time. The study area encompasses the wilderness areas of California's Sierra Nevada mountain range due to their extreme topography, relative inaccessibility, multiple SAR controlling agencies, and high visitor numbers – factors which increase the risk in the SAR process and complicate post-SAR analysis. To date, there are no academic studies that have analyzed mountain SAR patterns at this scale in California nor considered the influence of sat-comm devices on when and where rescue teams might be tasked. The goal of this research is therefore to remedy this gap and determine the impact of sat-comm devices on the spatial and temporal distribution of mountain SAR incidents. To meet this goal, this study presents methodology that may be adapted by SAR agencies to continuously evaluate their local SAR landscape. In this way, SAR agencies responsible for coordinating rescue teams might be better prepared to respond to future mountain SAR incidents.

This chapter begins with a definition of the terms used throughout this study. This is followed by an overview of sat-comm device types and services. The chapter then goes over the study area and describes what SAR datasets are available for the study area. The chapter concludes with a statement on the motivation behind the development of this project and a review of the methods employed to advance the research objectives.

1.1 Search and Rescue

Search and rescue efforts involve locating people in potential or actual distress and delivering them to safety. The goal of SAR agencies is to shorten the time from distress notification to resolution without compromising safety or mission success. The framework for operational success is laid out in regulatory publications and ultimately achieved by the real-time execution and sound judgment of rescue coordinators and rescue teams. International SAR organizations that fall under the United Nations, like the International Search and Rescue Advisory Group (INSARAG), International Maritime Organization (IMO), and International Civil Aviation Organization (ICAO), publish manuals that standardize procedures and articulate rescue responsibilities on a global scale. National- and state-level guidance builds off these documents to fit the needs of SAR operations in their respective coverage areas. This section describes the domestic SAR structure including the chain of responsibility for SAR response and the management of historical SAR data.

1.1.1 Governing Publications

The federal SAR agencies in the United States lean most heavily on the International Aeronautical and Maritime Search and Rescue (IAMSAR) Manual – which is the joint work of the IMO and the ICAO – to refine domestic procedures and offer structure to the civil SAR process. The National Search and Rescue Committee (NSARC) is the federal organization responsible for coordinating procedures for interagency standardization, and they publish the National Search and Rescue Supplement (NSS) to the IAMSAR Manual (NSARC 2016) and the Land SAR Addendum to the NSS (NSARC 2011). These two documents set out the terminology and organizational relationships used in this research.

1.1.2 Mountain SAR Incident Definition

Unlike most classifications of SAR operations, a mountain SAR incident is not explicitly defined in the Land SAR Addendum, though it is alluded to as a subset of land SAR, which is a subset of civil SAR. Figure 1 offers a visual breakdown of how mountain SAR is categorized within SAR terminology. Civil SAR efforts are defined as those that occur in a non-hostile environment, and they range from aeronautical and maritime emergencies to catastrophic disasters. Land SAR refers to SAR incidents that occur on land, outside of urban areas, and are generally not associated with natural disasters. The definition of mountain SAR used for the purpose of this research refers to a land SAR event which occurs in mountainous terrain away from the built environment, where the subject is participating in outdoor recreation, and which requires the assistance of specialty-trained SAR assets. Assets include technical ropes teams, swiftwater rescue crews, off-highway vehicle (OHV) SAR teams, and helicopter crews, all of which maintain specific qualifications and training.

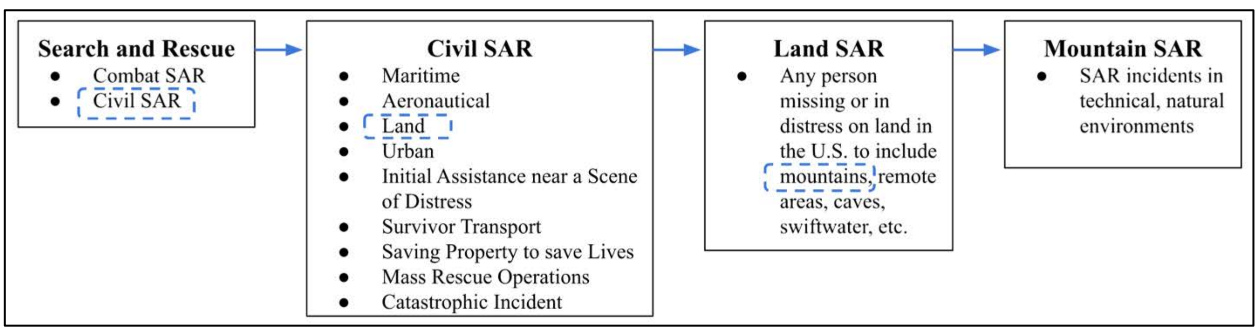

Figure 1. The placement of mountain SAR within the SAR typological structure

A SAR incident refers to a request for SAR assistance, but responders are uncertain as to whether a person is in actual distress. Geographic information science also has a term for incident data: an incident refers to a site corresponding to a single set of coordinates (Esri n.d.). Since the mountain SAR events in this research contain varying degrees of distress, from false alarm to death, and because they correspond to a single coordinate pair, all mountain SAR events considered for analysis in this research are referred to as mountain SAR incidents.

1.1.3 Five Stages of SAR

SAR consists of five stages: awareness, initial action, planning, operations, and conclusion (NSARC 2011). Figure 2 depicts these stages derived from the model found in the Land SAR Addendum. Each stage provides an opportunity for after-action lessons and process improvement. In particular, the Planning and Operations stage are a continuous feedback process, and advanced preparation (e.g., through research on historical incidents) can increase the efficiency of the Operations stage for a faster time to SAR Conclusion. The spatial and temporal analysis of historical SAR incidents identifies where and when incidents traditionally occur so SAR operations centers and rescue teams can develop appropriate training and response plans. For example, a consistent cluster of SAR incidents may be identified around climbing routes that straddle a jurisdictional boundary, but only one of the jurisdictions has a technical mountain rescue team on immediate recall that can respond to injured climbers. Questions asked during the Initial Action and Planning stages could be tailored based on an analysis of historical SAR incidents for optimized rescue asset preparation and utilization.

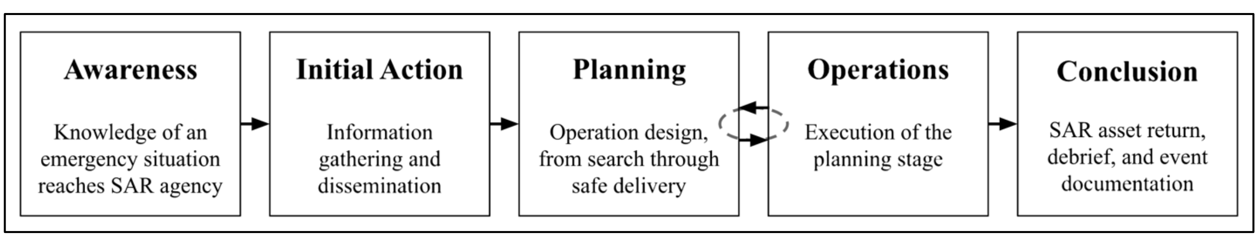

Figure 2. The five stages of SAR, as adapted from the Land SAR Addendum

1.2 Satellite Communication Devices

Owing to technological advances in sat-comm devices, calling for help is increasingly accessible to the general population from anywhere on the planet that can connect to the applicable satellite infrastructure. Sat-comm devices therefore have the potential to accelerate the SAR process from locations that previously would have had a delay in incident notification if subjects had to rely traditional notification methods or overdue procedures (i.e., when a person misses a check-in, often relayed to SAR agencies by friends and family). Many of these sat-comm devices have an "SOS" feature, the activation of which sends an emergency signal with location information via satellite to a rescue coordination center (RCC). The RCC then takes responsibility to inform the appropriate local rescue agency. Figure 3 presents a diagram of the sat-comm device emergency notification process and incident record keeping. It is worth noting that sat-comm device records are often saved in duplicate or triplicate: one record of an incident lies with the RCC, one with the local agency accepting the tasking (e.g. county), and one with the state agency (if they require the local agency to forward their reports). Along with coordinate data, some models of sat-comm devices can also send and receive text messages. Because modern sat-comm devices provide reasonably precise location data, they not only expedite the Awareness stage of a mountain SAR incident, but the Initial Action and Planning Stages as well.

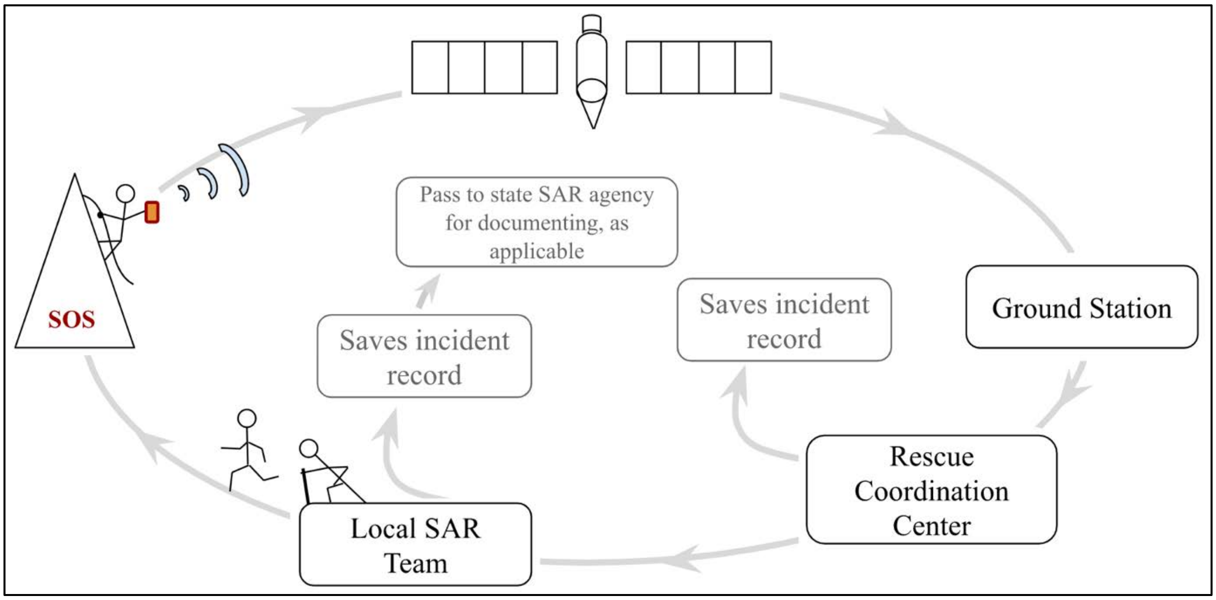

Figure 3. The relay of information from sat-comm device activation to rescue team launch

Because sat-comm devices make it easier to initiate a SAR response from remote locations, they conceivably increase the demand for SAR services, with implications for SAR asset management and support requirements. SAR agencies have a responsibility to investigate all requests for aid until an incident is resolved. Variations in mountain SAR incident spatial and temporal patterns, perhaps due to an increase in sat-comm device SOS activations, might therefore impact how agencies manage emergency resources. Resources include time, money, and lives: the time and money devoted to training; the time spent verifying the authenticity of an emergency incident; and the cost of ground and aviation SAR assets to search for, locate, and transport the subject in question. Agencies responsible for efficiently and safely planning and coordinating SAR efforts, and the rescue assets tasked to assist, therefore benefit from knowing not only when and where mountain SAR incidents traditionally occur, but how sat-comm devices might alter the patterns and trends of these incidents with implications for future caseloads.

1.2.1 Personal Locator Beacons

Personal locator beacons (PLBs) are portable devices that, once activated, act as both a radio beacon and a sat-comm device. The radio beacon function allows external assets with direction-finding capability to locate the PLB signal, while the sat-comm component increases communications coverage. PLBs send signals over the 406 MHz internationally recognized emergency frequency to initiate a SAR response once the signals are picked up by SAR sensors onboard international, publicly managed satellites. In addition to the 406 MHz frequency, PLBs also emit radio frequencies over designated emergency channels which rescue units can home in on. The modern, portable PLB has comparable functions to emergency position-indicating radio beacons (EPIRBs) traditionally carried by maritime craft, and to the emergency locator transmitters (ELTs) onboard aircraft. What differentiates PLBs from EPIRBs and ELTs is registration: instead of being registered to a transport system, PLBs are registered to an individual. PLBs were approved for civilian use in 2003 (US Air Force n.d.) and have since grown in global popularity as technological advances have improved their functionality and accuracy, with most models advertising satellite positional data accurate to within 100 m (US Air Force n.d.).

PLB activation signals are detected by the international COSPAS-SARSAT satellite constellation, passed to a ground station, and routed to the appropriate RCC (LandSAR n.d.). In the continental United States, the Air Force Rescue Coordination Center (AFRCC), located at Tyndall Air Force Base, Florida, is currently responsible for notifying the appropriate local agencies of device activation within their jurisdiction based on AFRCC and State coordination procedures (US Air Force n.d.). PLBs no longer have market dominance in portable, satellite-capable, emergency assistance devices, however, and consumers can currently choose from a range of products linked to commercial satellite systems like Zoleo, SPOT, and Garmin's InReach. These are discussed further in the section below.

1.2.1 Satellite Emergency Notification Devices

The commercial sat-comm products that have emerged over the past couple of decades are referred to as satellite emergency notification devices (SENDs). Depending on the device and the associated satellite system, SENDs can provide SAR responders with coordinate data accurate within 5-15 m under most operating conditions (Garmin n.d.; SPOT n.d.). Unlike PLBs, SENDs do not emit homing frequencies and instead rely solely on signal relay through the partnered satellite infrastructure. For example, Garmin and Zoleo products use the Iridium satellite network (Garmin n.d.; Zoleo n.d.), while SPOT uses Globalstar satellites and ground stations (SPOT n.d.). SEND activation results in coordination through a partnered RCC, with most devices going through the International Emergency Response Coordination Centre (IERCC) (IERCC n.d.).

Tracking data from SEND activations might provide a wealth of information, offering insights into patterns in SAR incidents and implications for future trends. For instance, as of October 2022, Garmin announced 10,000 SOS activations from its InReach products after just over a decade on the market, with over a third of activation originating from backpacking and hiking users and over half due to medical or injury needs (Garmin 2022). Emergency notifications reliant on satellite infrastructure will only increase as more devices connect to satellite networks. In 2022, Apple announced their iPhone 14 smartphone models will be capable of emergency notifications via satellite systems, and the company has invested in improving the Globalstar satellite infrastructure (Apple 2022). With the future looking like every person who goes into the wilderness will be able to call for help with the press of a button, SAR coordinators and responders would do well to be armed with as much advanced information as possible on the spatial and temporal trends associated with satellite-initiated mountain SAR incidents in an age of omnipresent connectivity.

1.3 Study Area

California's Sierra Nevada mountain range is of particular interest to mountain SAR operations due to high visitor numbers, diverse terrain features, and opportunities for recreation in backcountry areas. These characteristics also make the range interesting for spatial exploration, as spatial phenomena influence how visitors interact with the landscape. For example, trail networks tend to invite higher numbers of visitors than off-trail locations (Doherty et al. 2011), and some viewpoints might draw particularly large crowds of people looking to enhance their social media profile (Lu et al. 2021). The study area for this research falls within the portion of the range commonly referred to as the High Sierras, as this section includes world famous – and heavily traveled – trail systems weaving amongst some of the highest peaks in the continental United States (James and Eardley 2021).

Several websites that keep track of visitor permits provide an indication of the high traffic volumes. The National Park System (NPS) reports Yosemite National Park hosts more than four million visitors per year, and that permits for the John Muir Trail (JMT) – which runs from Yosemite to Mt. Whitney – doubled from 2011 to 2015, leading to a cap of 45 permits per day (NPS n.d.). The non-profit Pacific Crest Trail Association reports a similar jump in permit numbers, from 1,879 issued in 2013, to 7,888 issued in 2019 (PCTS n.d.). More visitors might equate to more opportunities for sat-comm device activation, intentionally or accidentally, and potentially an increased demand for mountain SAR support.

The Sierra Nevada mountains include several wilderness areas governed by three public agencies: the Bureau of Land Management (BLM), the Forest Service (FS), and the NPS. Wilderness areas are lands protected by federal law to provide opportunities for solitude and to limit access to man-made infrastructure and technology (Wilderness Connect n.d.). Due to the lack of infrastructure, wilderness areas effectively exclude non-mountain SAR events (e.g., car accidents), and the study area is based on the boundaries of these wilderness areas (Figure 4).

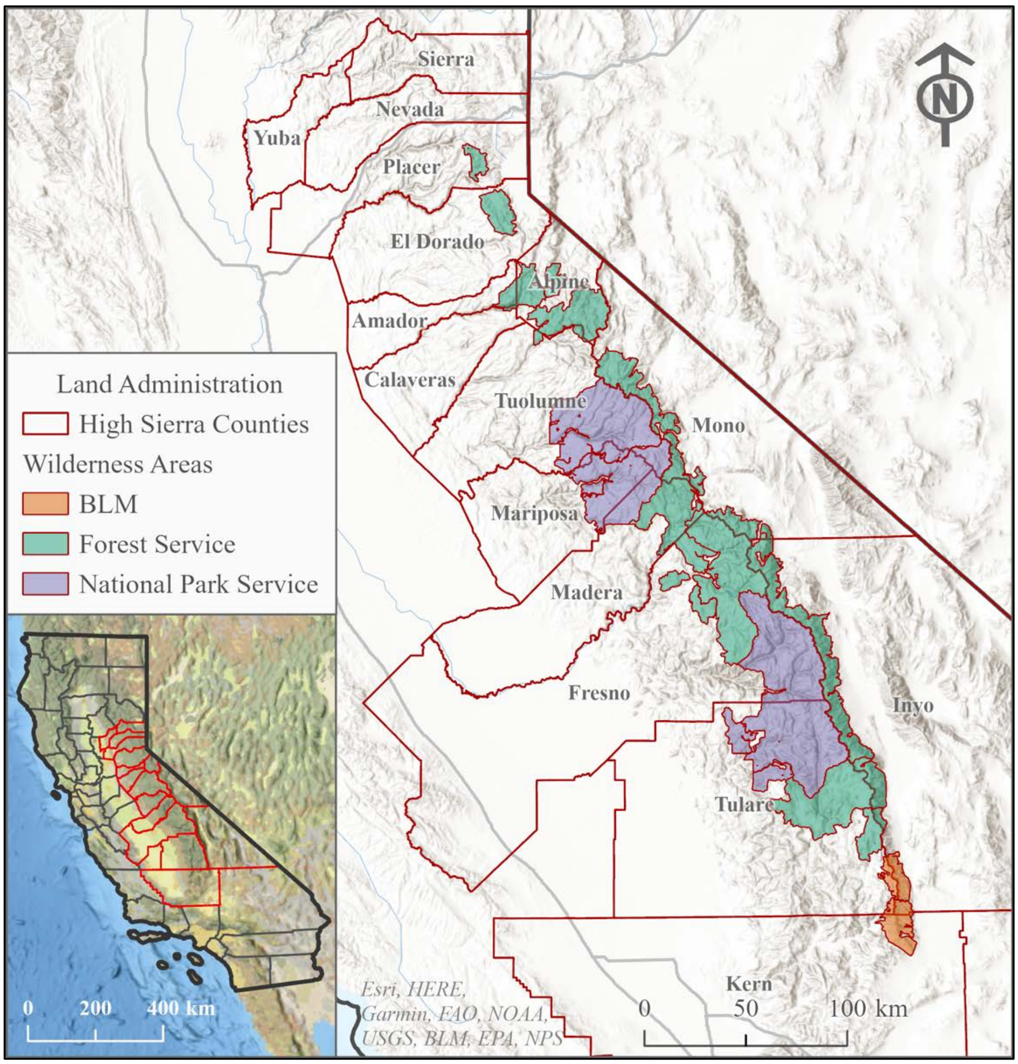

Figure 4. A map of the study area, detailing land divisions by jurisdiction

Sixteen of California's 58 counties include some portion of the High Sierras, and the study area crosses into thirteen of these. In California, the counties are responsible for developing procedures to respond to all Land SAR incidents not covered by federal agencies, i.e., excluding aviation emergencies, maritime emergencies in the navigable waters within the United States, and within the NPS lands (California Public Law n.d.; NSARC 2011). If the counties require additional assistance, they can coordinate with state and federal agencies for external assets. The NPS is a federal organization under the Department of the Interior, and it maintains its own SAR response for the lands it administers. While the NPS does not act in the capacity of a RCC, it maintains incident coordination functions, and NPS SAR assets may assist neighboring jurisdictions in the SAR process, if required (NSARC 2011). Since neither the BLM or FS are assigned federal SAR responsibilities, the county is responsible for SAR incidents within BLM and FS wilderness areas. Incidents originating with a sat-comm device enter the SAR process as depicted in Figure 3 above.

Regardless of who administers the land, the High Sierras encompass challenging environments for visitors and rescue teams alike. Mountain peaks reach upwards of fourteen thousand feet in some areas, and the higher elevations pose a risk to unacclimatized visitors, as well as to helicopters that have reduced performance at higher elevations. Hazardous conditions become more pronounced at night when rescue teams lose the benefits of daylight, and teams with infrared (IR) and/or night vision device (NVD) capabilities are often required. Exploring historical mountain SAR incidents and the influence of sat-comm devices on spatial and temporal distributions thus helps SAR organizations prepare for future SAR operations occurring in this challenging geographic region.

1.4 Search and Rescue Data

The quality of spatial and temporal analysis output depends on the quality of the input data. Incomplete datasets might suggest spatial patterns which are inaccurate, and temporal trends might also be conservative or exaggerated. Datasets which are limited to one administrative unit can fail to capture spatial relationships near their borders, as data from neighboring units would not be considered. One way to mitigate concerns over data completeness is to have one SAR agency set the standards for data collection and serve as a data repository.

There is precedent for SAR data standardization in the United States: maritime SAR operations are coordinated through the US Coast Guard (USCG), the agency which also manages the historical maritime SAR database. This database spans all USCG coverage areas – from inland lakes to the waters off Hawaii and Alaska – and adheres to detailed standards, making it ideal for studies exploring the spatial and temporal relationships of emergency events and looking for ways to improve the SAR process (Hornberger, Cox, and Lunday 2022; Malik et al. 2014). The USCG also employs a spatial analysis and predictive program, the SAR Optimal Planning System (SAROPS), to integrate real-time environmental conditions and geographic information for improved SAR asset response (USCG n.d.).

Unlike the maritime environment, mountain SAR – excepting NPS data – has neither an equivalent, comprehensive, national-scale dataset, nor SAROPS-type software available to first responders, although efforts are being made in this direction. The International SAR Incident Database (ISID), created with a grant from the US Department of Agriculture, intends to serve as a data repository for multiple nations – the United States included – to better understand lost person behavior in varying overland environments. However, the ISID currently does not represent data from all fifty states, and California is not yet a contributor (dbs Productions n.d.). SEND activation data through either the companies that support the devices or the IERCC could provide another source of national-scale data, but SEND data are not available from any private companies due to privacy concerns. Instead, public agencies currently offer the best available options to academic researchers. The US Air Force, as the responsible authority for PLB activations in the United States, is one data source that can offer nation-scale insights on a slice of mountain SAR incidents. Another source that can provide state-wide data on emergency incidents is the California Office of Emergency Services (CALOES).

1.4.1 Air Force Rescue Coordination Center PLB Dataset

The AFRCC offers a limited option for spatial and temporal analysis of mountain SAR incidents spanning administrative boundaries. The AFRCC is the primary inland SAR coordinator at the federal level within the continental United States (NSARC 2011). They are responsible for managing all distress calls originating from PLBs and ELTs. Since the latter are associated with aircraft, and the intent of this research is to examine patterns in mountain recreation, only PLB data are considered an appropriate representation of mountain SAR incidents per the definition used in this paper. While the AFRCC dataset is limited to PLBs and does not capture private sat-comm device activations, it could represent how people use sat-comm device technology in remote mountain areas to initiate the SAR process. Access to the AFRCC data requires a Freedom of Information Act (FOIA) request, and the request is restricted to no more than seven years' worth of records. While there are not enough PLB activations in the Sierra Nevadas to support meaningful spatial statistical analysis, the PLB data from the AFRCC complements the more numerous CALOES SAR incident dataset, serving to reinforce findings on the role of sat-comm devices in the mountain SAR process.

1.4.2 California Office of Emergency Services Dataset

The main option to assess mountain SAR incidents and sat-comm activations at the scale of the study area is to pull from the state-level dataset originating with the CALOES. In

California, all mountain SAR incidents except those within a National Park are managed at the county level, unless a county requests additional assets, at which point they reach out to state assets via CALOES and federal assets coordinated through AFRCC. One of the results of the division of SAR responsibilities is the lack of a historical data repository managed by one entity for the state. That changed in 2018 when CALOES started collecting SAR incidents from the array of jurisdictional entities. While the robustness of the CALOES dataset relies on the reporting quality of the counties and NPS, it offers unparalleled access to large numbers of SAR incidents with attributes on location, date, and time. Unlike the AFRCC dataset, the CALOES dataset includes all mountain SAR incidents regardless of means of distress notification, be it by cell phone, sat-comm device, overdue procedures, or other method of relay. Because AFRCC passes PLB distress notifications to the appropriate local rescue agency, it would be assumed both the AFRCC and CALOES datasets overlap, except for accidental PLB activations if AFRCC were able to verify the false alarm without involving additional assets. Together, these two datasets, the one from AFRCC which contains only PLB data and the one from CALOES which contains all land emergency incidents, are used for exploration and analysis of sat-comm devices in mountain SAR incidents.

1.5 Motivation

Knowing when, where, and what mechanisms are influencing mountain SAR incidents provides SAR agencies and rescue teams with actionable information to design effective training plans and maintain the appropriate equipment for safe rescue operations. Despite the benefits associated with understanding how sat-comm devices are impacting the mountain SAR landscape, no academic research has either applied spatiotemporal analyses to mountain SAR incidents or explored the impact of sat-comm devices in the SAR process. For California's High

Sierra mountain region specifically, filling this gap in the scholarly literature has the potential to improve the SAR process for multiple emergency response jurisdictions, as well as assist the additional state and federal assets the counties and NPS might call upon for assistance. Statistically supported results identifying locations where mountain SAR incidents are not only occurring year after year, but also where incidents are exhibiting a positive or negative trend, could support policy requests for new resource or funding allocations. SAR ground teams and helicopter crews could use the results from this study to train new members and better prepare them for conditions they can expect to encounter. One popular albeit unofficial SAR motto states, "the first rule of SAR is don't make more SAR." Having a thorough understanding of when and where mountain SAR incidents historically occur across an entire geographic area would bolster local experience, increase safety margins through adaptations to policy and training, and decrease the odds that the rescue team could become, in turn, a SAR case.

1.6 Thesis Overview

Chapter 1 has reviewed the background and motivation for this research, as well as provided a description of the terms and topics used in this study. Chapter 2 delves into where SAR features in the academic literature, supplemented by research on the spatiotemporal analysis of non-SAR emergency incident data to support the methods used in this study. Chapter 3 covers the methods employed in this research to identify and compare the spatial and temporal patterns of sat-comm device-initiated mountain SAR incidents against other means of SAR notification. Chapter 4 presents the results of this study. Chapter 5 offers a discussion of the results, a review of the study's limitations, and recommendations for future research and SAR policy makers.

1.7 Methodological Overview

The goal of this study is to explore the impact of sat-comm devices on mountain SAR in the High Sierras. The methods developed to accomplish this goal involve spatial statistics, a trend statistic, and visual analysis. Due to data constraints, only the CALOES dataset is examined using spatial and trend statistics, while the AFRCC dataset supplements the statistical results through comparison and visual analysis.

Individual mountain SAR incidents from the CALOES dataset are first explored using point pattern analysis techniques to detect the distances at which spatial associations appear. Global and local spatial statistics are then used to detect significant spatial patterns of aggregated mountain SAR incidents across the study area and within local neighborhoods respectively. Conducting trend analysis in conjunction with local spatial pattern analysis identifies emerging patterns within the mountain SAR neighborhoods, facilitating the interpretation of the mountain SAR incident spatial distribution over time.

Using visual analysis and distance measurements, mountain SAR incidents from the AFRCC dataset are evaluated in the context of the CALOES spatial statistical results to assess possible relationships. Spatial and temporal attributes from both datasets are explored and compared using descriptive statistics. The accidental activations of sat-comm devices from both datasets are then evaluated for their potential to increase the workload of mountain SAR organizations.

Chapter 2 Related Work

The intent of this research is to explore spatial trends in mountain search and rescue (SAR) incidents across a geographic region in order to assess how satellite communication (sat-comm) devices might affect the SAR landscape over time. To meet the research objectives, datasets containing mountain SAR incidents from California's Sierra Nevada mountain range are brought into a geographic information system (GIS) – a type of software that facilitates visual and statistical analysis of geographic data. The datasets are cross-jurisdictional to capture the spatial and temporal scope of incidents that, like the mountains they occur in, do not pay heed to administrative boundaries. Mountain SAR incidents originating with a sat-comm device are compared against incidents that do not rely on these devices using visual and statistical methods developed in Esri's ArcGIS Pro 2.9 software suite (Esri 2021). ArcGIS Pro offers a user-friendly interface to explore and assess historical incident data through spatial and temporal analysis. This study expands upon prior academic research to demonstrate how SAR professionals can incorporate GIS tools to examine SAR incidents over space and time and explore the influence of sat-comm device activations.

There are, however, relatively few research papers and books that consider both the spatial and temporal components of SAR incidents. Much of the academic literature to date examines maritime SAR incidents, and of these, a growing number leverage the benefits of a GIS to conduct spatial analysis of geographic data as computational processing capabilities improve (Goerlandt and Siljander 2015; Guoxiang and Maofeng 2010; Stoddard and Pelot 2020). While several maritime SAR studies examine the temporal attributes of SAR incidents (Malik et al. 2014; Sonninen and Goerlandt 2015; Stoddard and Pelot 2020), none assess the emerging trends of incidents tied to a specific location, possibly because the maritime domain is fluid and rarely constrained by stationary topographic features. There is a dearth of published research that reviews the spatial components of mountain SAR incidents, particularly at scales that span multiple jurisdictions. To supplement the thin body of work that deals explicitly with mountain SAR incidents, one needs to explore emergency incidents from other genres that occur at similar spatial and temporal scales. To this end, there is a burgeoning number of studies that examine the spatiotemporal patterns of wildfires (Aftergood and Flannigan 2022; Reddy et al. 2019; Visner, Shirowzhan, and Pettit 2021). Wildfires are similar to mountain SAR incidents in that they can occur across expansive environments and are often seasonal, making studies on wildfire patterns a suitable genre to reference. This chapter reviews the related literature covering these three categories of emergency incidents – maritime SAR, mountain SAR, and wildfires – and discusses how techniques and lessons from past research can inform the methodological design of this paper.

2.1 Spatial and Temporal Analysis of SAR Incidents

As of 2023, there are far more academic works advancing the maritime SAR process than land SAR missions. In respect to spatial analysis, the scope of maritime SAR differs from mountain SAR. Maritime SAR is largely two-dimensional: maritime SAR incidents are rarely associated with a topographic feature (exceptions would be narrow waterways and littoral hazards) and instead are vulnerable to the drift of currents and winds. By contrast, mountain SAR incidents occur in a three-dimensional space and tend to be stationary. Despite these differences, the spatial and temporal findings from maritime SAR studies offer implications on hazard identification and resource allocation that are similar to mountain SAR.

Though sparse, prior research on mountain SAR incidents covers a spectrum of topics, including demographics, injury patterns, lost person behavior, and the digitization of historical datasets. The scale of analysis conducted in prior research is, however, constrained, and often limited to a single SAR jurisdiction (e.g., a national park). Very few mountain SAR studies conduct analyses across a region that encompasses several administrative boundaries. Another limitation with the mountain SAR literature concerns the breadth of analyses employed: most research articles to date that examine historical mountain SAR incidents rely on aspatial analytical methods, which can reveal temporal patterns but lacks the spatial considerations available with a GIS. The few studies that do employ a GIS make use of datasets spanning several years but elect to conduct purely spatial rather than spatiotemporal pattern analysis. A review of past research on mountain SAR incidents highlights the gaps in analysis, but also reveals why a thorough understanding of mountain SAR is critical to mitigating the risks posed to rescue teams and subjects in distress.

2.1.1 Analysis of Maritime SAR Incidents

The maritime environment is the main domain for scholarly research on SAR incidents. This bias is possibly due to a drive to protect businesses and promote safety. Fishing, recreational boating, and commercial shipping operations all occur in potentially hazardous environments, and if there is a low chance of a successful rescue, poor SAR support could hurt public and private sector interests (Marven, Canessa, and Keller 2007). The bias might also be due to the relatively high profile of maritime emergencies compared to mountain ones: not only do ships and boats contain more lives than the average hiking party, but there are also environmental concerns associated with oil spills and contaminants entering the water (Goerlandt et al. 2017). The higher percentage of maritime SAR research studies might also be due to dataset availability. Comprehensive datasets for maritime SAR incidents are maintained by a nation’s Coast Guard, and these datasets generally suffer less from the fragmentation or varying standards seen with mountain SAR datasets at scale, though there are still data quality concerns associated with missing data (Malik et al. 2014; Stoddard and Pelot 2020). While spatial analysis methods are not always necessary to examine maritime SAR data, they are common in maritime SAR studies to account for the spatial nature of incident data.

2.1.1.1 Spatial analysis of maritime SAR incidents

A common theme in the academic research on maritime SAR incidents is the identification of incident hot spots and clusters, often to determine whether current rescue asset locations offer sufficient coverage. Azofra et al. (2007) conducted a type of point pattern analysis – weighted density analysis – to develop an objective, apolitical method to determine the best placement of maritime rescue assets. They designed two distribution models that categorized the suitability of a rescue boat's or rescue helicopter's base station represented by changes in a coefficient. Azofra et al. found their zonal distribution model, which involved constructing zones based on SAR asset capabilities, preferable to their individual distribution model, which considered a single asset to every incident. This is because a zone smooths out the effects of outliers. Within each zone, a single set of coordinates representing a "superaccident" site was identified and used as input in the model. The superaccident coordinates were based on the arithmetic mean of the incidents occurring within the zone and were weighted by the total severity of incidents. Severity was based on a four-point scale, and it encompassed medical concerns, sea surface temperatures, and hazards in the area. While Azofra et al.'s model offers an objective approach to guide decisions on resource allocation amongst local and regional entities, the authors recognize their model –since it is built from historical incident data – assumes future incidents will follow similar spatial patterns. They therefore recommended continually updating the model's inputs to identify the most efficient distribution of resources for SAR success.

While the identification of SAR incident clusters based on historical incident analysis may inform asset placement strategies, it may also provide insights as to whether existing administrative boundaries should be redrawn to facilitate more efficient SAR tasking. Marven, Canessa, and Keller (2007), in their book chapter on exploratory spatial data analysis (ESDA) and maritime SAR, reviewed how point pattern analysis and spatial statistics can support effective decision making and evaluate jurisdictional boundaries. The authors demonstrated their methods using the GIS tools of the day and the Canadian Coast Guard's (CCG) incident data from the Pacific Region, 1993-1999. After cleaning the CCG data to remove inaccurate or incomplete incidents, the authors were left with 11,457 maritime SAR incidents spanning approximately 157,000 km^2. Visualizing the point patterns of incidents revealed obvious spatial heterogeneity. Aggregating the incidents by jurisdiction would preclude a realistic assessment of spatial patterns, since jurisdictions encompass a large amount of open water, but maritime incidents are mostly distributed across the small area of sheltered waters. In contrast, point pattern analysis methods, like visual analysis and kernel density estimates (KDE), do not suffer from aggregation pitfalls like unnatural jurisdictional lines or the modifiable areal unit problem, but point pattern analysis does lack the significance metrics provided by spatial statistics.

In order to have a statistical foundation for spatial pattern analysis, Marven, Canessa, and Keller turned to CrimeStat version 3 (Levine 2004), a statistical software package that can analyze geographic incident data. The authors applied two point pattern analysis methods to the CCG dataset to find statistically significant spatial clustering: the Spatial and Temporal Analysis of Crime (STAC) and nearest neighbor hierarchical (NNH) clustering. Both methods require an element of subjectivity. With STAC, the analyst needs to specify a grid cell size and the minimum number of points in a cluster for comparing densities. With NNH clustering, the analyst needs to similarly define the number of points that constitute a cluster as well as the threshold distance between points to consider them neighbors. The authors found NNH useful for comparing incident clusters over time, though they felt KDE was the best for a visual comparison of datasets. While Marven, Canessa, and Keller provide an expert review of how to maximize the benefits of spatial analysis to advance maritime SAR efforts, the authors did not discuss the efficacy of using a GIS at a regional scale, nor did they provide guidance on how analysts should set parameters to achieve results that most closely represent the underlying spatial associations.

Spatial analysis tools available in a GIS can produce intuitive and visually accessible results, although the spatial conclusions are based on an imperfect representation of reality largely due to computational processing limitations. Goerlandt, Venäläinen, and Siljander (2015) constructed a risk-based model to review rescue boat capabilities in the Gulf of Finland from 2007 to 2012, in which they used a GIS to identify high-density accident sites. Their study area stretched along the southern coast of Finland and covered about 11,500 km^2. The authors used descriptive statistics and charts to evaluate several risk indicators that were not associated with specific coordinates (e.g., the temporal distribution of incidents and mission attributes). They used GIS tools to evaluate the spatial distribution of incidents and run a cost-distance analysis of rescue boats to high-density accident site. Using ArcMap software, the authors created a density surface of the study area for a visual analysis of incident hot spots and to measure rescue boat response times to the high-density sites under a variety of wind and wave simulations. Goerlandt, Venäläinen, and Siljander found the ArcMap tools offered a higher level of fidelity than aspatial methods when developing their spatial risk indicators. However, the authors noted their methods were time consuming, owing to the 10 m resolution cost surface required to accurately represent the coastal topographic features (e.g. islands and waterways). The authors discussed the limitations of resolution further, as well as specific ArcGIS software model limitations when modeling the maritime environment, in another paper published the same year (Siljander et al. 2015). While GIS-based analysis facilitates the exploration of geographic data, models and methods reliant on GIS products must balance the study area size and scale of analysis with computational demands for effective research.

2.1.1.2 Temporal analysis of maritime SAR incidents

Although maritime and mountain SAR incidents occur in different operating environments, the emphasis by maritime SAR researchers to identify SAR incident clusters and improve maritime SAR policy is equally applicable across domains. Similarly, maritime SAR studies that explore temporal patterns of SAR incidents offer relevant methodological techniques to mountain SAR research due to the emphasis on resource distribution and hazard mitigation. In the academic research to date on maritime SAR, temporal analysis is generally aspatial, often taking the form of a graphical representation or a trend statistic.

Whether it is a GIS-derived map, a chart, or a matrix, a visual representation of spatial and temporal data often increases the accessibility of research products to a broad audience base and prompts new questions about what drives the patterns under observation. To assist the USCG Ninth District, whose area of responsibility covers the Great Lakes, Malik et al. (2014) created an interactive visual analytics system for exploring spatial and temporal patterns of historical incidents in the region. Their system is based on a custom GIS supported by Microsoft Windows software, and it incorporates OpenStreetMap base layers through several programming languages. SAR incidents may be viewed as unique values or as density-based heatmaps, and they may be selected by attributes and color-coded. Users can interact with the data through linked windows that present graphical representations of attributes over space and time. Graphics include line and bar graphs, as well as calendar and clock graphs. This visual analytics system successfully incorporates a large quantity of data and creates temporal visualizations of SAR incidents that support the USCG decision making process; for example, Mondays and Tuesdays look particularly busy, so the USCG might want to rethink making some stations operate only on the weekends. The authors do, however, recommend future work integrates temporal prediction algorithms rather than relying purely on graphical representations.

Exploring SAR incidents over time does not necessarily require the manufacture of a new analytics system, and there have been commercial products to date other than a GIS that can help policy makers explore the temporal attributes of their data. Stoddard and Pelot (2020) reviewed how an open-source JavaScript library, Data-Driven Document(D3), can increase the accessibility of the CCG's SAR Program Information Management System (SISAR) dataset. The authors focused on SISAR data from 2005 to 2013, with 2007 omitted as it was unavailable. D3 takes an underlying spatial and temporal dataset like SISAR and creates web visualizations that a user can manipulate as a web dashboard. The authors organized the maritime SAR incidents by hour, day, month, and year to support temporal analysis via graphical representations (i.e., graphs, pie charts, and incident heat maps). The authors found the dashboard-style visual analysis techniques to be effective decision-making tools, highlighting when and where the CCG should concentrate their resources. While Stoddard and Pelot acknowledged there were concerns associated with under-reporting of incidents, they concluded a visual analysis of maritime SAR incidents over time and space supports effective decision making. However, neither Stoddard and Pelot nor Malik et al. (2014) discussed how merging temporal and spatial analysis could provide their target audience with enhanced information on how incidents may change in space over time, which could possibly reveal underlying processes of interest to the CCG and USCG.

Graphing incident attributes that are specific to when an incident occurs is another temporal analysis technique. Environmental and meteorological conditions vary throughout the days, months, and seasons. While such ambient conditions may be a contributing factor to a SAR incident, they also influence the types of hazards a SAR rescue team may encounter when responding to a distress notification. Using maritime SAR incident data from 2007 to 2012 in the Gulf of Finland on boating accidents, Sonninen and Goerlandt (2015) were able to match historical environmental and meteorological conditions to when an incident occurred. They could then analyze the incidents aggregated by day, weekend, holidays, week, month, and year. Their goal was to determine whether incidents occurred more frequently under certain conditions, and to identify which graphical representations were optimal for revealing temporal patterns and outliers. The authors pulled meteorological conditions from several temporal scales: for instance, most weather stations collected data every 10 minutes, while precipitation was recorded by the hour. Wave data came from a single buoy, so while it was representative of the study area, results could not be considered accurate for each accident site. The authors examined the attributes through graphical products created in the GeoViz Toolkit, a software that supports geographic data. They found a parallel coordinate plot was the most effective presentation for detecting attribute patterns over time, as it allows multiple variables to be displayed at once and clearly reveals outliers. The multiform bivariate matrix was the best option for a comparison of two variables. While the authors demonstrated methods to graph SAR incident attributes over time, their work lacks a combined spatiotemporal element. Furthermore, Sonninen and Goerlandt's graphical representations were difficult to interpret if too much data were visualized in a single plot, whereas a density surface on a map would hold up better, particularly for non-scientific viewers – a useful insight for future research if attempting to visualize temporal patterns and detect trends.

2.1.2 Analysis of Mountain SAR Incidents

As the work above demonstrates, understanding when and where maritime accidents tend to occur can support an effective distribution of rescue resources and provide insights into the risks associated with the highest densities of SAR incidents. A spatial and temporal analysis of mountain SAR incidents similarly impacts resource management decisions to increase the safety margins for rescue assets and persons in distress alike. However, there are few studies to date that explore the spatial components of mountain SAR incidents.

2.1.2.1 Aspatial statistical analysis of mountain SAR incidents

A review of the professional literature on mountain SAR makes it clear that aspatial statistical analysis is the most common method to evaluate historical SAR incidents. The dominant software used in studies from the past couple of decades is SPSS, a statistical software suite developed by IBM that offers statistical results and graphics (IBM n.d.). The benefits to aspatial statistical analysis methods include fast processing times and easy integration with user-friendly, graphical products. Then downside is the results cannot be connected to a specific geographic location, making it difficult to detect changes in SAR incident accessibility over time, or to explore spatial attributes that could contribute to an incident or alter the tasking for rescue teams.

Traditional statistical analysis can incorporate temporal attributes. Kaufmann, Moser, and Lederer (2006) looked at changes in the frequency and types of incidents involving helicopter-based emergency medical services (HEMS) in Tyrol, Austria, from 1998 to 2003. Their working hypothesis was that the types of emergency requests were changing in favor of less critical injuries, which would reduce the demand for air-ambulance transport but not necessarily for helicopter-based intervention. The authors created a severity score for incidents based on the National Advisory Committee of Aeronautics, and binned incidents into categories of minor, serious, severe, and critical. Separate scores for head injuries were based on the Glasgow Coma Scale. They then broke the dataset into two temporal bins, 1998-2000 and 2001-2003, to identify patterns and detect changes using SPSS version 11. The authors found 5% of all incidents were false alarms, and leisure-related requests for HEMS support increased in frequency by almost 40% each year. Based on the injury patterns and changes in injury severity over time, the authors surmised that the relative accessibility of HEMS services, increased use of mobile phones, and popularity of technical equipment without matching experience levels might contribute to greater risk exposure with the assumption a HEMS could always get a subject out of a bad situation. The authors also found a seasonal influence on injury patterns, likely due to the exposure of ground hazards. Kaufmann, Moser, and Lederer acknowledged their study is limited by a reliance on incident figures from a single HEMS agency when several operate in the same area, potentially creating a bias. However, they believe their results offer useful information to HEMS agencies on how they can best support their helicopter rescue teams. For example, the very small number of incidents requiring technical gear for recovery from canyons, crevasses, and ledges could justify removing those capabilities, since cliff-side rescues require a lot of training for proficiency and the cost may not be justified. While not spatial in nature, the authors demonstrate how statistical analysis can reveal temporal patterns in incident attributes that can inform SAR management services.

High resolutions of temporal and spatial data may be desirable for accurate interpretation of spatial incidents: the weather conditions, slope, and elevation at the site of a SAR incident would mean more to stakeholders than the average conditions for a geographic area. However, analysis that intends to assess jurisdictional characteristics and funding requirements would not necessarily require data at the individual level. Heggie and Amundson (2009) noted there were no national-scale studies assessing land SAR incidents, and so they designed their research to compare SAR incidents in national parks across the United States using SPSS version 15. The authors pulled data from National Park Service (NPS) reports spanning 1992 to 2007, and aggregated incidents by national park unit and by year. The authors decided to only look at the total number of incidents, the number of subjects, rescue outcomes, and costs, since other attributes suffered from a lack of standardization. Additionally, the authors examined 2005 data at the same spatial scale but a finer temporal scale, considering the date, time, operating environment, demographics, activity, and the SAR process. The authors were able to compare the number of SAR incidents against the total costs per NPS region by year, how those costs were broken up, and discuss what the results meant for NPS fiscal planning. For example, they found there was an average of 11.2 SAR missions in the US national parks every day, costing about $895 each. Using the 2005 data, the authors demonstrated how they could assess incident attributes, finding about a quarter of SAR incidents were in mountainous terrain between 1,524-4,572 m, followed by canyon areas, and that hiking was the most common activity driving a SAR call, followed by boating and suicides. Heggie and Amundson demonstrated how a national incident dataset could reveal patterns not captured by individual NPS units. However, an analysis of incident patterns at the same scale would provide a higher fidelity analysis on where within each national park incidents were historically occurring, which could possibly support mitigation measures that could save costs over time.

To understand how to mitigate the number of SAR incidents requiring a rescue response and better prepare rescue teams, SAR agencies require details on what factors contribute to the severity of an incident. While an analyst can gather some attributes after-the-fact, like weather or topography, behavioral attributes require input from the subject of a SAR case. Boore and Bock (2013) wanted to ascertain the causal factors in backcountry SAR cases in National Parks in order to recommend prevention measures, since they found research on SAR in the NPS tended to focus on patterns of incident outcomes (i.e., medical injuries). The authors defined backcountry SAR as incidents unreachable by ground ambulance. The authors pulled data from Yosemite National Park Patient Care Reports from 2000 to 2009, since prior to 2000 SAR cases were inconsistently reported. The authors also sent out surveys to the subjects of the most recent cases (i.e., from 2007 to 2009, to mitigate recall bias) where there was a valid mailing address on file. The authors asked for the subject's experience levels, the time of day when they found themselves in distress, the stage of activity, environmental conditions, and what the subject thought would have helped them avoid the incident (e.g., better equipment). Incidents were aggregated by subdistrict within Yosemite National Park. Statistical analysis was run in SPSS, to include Pearson's chi-squared test to check for significant correlation between demographics against type of activity, injury against type of activity, and incident attributes against subdistrict.

Boore and Bock found most backcountry SAR incidents occurred during the day, in clear weather, and during the second half of the subject's activity. Of interest to this research, 6% of the survey respondents reported having a GPS device and considered themselves experts, and no respondent believed the GPS device would have prevented their incident. Respondents who only had a cell phone self-reported as beginners. The authors acknowledged their results likely suffer from low survey response rates, researcher bias and subjectivity, and the omission of incidents whose outcome was self-rescue. While their study provides context to backcountry SAR cases, they recommend future NPS efforts incorporate more details at the time a Patient Care Report is written to offer more details for future analysis and support mitigation measures.

2.1.2.2 GIS and mountain SAR

In contrast to the mountain SAR studies that rely on aspatial software, a GIS incorporates the spatial attributes of an incident to provide location-specific pattern and trend analysis. A review of the SAR literature shows there are only a handful studies incorporating GIS tools to explore the mountain SAR process, and these studies either employ a GIS for real-time SAR tasking or for post-task analysis. No academic research on historical mountain SAR incidents to date has taken a spatiotemporal approach.

GIS tools and products can assist real-time decision making. When GIS tools started to become mainstream for emergency management, Ferguson (2008) presented a paper at an Esri Federal User Conference to showcase how a GIS could support a wilderness SAR mission, using a case study of the search for a missing child with autism in West Virginia. Ferguson had observed a reluctance by land SAR organizations to use a GIS due to a lack of familiarity with the tools available to conduct spatial assessments of SAR incidents in a multidimensional environment. Ferguson demonstrates how different spatial layers, like satellite imagery or trail networks, can increase an analyst's situational awareness of the environment for improved planning operations. He also discussed how some GIS tools can operate in three-dimensions, potentially identifying locations where two-way line-of-sight communications might not be possible, and how software extensions available at the time could support the real-time tracking of rescue teams within the GIS representation of reality. While Ferguson does not consider the after-action analysis of historical SAR incidents, his paper reveals how the adoption of GIS software by land SAR agencies is a relatively new development.

Maximizing the benefits of a GIS, however, requires some degree of training. Durkee and Glynn-Linaris (2012) aim to provide SAR teams with some basic training on how to incorporate a GIS into the SAR process. The authors use the term "wildland SAR" to refer to incidents which happen in open spaces like parks, wilderness areas, and mountainous terrain. Durkee and Glynn-Linaris describe how, with proper training, a GIS can help planners and first responders shorten the time from receiving a distress call to mission resolution in a repeatable and professional manner. They detail how field operations, data management, planning, and analysis all benefit from the integration of SAR data in a GIS and the resulting increase in an analyst's situational awareness. The ebook is an Esri product that focuses on how to use the MapSAR template in ArcGIS software, starting with the basics of how to choose coordinate systems, and reviewing the different types of data a GIS can handle. MapSAR provides integrated layers compatible with mobile and desktop dashboards for quick visual and statistical analysis, and the template originates from the National Alliance for Public Safety GIS (NAPSG) Foundation's WiSAR project (NAPSG n.d.). Even with the training offered in their ebook, Durkee and Glynn-Linaris advocate for a GIS specialist to be activated whenever a SAR case opens, and the overall focus of the ebook is on improving the SAR process through managing and presenting information real-time, whether you are in an office or the field, rather than on the spatial and temporal analysis of historical incidents.

The studies to date that have incorporated a GIS to explore historical mountain SAR incidents are limited by data availability and data quality. In order to use historical incident data as point data in a GIS, the incidents need to be tied to coordinates. This can become complicated if the source records rely on descriptive locations of where the incident occurred, or if rescue teams record incidents under different coordinate systems. Doherty et al. (2011) considered a couple of techniques to georeference historic SAR incidents from 2005 to 2010 in Yosemite National Park to input the data into a GIS to visualize and assess for spatial patterns and possible spatial dependence. Their study explored the challenges of conducting spatial statistical analysis on data that was collected without an anticipation of digitization and the analytical capabilities to processes large amounts of spatial data.

Doherty et al. (2011, 776) claim they are the "first spatially-explicit study of SAR incidents." Using a blend of commercial GIS software and web-mapping applications, the authors georeference data from Yosemite SAR incident reports using either a 'point-radius' or a 'shape' method. The former creates a radius of uncertainty around a location based on the description found in the SAR incident report, which was faster to develop than the latter, and required careful exclusion of areas that did not fit the description in the incident report. The authors used the point-radius method for further analysis on 1,356 incidents. Since 95% of the uncertainty radii were just over 2,000 m, the authors created a two-kilometer grid cell fishnet to aggregate the data for spatial analysis. Smaller cells, though perhaps more appropriate to accommodate topographic variation, may not have included the actual coordinates of the incident within the area of uncertainty. The fishnet came to 1,560 grid cells, or over 6,000 km^2, with cells containing an incident count of 0-226 SAR incidents. The authors found statistically significant clustering amongst the incidents after running the Global Moran's I statistic, as well as 10 cells to be statistically significant hot spots based on Getis-Ord Gi* statistic. A visual analysis of the hot spots in relation to the terrain suggested a correlation between incidents and the Yosemite

Valley trails, as well as one backcountry location by a camp. Based on this study, Yosemite SAR teams will be required to carry GPS devices for accurate location data and integration with the park's new digital records management system. The authors recommended future studies consider temporal as well as spatial uncertainty of historical SAR incident datasets.

The application of a GIS to SAR incidents should match the end users' needs and capabilities, particularly since GIS training can be time consuming or require the hiring of a GIS specialist. Using spatial analysis, Pfau and Blanford (2018) found the Alpine Rescue Team (ART) were able to complete 75-95% of searches within 6-12 hours, and they recommended ART personnel leverage the benefits of a GIS for post-mission analysis rather than real-time application since the ART's search time is within safe margins. ART is a non-profit group accredited by the Mountain Rescue Association (MRA), which is a standardizing and educational agency (MRA n.d.). ART responds to SAR incidents in three counties in Colorado, an area of approximately 1,309 mi^2 (about 3,400 km^2). Pfau and Blanford pulled incident data from 2008 to 2011 from the International Search and Rescue Incident Database (ISRID) to demonstrate how ART can use a GIS to explore lost person behavior based on historical cases and improve their SAR process. After cleaning the data, the researchers were left with 133 missions for spatial analysis. Pfau and Blanford used descriptive statistics to explore incident attributes on subject's activity and time of year. Incidents that involved a missing person were further analyzed in a GIS to determine distance, direction, time, and elevation attributes between lost and found locations. Found locations were further run through KDE to assess the terrain most common to high density areas. Pfau and Blanford found lost persons traveled on average 4.41 km (SE +/- 1.1) and had an elevation change between lost and found locations of 259 m (+/- 80.1). There was little variation between the type of activity and lost person behavior. The authors described how locating SAR incident hot spots would be useful for training new ART members and developing relevant training scenarios. Pfau and Blanford recommend their methods to encourage familiarity with typical mission patterns and, assuming future incidents follow historic patterns, increase the efficiency and safety margins of non-profit SAR groups responding to distress calls within their jurisdiction.

The studies reviewed in this section demonstrate the interest in understanding patterns in historical SAR incidents to increase the safety and efficiency of future SAR response. They also highlight the growing awareness of what spatial analysis can provide to the SAR planners and rescue assets tasked with a distress call. What is lacking in the literature to date, however, is an exploration of mountain SAR incidents over space and time and a consideration of how changes in spatial and temporal patterns could reveal the influence of sat-comm device activations on mountain SAR.

2.2 Spatial and Spatiotemporal Analysis

A spatial analysis of mountain SAR incidents provides a means to measure the influence of sat-comm technology over space. This research relied on three types of spatial analysis methods: point pattern analysis, where each incident is examined independently; spatial statistical analysis, where incidents are assessed in aggregate; and visual analysis, where incidents are inspected for spatial relationships on maps. Spatial analysis methods reveal first and second order spatial effects that are useful for organizing and interpreting the data and statistical results. First-order effects describe the influence of topography and environmental conditions on spatial patterns, while second-order effects represent the patterns formed through incident interactions (O'Sullivan and Unwin 2010, 163). Mountain SAR incidents are highly unlikely to contribute to another incident nearby – with the rare exception of when rescue personnel become a SAR incident themselves during the course of a mission – and this study focuses on the influence of first-order spatial variation in mountain SAR incidents.

Analytical techniques that rely on both spatial and temporal attributes are considered spatiotemporal. The application of a temporal trend test in conjunction with a spatial statistic facilitates a spatiotemporal exploration of how sat-comm device activations affect the distribution of mountain SAR incidents over both time and space. However, spatiotemporal analysis requires unique structuring of the incident data to run properly in a GIS.

This section of the study gives an overview of the spatial and spatiotemporal analysis techniques used in the literature to date that contribute to the methodological design of this study. Several papers that review historical SAR incidents demonstrate how point pattern analysis and spatial statistical analysis methods may apply to mountain SAR incidents. Since there are no academic studies to date that have explored the spatiotemporal patterns of mountain SAR incidents, this paper reviews research on the spatiotemporal distribution of wildfires, as wildfires – like mountain SAR incidents – are seasonal and often occur in remote environments.

2.2.1 Point Pattern Analysis

Point pattern analyses explore potential second order spatial variation, while also providing insight into the first order effects on incidents' spatial distribution. One common point pattern analysis method to assess whether incidents demonstrate statistically significant clustering is to compare the actual mean distance between incidents against the expected mean for the study area. The expected mean between incidents is based on the null hypothesis of complete spatial randomness. The nearest neighbor (mean) distance may be represented by a ratio of the actual mean to the expected mean, and it is calculated by:

$$\text{Nearest Neighbor Ratio} = \frac{\bar{d}_A}{\bar{d}_E} = \frac{\frac{\sum_{i=1}^{n} d_i}{n}}{\frac{1}{2\sqrt{\rho}}} \tag{1}$$

where *d* is the distance between incidents, *n* is the number of incidents, and ρ is the incident density for the area considered a possible location for incidents (Clark and Evans 1954). If the ratio equals one, then there is complete spatial randomness; if the ratio equal zero, there is complete clustering. The p-values and z-scores associate with this statistic could be used to compare incidents from different layers within the same area of analysis. However, average nearest neighbor analysis only describes whether incidents have spatial clustering, not where those clusters are located.

Another point pattern analysis method that can help identify sites of incident clusters is kernel density estimation (KDE). KDE uses a kernel function to produce estimates of incident density for locations throughout a study area. Locations may be based on a grid overlay, and the density value for each grid depends on a kernel function to weight incidents based on their proximity to the center of the kernel (O'Sullivan and Unwin 2010, 69). The kernel density estimator is given by:

$$\hat{f}(x) = \frac{1}{nr^2} \sum_{i=1}^{n} K \left\{ \frac{1}{r} (x - X_i \right\} \tag{2}$$

where *n* is the number of incidents within the kernel, *r* is the kernel bandwidth, *K* is the kernel function, *x* is the grid cell where the function is being estimated, and X_i are the locations of each observation *i* (Silverman 1986). The distance selected for *r* is subjective and depends on the incidents under examination, though the mean nearest neighbor results can provide a starting point. Like Azofra et al.'s (2007) zonal distribution model, the kernel function can smooth the effects of outliers to draw attention to possible cluster locations at selected bandwidths and encourage effective visual analysis. The KDE output is a raster surface of density values that lends itself to an inspection of incident hot spot locations.

Both nearest neighbor and KDE point pattern analyses feature in the research on the spatial distribution of wildfire incidents. Wing and Long (2015), in their study on wildfires in Oregon and Washington from 1984 to 2008, used point pattern analysis techniques to explore wildfire hot spot locations and global spatial statistics to explore clustering amongst attribute values. They calculated the centroid for over one thousand wildfires to use as input for average nearest neighbor calculations, KDE, and quadrat analysis (which compares incident frequencies across quadrat cells). The resulting nearest neighbor ratio of 0.66 at $p < 0.01$ suggested statistically significant spatial clustering of wildfires across the two states, results which were validated by the quadrat analysis. For KDE, the authors used a quartic kernel function to create a smoothed density surface, which they used for visual analysis and were able to identify several wildfire hot spot locations. Wing and Long also found significant clustering of temporal and climatic wildfire attributes using the Moran's I and Getis-Ord G global spatial statistics. The authors conclude that point pattern and spatial statistical analyses can detect changing trends in historical wildfire spatial patterns, but that future research should incorporate more recent fire data for comparison.

Aftergood and Flannigan (2022) also used average nearest neighbor analysis to identify and measure wildfire clusters in their study on 97,921 lighting-ignited wildfires in six provinces of Western Canada from 1981 to 2018. Only fires from the beginning of April through the end of September were included for analysis, as these are the official fire season months in the study area. Instead of evaluating the nearest neighbor distances for all years, as Wing and Long (2015) did, Aftergood and Flannigan ran nearest neighbor calculations for each wildfire year separately using R Core Team software. The results for all years suggested positive spatial clustering. The mean values for all years were: a mean nearest neighbor statistic of 154 km, a mean nearest neighbor ratio for all the years of 0.474, a median z-score of -48.12, and a median p-value of .0001. The range of average nearest neighbor values was 104 km (1994) to 272 km (2011), which the authors hypothesize could be related to thunderstorm spread size at 170 km^2. The average nearest neighbor results contributed to the conceptualization of wildfire spatial distribution.

While point pattern analyses are generally considered exploratory, they can be one of the more viable means to assess spatial patterns if dealing with imprecise data. Koutsias, Kalabokidis, and Allgöwer (2004) applied KDE for an exploration of wildfire incidents in the Halkidiki peninsula in Greece, using wildfire ignition data from 1985 to 1995 that had up to 700 m and 925 m inaccuracies in the x- and y-axis respectively. Their intent was to review three methods of point pattern analysis – quadrat analysis, moving window analysis, and KDE – to determine which method best accommodated positional inaccuracies in historical wildfire ignition coordinates. The authors started with a KDE bandwidth equal to the mean distance between randomly distributed incidents. For a 3,257.63 km^2 study area with 218 wildfire incidents, the mean random distance is 1,933 m. The authors therefore selected 2,000 m as their intended bandwidth for exploration, although they also conducted KDE at 1,000, 4,000, and 6,000 m, all using a 250 m grid. KDE was conducted using CrimeStat version 1.1. software. KDE using the same bandwidths was also conducted on a simulated dispersion of wildfire ignition points with the same positional inaccuracies as the historical dataset, and the actual and simulated results were compared. They found the 2,000 m bandwidth to be the best balance of a large enough distance to capture positional inaccuracies but small enough to prevent overgeneralization that would mask the spatial influences on ignition locations. The authors also found KDE performed the best of the three point pattern analysis methods, as KDE evaluates the relative position of incidents to each other over space thereby accounting for positional inaccuracies when set with the proper bandwidth parameter.

2.2.2 Global Spatial Statistics

To conduct spatial statistics that measure attributes over space, incidents need to be aggregated to create a metric – incident frequency – whereby the spatial relationships may be evaluated. The aggregation scheme may be based off an irregular polygon pattern, like enumeration units, or off a repeating grid of squares or hexagons. Incident frequency may then be compared amongst neighboring units using a neighborhood scheme defined by the analyst.

Global spatial statistics evaluate incidents within the context of the entire study area and are a useful tool for assessing spatial trends. The Global Moran's I statistic is used to measure how observations correlate over space, a concept termed spatial autocorrelation. The Global Moran's I statistic is calculated with:

$$I = \frac{n}{\sum_{i=1}^{n}(x_i - \bar{X})^2} \times \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{X})(x_j - \bar{X})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \qquad (3)$$

where x is the attribute value at a given location, $\bar{X}$ is the mean attribute value across the study area, w_{ij} is the weight of the distance between a location i and its neighbor j, and n is the number of features within a specified distance band from location i (O'Sullivan and Unwin 2010). Should the incident frequency at location i and at its neighbor j both be higher or lower than the mean incident frequency for all features in the study area, then the index is positive, indicating positive spatial autocorrelation. If x_i and x_j fall on different sides of the mean, then the index is negative. The degree of spatial autocorrelation is impacted by w_{ij}, since it accounts for spatial proximity. The range of possibilities for I is from -1 to +1, i.e., from complete dispersion to complete clustering. Should $I = 0$, there is no spatial autocorrelation, and the distribution of incidents is considered random. The variance and expected values assume complete spatial randomness, and the output is the index value, a p-value, and a z-score.

Like average nearest neighbor calculations, the Global Moran's I statistic indicates whether incidents exhibit clustering or dispersion across the entire study area without defining which areas have clusters and which are dispersed. Unlike a nearest neighbor distance, the distances at which clustering or dispersion is most apparent can be affected by weights assigned to incidents within a defined neighborhood. Spatial weights represent the impact of incident interactions. Doherty et al. (2011) in their study of historical Yosemite SAR incidents used an inverse distance squared approach based on the assumption that the incident frequency at sites near each other should be more similar than those further away. Based on their 2 km grid of SAR incident frequency, the Global Moran's I results indicated statistically significant spatial clustering, with $I = 0.310$, a z-score of 24.5, and a p-value $< .001$. Doherty et al. then ran the data through the Getis-Ord Gi* local spatial statistic to identify where the grids comprising the clusters were located since the global version does not describe where the clusters lie, only whether statistically significant clusters are present in the study area.

2.2.3 Local Spatial Statistics

In contrast to a global spatial statistic, local spatial statistics account for the spatial heterogeneity of incidents. Two dominant local spatial statistics in the field of geographic information science are the Getis-Ord Gi* statistic, which helps define incident hot spots, and the Anselin Local Moran's I statistic, which can identify outliers in addition to clusters. The GIS tools that use local spatial statistics create layers where each areal unit is assigned to a cluster or outlier category depending on the z-score and p-value at each location. In this way, the locations of hot spots, clusters, and outliers may be identified on a map and compared across layers.

The Getis-Ord Gi* statistic helps identify sites with high or low values that lie amongst neighbors of high or low values, termed hot spots and cold spots respectively. The Gi* statistic is given as:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{ij}\, x_j - \bar{X} \sum_{j=1}^{n} w_{ij}}{S \sqrt{\frac{n \sum_{j=1}^{n} w_{ij}^2 - \left(\sum_{j=1}^{n} w_{ij} \right)^2}{n-1}}} \tag{4}$$

where:

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - \bar{X}^2}$$

and *S* is the variance (Getis and Ord 1992; Ord and Getis 1995). This version of the Gi* statistic accounts for the variance and expected values and its output is the z-score. The p-values are calculated based on a rejection of the null hypothesis that incident frequencies have a random distribution. In the Gi* statistic, *j* may equal *i*, as *i* can be its own neighbor. The Gi* statistic does not, however, identify neighborhoods containing spatial outliers since it only gives significance to locations surrounded by similar incident values.

The Anselin Local Moran's I statistic enables the categorization of incident sites based on how their values compare to the values of other sites within the neighborhood. It is given by:

$$I_i = \frac{x_i - \bar{X}}{S_i^2} \sum_{j=1, j \neq i}^{n} w_{ij} \left(x_j - \bar{X} \right) \tag{5}$$

where: $$S_i^2 = \frac{\sum_{j=1, j\neq i}^{n}(x_j - \bar{X})^2}{n-1}$$

and the summation of distance weights and the incident-frequency attribute are for only the neighbors of i – i.e., j – and i cannot be considered its own neighbor (Anselin 1995; Ord and Getis 1995). Like the Global Moran's I statistic of (3, the local version adapted by Luc Anselin (1995) measures how the incident frequency at one site correlates with its neighbors, but it does so at a localized scale. If x_i and x_j fall on the same side of the mean, either smaller or larger, then the index is positive. If they are different, as would be seen when a location has a high incident frequency, but its neighbors do not, then the index is negative. The sign of the index and the magnitude of the z-score marks two types of clusters and two types of outliers: a high-high or low-low cluster refers to a location surrounded by similarly high or low values; a location that is identified as having a high value surrounded by low values is considered an outlier, as is a location with a low value in a high-value neighborhood. The p-value reflects the likelihood the spatial pattern is random.

Local spatial statistics can prove useful for detecting fine scale spatial incidents across broad study areas. Potter et al. (2016) compared the hot spot outputs from the Getis-Ord Gi* statistic to present their concept of the spatial association of scalable hexagons (SASH), a technique they found useful for analysts and policy makers alike to communicate the impacts of an ecological phenomena. The SASH method involved creating scalable hexagons and identifying statistically significant clusters to track macro-scale patterns. Using this method, the authors considered three ecological phenomena across broad portions of the United States collected by three different methods. Data on invasive plants in the south eastern United States had been collected through ground observations of US Department of Agriculture (USDA) forest plots, and each hexagon cell represented two metrics: native plant species richness and the percent cover of invasive species. Data on the spread of the mountain pine beetle in forests in the central and western United States was captured by USDA low-altitude aerial surveys, where hexagon cell values represented the percent of surveyed forest area that had beetle damage. Data on wildfires in the central and western United States came from satellite sensing where each hexagon aggregated the number of fires per 100 km^2. Data processing and spatial statistics were conducted in Esri's ArcMap 10.1.

In order to restrict the study area to environments where the phenomena could occur, Potter et al. only evaluated forested areas based on ArcMap's forest cover layer. The size of the aggregating hexagon unit was determined through phenomena-appropriate methods: invasive species hexagons were near the average size of US southern counties (1,452 km^2) to align with USDA program goals; a mountain pine beetle generally moves within three kilometers, so the hexagon size was 54 km^2 with about 3.8 km from the center to the edge; the authors used semivariograms to test the spatial autocorrelation of wildfires aggregated to 54 km^2 hexagons, settling on a hexagon size that was as wide as the spatial autocorrelation range, at 635 km^2. The local neighborhood considered by the Gi* statistic encompassed the 18 first and second order neighbors around each hexagon. Potter et al. found their SASH method produced meaningful patterns that could be applicable to policy decisions and organizational tracking of ecological threats. The authors mention that, while Local Moran's I statistic can reveal outliers while the Gi* statistic cannot, they felt the Local Moran's I statistic's inability to capture the impact of spatial autocorrelation at values near the mean to be a disadvantage and thus did not test for outliers in their SASH demonstration.

2.2.4 Spatiotemporal Analysis

While spatial analysis can help agencies assess the distribution of incidents, spatiotemporal analysis allows agencies to tailor policy to reflect recent trends. One method to evaluate an incident's spatial relationship over time is through the construct of a space-time cube (STC). An STC incorporates time as a third dimension, allowing incidents to not only be binned by location, but also by time, creating an array of values suitable for analysis with temporal and spatial neighborhoods.

STCs have supported spatiotemporal research in fields as diverse as human behavior after an earthquake (Gismondi and Huisman 2012), crime patterns (Nakaya and Yano 2010), public health (Nielsen et al. 2019), cetacean strandings (Betty et al. 2020), and tornados (Allen et al. 2021). The field of wildfire management has benefited from the STC construct since accessible STC-building tools became available with ArcMap 10.3 in December 2014 and ArcGIS Pro 1.0 in January 2015 (Esri n.d.). To date, there are several studies that have explored historical wildfire incidents using spatiotemporal analysis methods facilitated by the STC design.

One spatiotemporal analysis tool commonly employed in the research on wildfire incident patterns is Emerging Hot Spot Analysis (Esri n.d.). The Emerging Hot Spot Analysis tool compares incident hot spots over time using the Getis-Ord Gi* local spatial statistic and a trend test. The tool uses the Mann-Kendall trend test to evaluate hot spot bins against their temporal neighbors to determine how past incident patterns relate to more recent incident distributions. The Mann-Kendall trend test is given by the statistic:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} a_{ij} \qquad (6)$$

where: $$a_{ij} = sign(\, x_j - \, x_i \,) = \begin{cases} 1 & x_i < x_j \\ 0 & x_i = x_j \\ \text{-1} & x_i > x_j \end{cases}$$

and where x_i and x_j are ranked in the time series. The values of newer and older bin pairs are summed to represent a trend (Mann 1945; Hamed 2009). An $S > 0$ would indicate a positive trend while the opposite would indicate a downward trend. If $S = 0$, then the trend is neither constantly increasing nor decreasing and the null hypothesis is met. Depending on the trends detected at an STC location over time, the Emerging Hot Spot Analysis tool assigns one of eight trend types: new, consecutive, intensifying, persistent, diminishing, sporadic, oscillating, and historical (Esri n.d.). These categories provide analysts with a means to ascribe the relative importance of incident patterns within a study area.

Similar to the near-precise location information sat-comm devices provide to SAR agencies, satellite-based sensors used to detect fires offer accurate fire location data to researchers interested in fire patterns. Reddy et al. (2019) took fire detection data collected by moderate resolution imaging spectrometer (MODIS) sensors on board NASA satellites to examine emerging hot spots of forest fires in South Asia from 2003 to 2017. The authors restricted the one square kilometer MODIS fire raster to only those areas with forest cover, resulting in 522,348 fire incidents considered in the study. Only the months that had a greater than 2% contribution to a nation's annual fire count were used for descriptive statistical analysis. Using ArcGIS software, the authors aggregated the incidents by five-kilometer grid cells and grouped by year to create the dimensions of an STC. The authors also selected five kilometers as the neighborhood distance to detect emerging hot spots and capture local trends. Within the study area, they found over 30% of fires from the 15-year time span were sporadic hot spots, making it the dominant category, and just under 8% of fires were considered new hot spots at the low end. The authors acknowledged that a change in neighborhood size could dramatically alter the results, but as their intent was to identify areas for forest conservation, they decided five kilometers was optimal. However, the impact of neighborhood size on spatial and spatiotemporal statistical analysis highlights the highly subjective nature of these methods.

Spatiotemporal analysis can advance studies seeking to assess why historical wildfires occur in some locations and not others. In their exploration of how bushfires in New South Wales, Australia might evolve in response to controlled burns, Visner, Shirowzhan, and Pettit (2021) looked at data spanning 100 years of fire history using a mix of regression analysis, correlation analysis, and spatiotemporal analysis. The authors ran a general linear regression model and bivariate Pearson correlation statistical analysis in R statistical software, which can handle geographic data, to identify relationships between older controlled burn areas and newer bushfires. They then created an STC in ArcGIS Pro and used the Getis-Ord Gi* statistic and Mann-Kendall trend test via the Emerging Hot Spot Analysis tool to identify emerging hot spots for visual data mining. Fire polygon centroids were converted to points, and then aggregated by municipality. The authors selected this unit of aggregation since municipalities are responsible for fire mitigation efforts. Visner, Shirowzhan, and Pettit visually inspected the emerging hot spots for all years, as well as for each individual year between 2010 through 2020. They concluded most municipalities had sporadic bushfire incidents, although the authors were able to identify four new municipality fire hot spots from the 2019 to 2020 fire season. While the authors did not find a correlation between controlled burns and bushfires, they did find a positive trend in the total number of bushfires occurring in New South Wales. To make their findings accessible to the public, the authors published their findings as an Esri dashboard.

While fires are often characterized by burn area, fire point incident data could be useful when pulling from a large historical dataset where location information originates from a variety of sources. Aftergood and Flannigan (2022) used spatial and spatiotemproal pattern analysis to explore 97,921 wildfires incidents representing the central ignition location of a lightning strike in six provinces of Western Canada from 1981 to 2018. Only incidents occurring from the beginning of April through the end of September were included for analysis, as these were the official fire season months in the study area. Within ArcGIS 10.7, incidents from the fire season and each summer month were aggregated by a grid of 30 km-wide hexagons, as this size hexagon produced the most robust results during ESDA. The authors selected a yearly time unit when creating the STC of the incidents, which mitigated the effects of seasonality for trend analysis. Aftergood and Flannigan found the Mann-Kendall trend statistic revealed an overall non-significant negative trend for the total number of incidents for all layers, though there were areas with significant increasing and decreasing trends within the provinces. These patterns varied in location across the summer months. The authors considered how data quality issues related to working with a historical dataset composed of different sources of incident locations could contribute to inaccurate results, explicitly mentioning how data from recent years might be biased due to technological improvements that are able to capture incidents that were previously overlooked. However, the authors felt they were able to successfully demonstrate how trend analysis of spatial data using an STC enables an intuitive visualization of regional trends and consolidates the variation of incidents over time into accessible map imagery.

2.3 Summary

This research aims to identify the influence of a sat-comm device usage on the spatial distribution of mountain SAR incidents. However, when reviewing the related literature that incorporates an analysis of historical SAR incident data, it was found that very few studies use spatial statistics to explore the patterns of mountain SAR incidents. There is also a gap in the SAR research examining location-specific temporal trends. Maritime SAR is the dominant genre advancing the literature on the analysis of historical SAR incidents. While several studies consider the temporal attributes of maritime SAR incidents through graphics and visual analytics software, no maritime nor mountain SAR studies to date incorporate spatiotemporal analysis enabled through the STC construct, possibly due to tradeoffs between the relatively large study area sizes, fine scale spatial phenomena, and computational processing times.

As addressed by Ferguson (2008), Durkee and Glynn-Linaris (2012), and Pfau and Blanford (2018), the low number of wilderness SAR studies incorporating a GIS, which facilitates spatiotemporal analysis, is likely due to SAR agencies' lack of familiarity with the GIS toolsets and application. Since this paper aims to demonstrate how a combination of spatial and temporal analyses can inform SAR organizations for safer and more efficient operations, studies on the spatiotemporal patterns of wildfires were reviewed for their capabilities and limitations. Several studies on wildfires successfully applied the STC construct and ran spatial trend analysis at relatively large scales using a variety of spatial and temporal aggregation schemes selected by the authors. This study takes the lessons offered in these wildfire studies and applies them to mountain SAR incident analysis in order to explore the impact of sat-comm devices activations on mountain SAR operations.

Chapter 3 Methods

The intent of this research is to explore the impact of satellite communication (sat-comm) devices as a notification method on the spatial and temporal patterns of mountain search and rescue (SAR) incidents in California's Sierra Nevada mountains in order to help SAR agencies and rescue teams prepare for future incidents. SAR organizations can use the methodology presented in this research to assess the influence of sat-comm device activations within the context of their sphere of influence, adjusting the allocation of resources and tailoring training plans, as required.

The methods in this research involved three main components: data preparation, spatial and spatiotemporal statistical analysis of incidents, and an evaluation of incident attributes. Figure 5 presents the flow of this study and the data associated with each step. The first steps in the methodology involved data preparation so only incidents that met the definition of mountain SAR and occurred within the study area boundary would be considered for analysis. This study then evaluated the CALOES mountain SAR incidents for first-order effects in ArcGIS Pro 2.9 (Esri 2021), the results of which informed the creation of neighborhood parameters. This study used GIS tools relying on local spatial statistics and the newly defined spatial neighborhood to reveal the presence of incident hot spots, clusters, and outliers. Developing a space-time cube (STC) of the CALOES incidents provided the structure for spatiotemporal analysis. Lastly, the AFRCC PLB activations were evaluated against the CALOES results through visual analysis and descriptive statistics, as were all accidental sat-comm device activations. The comparison of statistical results alongside an evaluation of incident attributes over time and space enabled a holistic review of how sat-comm device-initiated mountain SAR incidents impact the traditional SAR process.

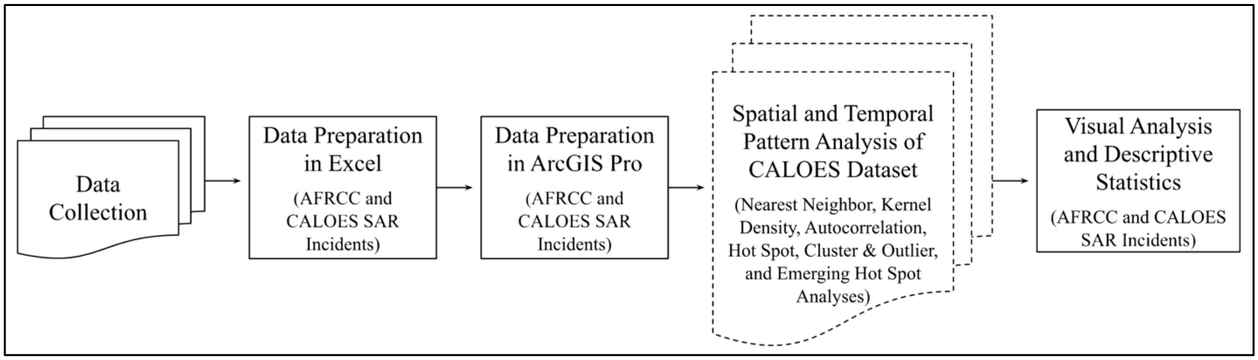

Figure 5. An overview of the study's methodology

3.1 Data

This research drew from two datasets to adequately encompass the size of the study area: one is a subset of a national-level record of personal locator beacon (PLB) activations from the Air Force Rescue Coordination Center (AFRCC), and the other comes from the California Office of Emergency Services (CALOES) and covers all SAR incidents originating with multiple notification methods within the state of California. This research only ran spatial statistics on the CALOES mountain SAR incident dataset, as it provided enough incidents to perform meaningful analysis, whereas the AFRCC dataset was too sparse; to have statistical significance, the distribution of incidents needs to reject the null hypothesis that incidents arise due to random chance, which requires enough incidents associated with the physical landscape to not appear random. Likewise, the CALOES dataset was the only input for spatiotemporal analysis. The AFRCC's PLB activation records supplemented the conclusions drawn from the CALOES statistical results, and both datasets were compared through visual analysis and descriptive statistics of incident attributes. In this way, a state- and national-level dataset complemented each other in an exploration of sat-comm device activations across a geographic region.

The study area's boundary was based off wilderness area shapefiles accessed through Wilderness Connect (n.d.), from which the High Sierra wilderness areas were isolated and projected into the projected coordinate system used in this study. The state and county lines that were included in this study's maps to orient the target audience came from a national boundary shapefile from the USGS national map downloader (USGS n.d.). The state and county lines also required projection.

Spatial and temporal attributes were added to the datasets to explore the environments in which SAR incidents occur. Elevation data came from a 30 m digital elevation model (DEM) from Esri's World Elevation services (Esri n.d.), which sources US elevation data from the US Geologic Survey (USGS n.d.). Elevation impacts rescue team performance capabilities: SAR helicopter engines have degraded performance as elevation increases, and higher elevations increase the risk of ground teams and subjects experiencing the effects of hypoxia and exposure. This research determined incident notification time of day based on incident location and apparent sunrise and sunset times through the National Oceanic and Atmospheric Administration's online solar calculator (NOAA n.d.). Four categories represented the notification time of day: within an hour prior to sunrise, day, within an hour prior to night, and night. The time of day when SAR agencies receive incident notification impacts rescue team preparation. If notification is received within an hour to sunrise, there is a good chance contact or rescue will occur during daylight hours. If notification is within an hour of sunset, then the SAR process will most likely unfold during periods of darkness when specialized gear like night vision goggles (NVGs) or infrared (IR) systems are required. This additional data on elevation and time of day enabled another avenue to explore the impact of sat-comm devices on SAR incident operating conditions through descriptive statistics.

3.1.1 Dataset Acquisition

The AFRCC dataset structure arrived based off the specifications made in a Freedom of Information Act (FOIA) request to the US Air Force. Specifications included a spreadsheet format of PLB activations in California's Sierra Nevada mountain range from 2015 through the date of request (i.e., September 24, 2022), as the request could not exceed seven years of records. The FOIA request was also for the following incident attributes: coordinates, date, time, responding assets, accidental or intentional PLB activation, and mission outcome. The FOIA process took about two months, mainly due to the time required to search through individual reports of PLB activations and verify incidents fell within the study area dimensions placed in the FOIA request, since the PLB activation records are not stored in an easily searchable database. Upon receipt, the AFRCC dataset appeared as in Figure 6, and it included 148 PLB activations spread out across much of California. The dates of the PLB activations ran from March 24, 2015, through September 11, 2022.

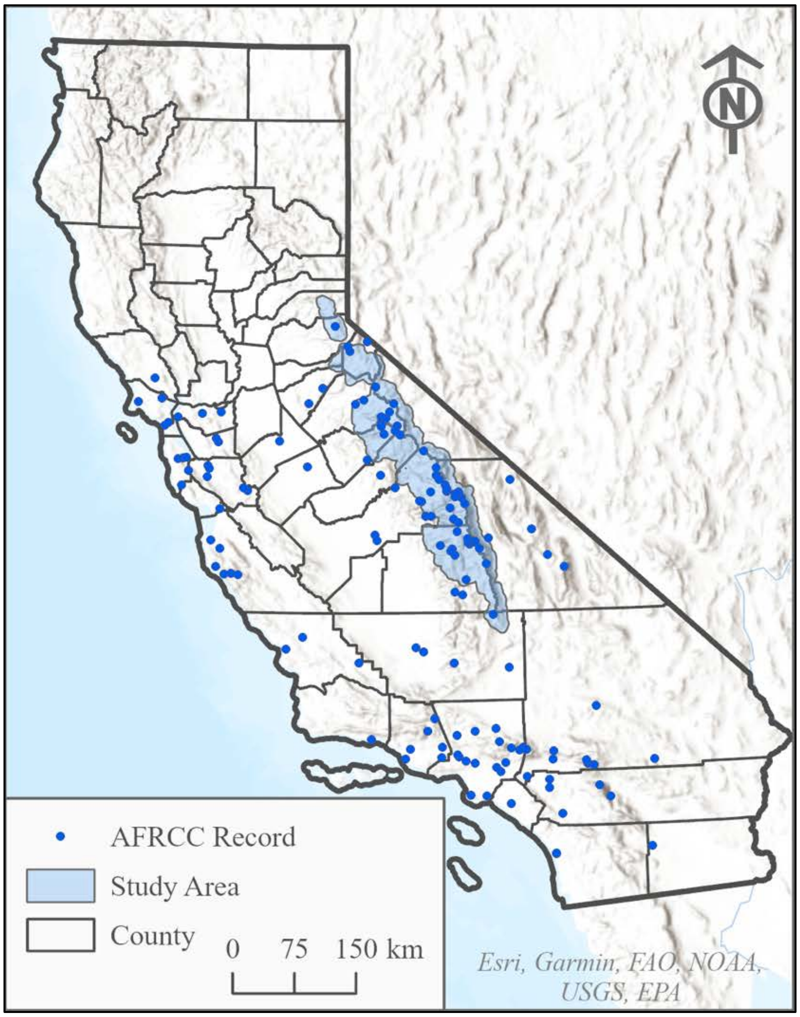

Figure 6. A map of the AFRCC dataset records

Acquiring the CALOES dataset involved a Public Records Act request, the processing of which took about a month from the date of request on September 16, 2022. The request was made for the same information as the AFRCC FOIA request except for dates: CALOES started collecting state-wide SAR incident data from the counties in 2018, so January 1, 2018, was the beginning date of the requested data range. CALOES provided a dataset output from ArcGIS Survey123, a software product that integrates mobile device applications, desktop programs, and online tools to create "surveys" that SAR teams may use to fill out an incident report (Esri n.d.). The dropdowns for the different requirements of the report specify which information to include.

For the temporal information on “Incident Start Date and Time,” the guidance is, “Choose an approximate time when the mission was initiated (Earliest action recorded, e.g., 911 phone call, team callout, etc.).” An incident’s coordinates come from either the recording party inputting the coordinates directly, providing a place name attached to coordinates and searching for the location in the software, or moving a pin on a map that identifies the initial planning point for a search, the site of injury, or the location of rescue or contact. Accidental sat-comm device activations were annotated as such. The dataset sent from the CALOES is depicted in Figure 7. It contained 1,679 incidents spanning the entire state, from January 1, 2018, to July 24, 2022.

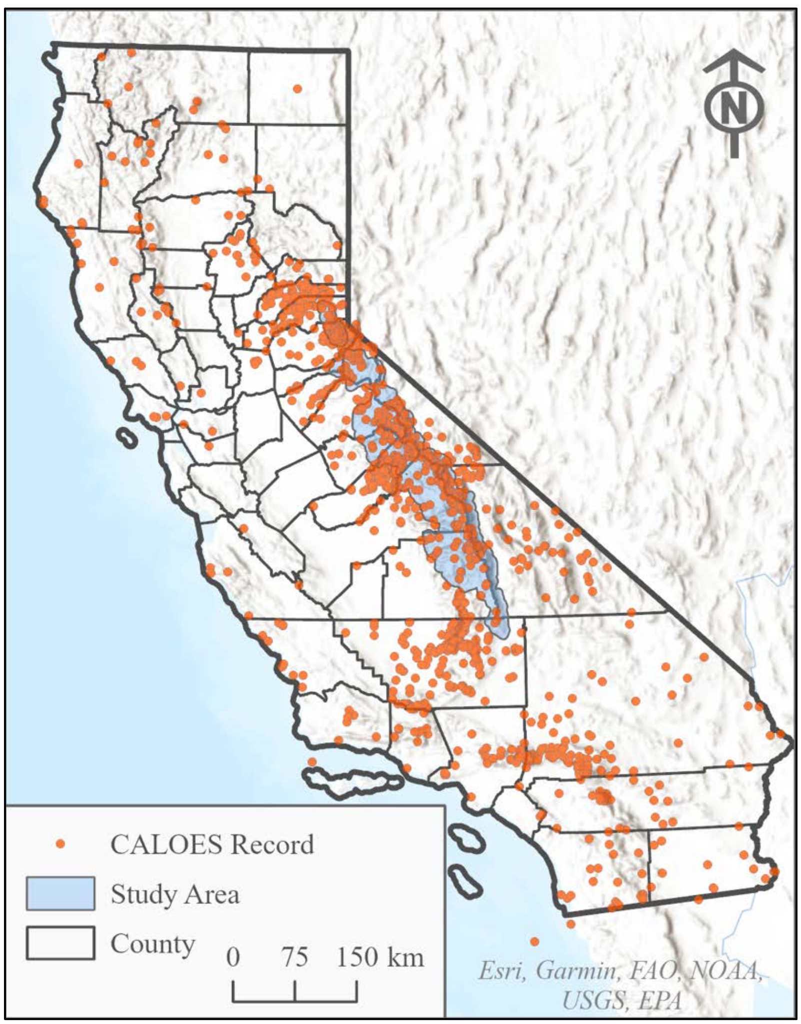

Figure 7. A map of the CALOES dataset records

3.2 Dataset Preparation

Both the AFRCC and CALOES SAR datasets required review and refinement to make sure the data met the definition of a mountain SAR incident and fell within the study area. Datasets were brought into Microsoft Excel (2022) to standardize attribute categories and to remove incidents with inaccurate or incomplete spatial and temporal attributes. The datasets were then brought into ArcGIS Pro, projected, clipped within the study area boundaries, and inspected for inaccuracies and redundancies. This research then split the dataset into categories depending on if they were an actual mountain SAR incident, an actual mountain SAR incident beginning with intentional sat-comm device activation, or an accidental activation of a sat-comm device in order to facilitate the evaluation of analytical results.

3.2.1 Dataset Preparation in Excel

Bringing the datasets into Excel enabled an expeditious review of both datasets for completeness as well as attribute standardization. Incidents that occurred in counties outside of the study area or lacked coordinate or temporal information were removed. Attributes were standardized across both datasets, with several fields added for temporal analysis. Additional attribute fields resulted from isolating the day of the week, month, and year from the date-time-group. For the AFRCC dataset, the dates and times needed to be converted to California's local time to match the CALOES dataset, as they arrived in Zulu time (i.e., the time based off the prime meridian).

This research needed to refine the CALOES dataset to only include incidents that met the definition of mountain SAR; the AFRCC PLB activations did not require any adjustment in this respect. This study defines a mountain SAR incident as a land SAR event which occurs in mountainous terrain away from the built environment, where the subject is participating in outdoor recreation, and which requires the assistance of specialized SAR assets that must maintain specific qualifications and training. Incidents that involved natural disasters, law enforcement, body recoveries, searches, and suicides were removed. While the argument could be made that body recoveries could reveal a pattern of hazardous areas, the comments for the recovery cases revealed a variety of missions that did not necessarily meet the mountain SAR criteria. For example, some recovery cases had a distress call go out, but rescue teams arrived to find the subject dead-on-arrival, but others involved the discovery of skeletal remains – not necessarily human. Since the comments were too incomplete to appropriately categorize body recoveries as a mountain SAR incident or not, they were all excluded from analysis.

In the CALOES dataset, incidents that originated with a sat-comm device activation could be labeled in the ArcGIS Survey 123 report as "PLB activated" or "SEND activated." However, several incidents' comments indicated the appropriate labeling was not always used, with incidents originating with a SEND product (e.g., the comments state the subject used a Garmin InReach) getting labeled as PLB-activated. Thus, a new field was made to mark an incident as either originating from a sat-comm device or not, rather than relying on potentially inaccurate PLB and SEND labels. Incidents that did not originate with a sat-comm device activation stemmed from an 'other means of notification,' a description used henceforth in this paper to account for overdue procedures, verbal, and cellular methods of notification.

After cleaning, this research divided the datasets into separate layers based on their method of notification and whether sat-comm device activation was intentional or accidental. The breakdown of dataset preparation and incident categorization is depicted in Figure 8. For the CALOES dataset, this resulted in four layers, while for the AFRCC dataset on PLB incidents, this resulted in two layers. In this way, accidental sat-comm device activations could have their locations and attributes assessed, and actual SAR missions could be compared between sat-comm device usage and other means of communication.

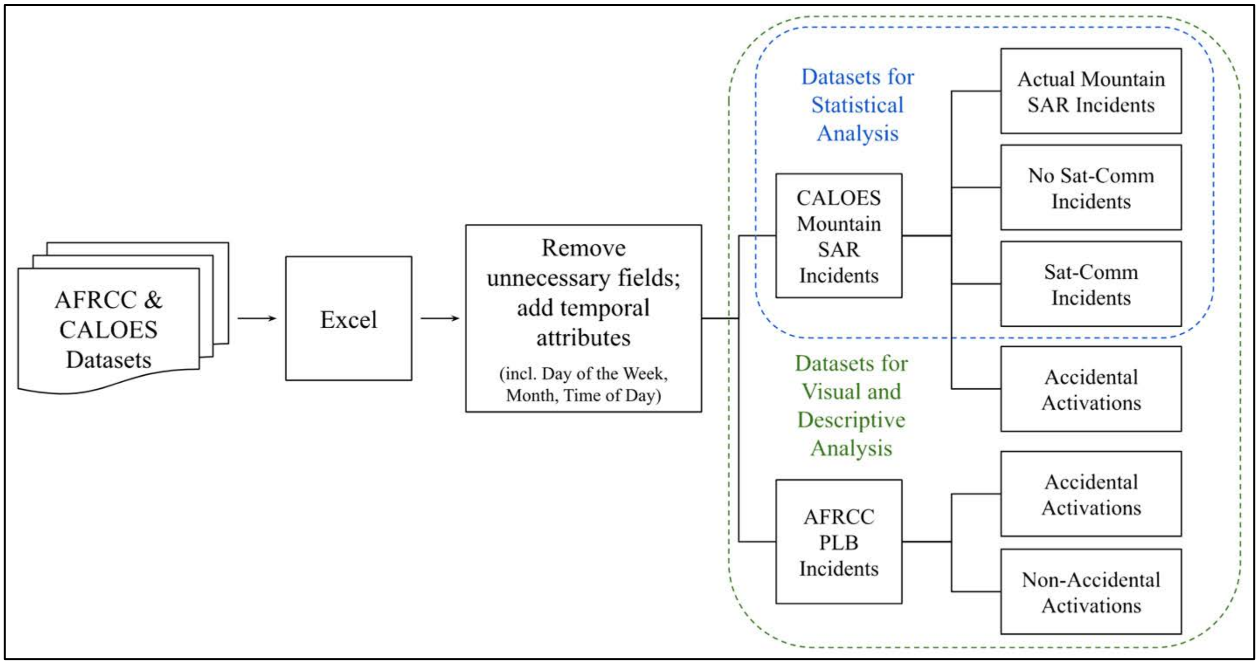

Figure 8. Initial dataset preparation and organization in Microsoft Excel

3.2.2 Dataset Preparation in a GIS

To be used as input for spatial analysis, the mountain SAR incidents from both datasets needed to represent locations on a planar surface for distance measurements. The original coordinates in the CALOES and AFRCC datasets were in the WGS 1984 geographic coordinate system and required projection in ArcGIS Pro. The WGS 1984 coordinate system can support meaning visual analysis since it is a realistic representation of spatial relationships. However, since geographic coordinate systems are based on a three-dimensional representation of the earth, a projected coordinate system that presents a planar version of reality is required to measure the distance between points or features during spatial statistics. This research selected the California (Teale) Albers in NAD 1983 (meters) projected coordinate system based on guidance set by the CDFW. The CDFW recommends using this modified Albers Conical Equal

Area projection for statewide datasets that require accurate distance and area measurements (CDFW 2022). The origin of the quadrants defining the two-dimensional landscape is roughly centered in the middle of the High Sierras, and measurements made throughout the study area can be considered relatively accurate representations of reality since distortions increase with distance from the origin.

Since mountain SAR incidents cannot occur in the parts of the study area devoted to roads, housing, towns, and industry, this research needed to define a study area that would only include land where a mountain SAR incident could occur. To this end, a shapefile representing the wilderness areas within the High Sierras (Wilderness Connect n.d.) was brought into ArcGIS Pro to effectively eliminate non-mountain SAR incidents and provide a landscape with the potential for mountain SAR incident distribution. A five kilometer buffer was made around the wilderness areas' boundaries in order to capture incidents that bled beyond the boundaries and to account for edge effects during subsequent spatial analysis. This buffer distance was based on the finding by Pfau and Blanford (2018) that lost people in the mountains travel on average 4.41 km. While the present study does not take into consideration searches and lost person behavior, Pfau and Blandford's research offers insight into how far subjects might wander before finding themselves in distress and initiating a call for help.

The mountain SAR incidents from the CALOES and AFRCC datasets were clipped to within the boundaries of the five kilometer wilderness area buffer and assessed for overlap within and between the two datasets. All incidents sharing the same date and time were visually inspected for spatial proximity, and if enough information was available in the comments to verify they recorded the same incident, then one was removed. Figure 9 depicts the selection process amongst CALOES incidents. In this example, all the incidents originated with a means of notification other than a sat-comm device. If incidents had the same date and time, but not enough detail was available in the comments to determine if they were unique or separate (e.g., through demographic information), then both incidents were retained for analysis. Of note, one of the comments for the records sharing dates and time in Figure 9 did have demographic information, but it is not included in the figure to protect the subject's privacy. Since the other incident sharing date and time did not have demographic information that could confirm or refute the match, both were retained per this example.

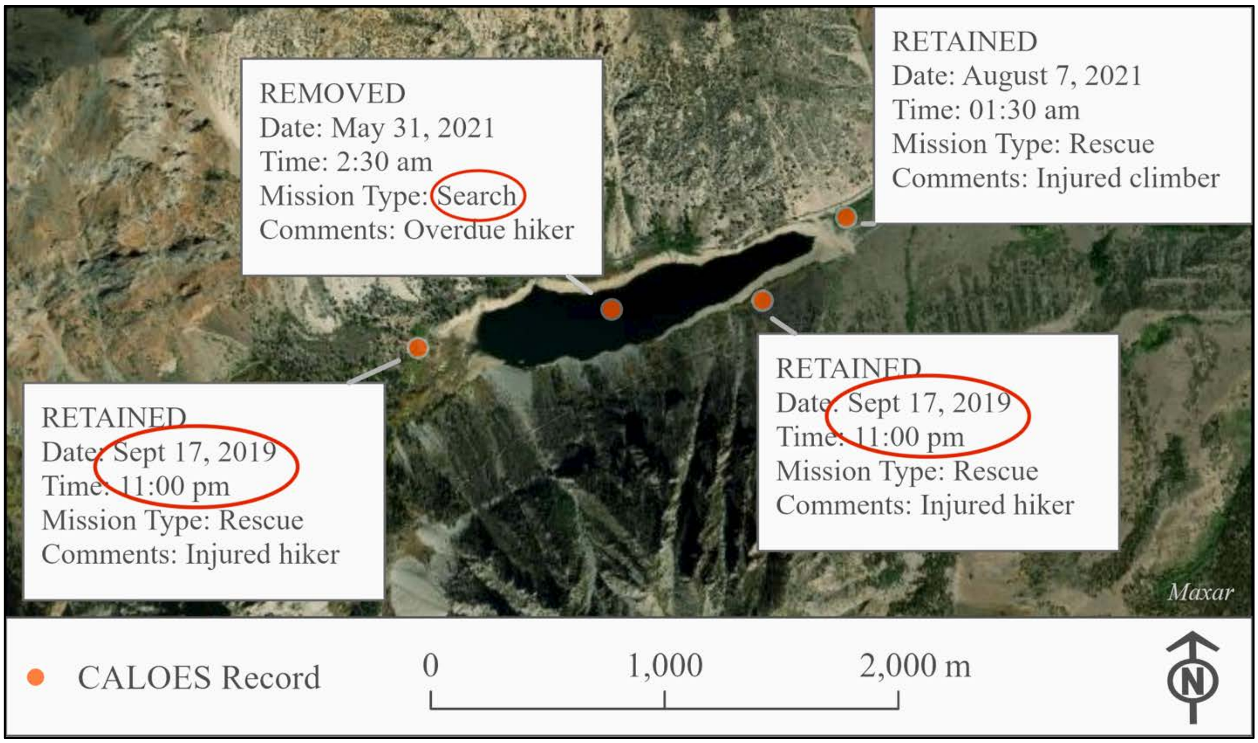

Figure 9. Depiction of incidents that were removed or retained

This research likewise identified and reviewed all incidents that shared geographic coordinates within and between the two datasets to eliminate redundancies which would impact analyses based on distance measurements. It is also almost impossible for incidents to occur in the exact same location, since coordinates were accurate to at least 0.1 meter. If one of the incidents could be determined by its attributes to be an accurate representation of a mountain

SAR incident, it would be retained while its duplicate or triplicate was removed. Otherwise, this research removed all incidents in that location. For example, if two incidents appeared in the middle of a lake under the same coordinates, but had different dates, times, and non-water sport activities per the comments, then were both removed. Not a single AFRCC mountain SAR incident shared the same coordinates nor same date and time as a CALOES incident. In theory, all the AFRCC records from January 2018 through July 2022 should match a CALOES record, since the AFRCC passes the notification of a SAR incident to the appropriate local SAR agency (e.g., county or NPS), who in turn should record the incident and provide that information to CALOES (reference Figure 3 in Chapter 1 above). Several CALOES sat-comm device activations (which are a mix of PLB and SEND activations) and AFRCC PLB activations lay near each other in time and space (see Figure 10), but due to insufficient information, all were retained. Note in the example in Figure 10 the similarities between the CALOES local time and AFRCC Zulu time. This was a reoccurring observation in this study, possibly pointing to a miscommunication of date and time formats between agencies.

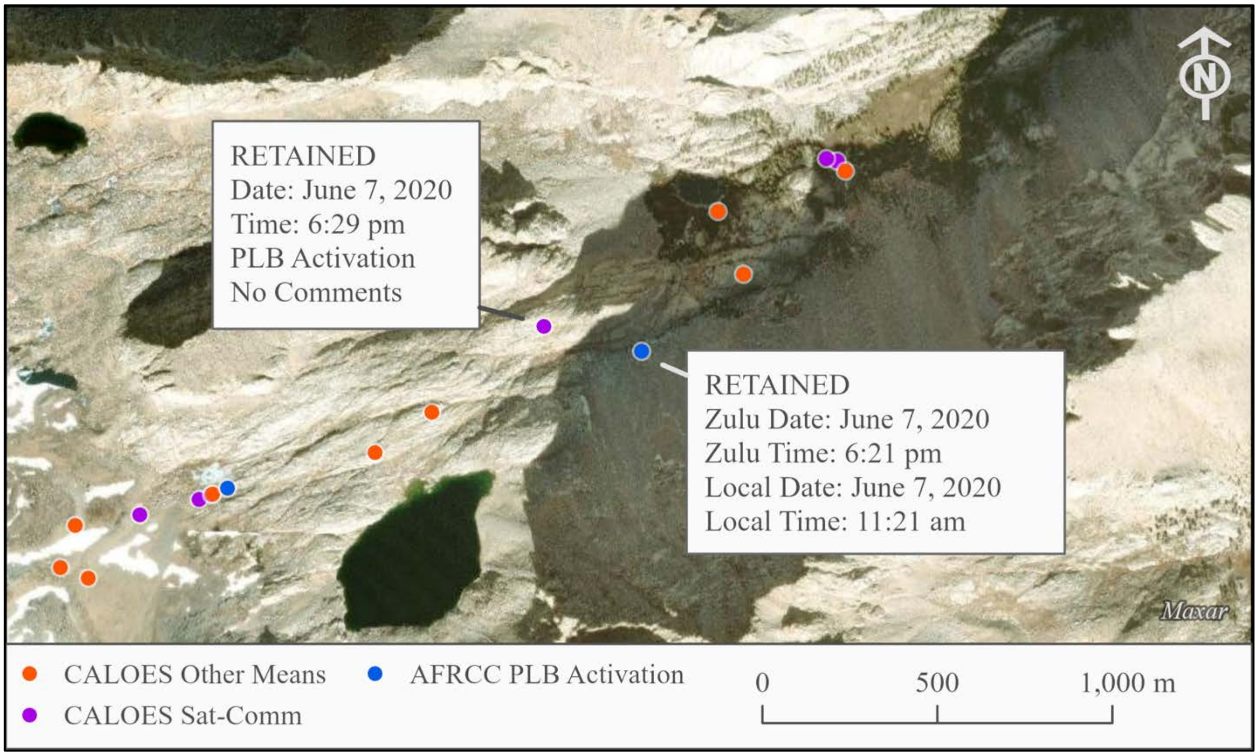

Figure 10. Example of similar incidents that were retained

This research also removed incidents from the five kilometer buffer area if ArcGIS Pro's satellite imagery basemap revealed they were near the built environment, such as paved roads, parking lots (a common trail head feature), or lodging. Since wilderness areas are largely devoid of man-made infrastructure per federal regulations, a visual inspection was not required. The exception to the built environment restriction were incidents that occurred in winter months when there was a high chance of snow (November through March), since several paved mountain roads close through the winter but are available for other forms of recreation, legal or not. This research also retained OHV incidents, as they would likely require the assistance of a specialty-trained SAR team and would not be accessible to standard vehicles or ambulances. This research considered the entirety of the wilderness areas a potential distress location, since even though humans tend to follow trails (Doherty et al. 2011), they are a wily species that tend to venture from the beaten path – or fall off it.

Once the feature layers only contained mountain SAR incidents within the study area, additional spatial attributes were added using the ArcGIS Pro Summarize Elevation tool. This tool assigns elevation, slope, and aspect to each incident based on a DEM selected by the analyst. This research selected the 30 m DEM for reference, as it is the size that most closely resembles the area of uncertainty associated with coordinates coming from sat-comm devices: some PLBs set satellite position accuracy at 100 ft, which corresponds to 30.48 m (US Air Force n.d.). This research elected to retain only the elevation output for further exploration, as slope and aspect can vary dramatically within short distances and a single value measured at the incident-level could be an inaccurate representation of surrounding topographic challenges. In contrast, a single measurement can adequately represent the effects of elevation on rescue team capabilities. Table 1 presents the attributes available for analysis in each feature layer now that temporal attributes had been added in Excel, and spatial attributes had been added in ArcGIS Pro. The only attributes that did not overlap across datasets were the Zulu dates and times in the AFRCC data.

Table 1. The attributes associated with each dataset available for subsequent analysis

Dataset	Attributes
CALOES and AFRCC	Date, Time, Time of Day, Year, Month, Day of the Week, Mission Type, Notification Method, Accidental Activation, Elevation, Comments, Latitude, Longitude
AFRCC Only	Zulu Date, Zulu Time

3.3 Spatial Analysis of the CALOES Dataset

The spatial analysis of mountain SAR incidents involved two main steps: point pattern analysis and spatial statistical analysis. Due to the sparse distribution of AFRCC mountain SAR incidents, this research only conducted statistical spatial analysis on the CALOES-derived incidents. Figure 11 provides an overview of the analytical techniques used in this research and the ArcGIS Pro tools applied to execute them. The point pattern analysis methods of nearest neighbor measurements and kernel density estimates (KDE) provided a means to measure incident spatial interactions. Point pattern analysis results, backed by expert opinion, aided in the development of a neighborhood structure. Neighborhoods were structured off hexagonal grids, and incidents were aggregated by grid cell, creating a metric for comparison: incident frequency. Once this research had a neighborhood structure defined, local neighborhoods were compared to the study area as a whole and tested against random simulations to determine the significance of first-order spatial interactions that could reveal hot spots, clusters, and outliers.

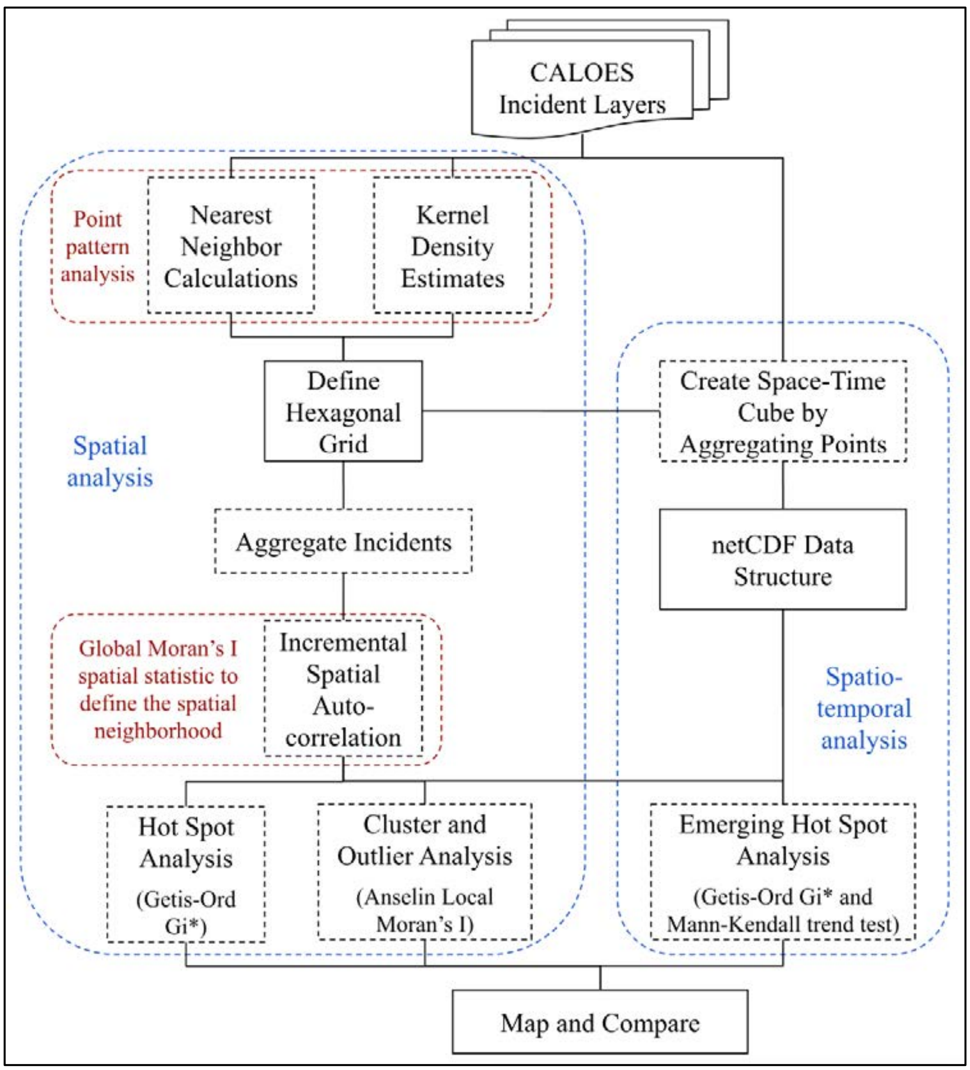

Figure 11. Overview of the methods and corresponding ArcGIS tools used for analysis

3.3.1 Point Pattern Analysis

This research evaluated all mountain SAR incidents by a single set of coordinates without considering the area of positional uncertainty inherent to satellite devices caused by signal obstructions in the environment. While positional uncertainty could have been represented using the point-radius technique described by Doherty et al. (2011), this study maintained a single coordinate pair rather than an area to represent sat-comm device activations for three reasons: satellite positional uncertainty is not uniform and depends on the topography; positional error varies by device and make-and-model attributes were unknown; and if areas of uncertainty were created, polygon centroids would still form the basis for point pattern analysis and incident aggregation due to their computational efficiency.

Evaluating the distances between mountain SAR incidents can offer insights into how incidents interact with each other over space. While such second-order effects were not expected amongst mountain SAR incidents, exploring the distance relationships between incidents gave a sense of their spatial distribution and helped define the dimensions of repeat sites for rescue teams. This research conducted average nearest neighbor analysis for an initial assessment of spatial clustering. Since the layer with all the actual mountain SAR incidents would have the largest minimum bounding rectangle to run the nearest neighbor statistic, the area of this rectangle was also applied to the layers representing only sat-comm devices or only other means of notification. Additionally, the distances between an incident and n nearest neighbors – where n in this case represents the number of neighbors when the minimum distance exceeds a reasonable definition of a single topographic area – were calculated for the CALOES layer representing actual mountain SAR incidents, since it was the layer containing the most incidents.

Comparing the minimum, average, and maximum distance values provided initial insights into how incident clusters and outliers might be spaced.

This research next examined incidents for first-order effects using KDE. The kernel size which made the most sense based on the underlying topography became a reference for spatial neighborhood analysis. The KDE output is a raster surface, where each raster cell value represents the density of incidents per the search distance set by the analyst. The quartic kernel function that defines the shape of the kernel smooths the transition between cell values for a visually appealing output that facilitates the visual analysis of point incidents across a broad area. Cells near the edges of the study area might exhibit lower values than interior cells since fewer incidents might lie within the kernel search distance. This research mitigated this edge effect by the 5 km buffer around the wilderness areas that accounted for incident bleed beyond the study area boundaries. This research explored several kernel search distances to assess which distance resulted in clusters that corresponded to the topographic environment. Since KDE is less computationally demanding than other forms of spatial statistical analysis, the KDE output refined the range of distance parameters to explore in future computations.

3.3.2 Incident Aggregation and Neighborhood Structure

This research next aggregated the mountain SAR incidents so spatial statistical analysis could be used to assess the statistical significance of the incidents' distributions. The aggregating unit needed to represent a site that rescue teams would associate with similar operating conditions and consider a repeat location. For example, reoccurring SAR calls for a steep trail section is an identifiable location to which rescue teams could develop realistic training scenarios. Multiple incidents at that site will have different coordinates, but the site would present similar hazards to a rescue team, like the steepness of the slope, the type of ground cover, or the elevation. Hexagons were chosen as the aggregating unit because they reflect human movement patterns more realistically than a rectangular grid and because hexagonal edges conform better with terrain than right angles (Birch, Oom, and Beecham 2007). Expert opinion supplemented the point pattern analysis results when settling on hexagon size by considering how the size related to the ground and airborne rescue teams who must contend with reaching or moving subjects in distress. The hexagon size needed to be small enough to capture topographic variation (e.g., a climbing route, a switchback on a trail, an alpine meadow, etc.), large enough to mitigate computational demands, and reasonable enough to represent rescue team capabilities. Mountain SAR incidents were aggregated by grid cell, resulting in a single layer containing three fields of incident frequencies: all actual mountain SAR incidents; actual SAR incidents that began with a sat-comm device activation; and actual SAR incidents that originated from a notification source other than a sat-comm device.

While the size of the hexagon reflects a single operating site for rescue teams, the size of a SAR incident neighborhood represents a broader area of concern for SAR agencies that could correspond to a recreational destination or pathway. Mountain SAR incidents, which have spatial attributes related to the terrain, are not expected to occur randomly across wilderness areas. An OHV area would presumably contain mostly OHV-related accidents, while a rock-climbing area would have mainly technical SAR incidents. Busy areas could have a high number of cases due to a mix of recreational experience levels. SAR incidents near each other in space will likely have more similar attributes than those farther away. This correlation of attributes over space is termed spatial autocorrelation. Tests for spatial autocorrelation help identify the typical neighborhood size of mountain SAR incident locations.

This research used the Global Moran's I statistic to measure the spatial autocorrelation of mountain SAR sites based on their incident frequency across the Sierra Nevada wilderness areas. Running the statistic for multiple distance provided a series of z-scores. A fixed distance band was selected to conceptualize spatial relationships so as to explore multiple distances to detect trends, since mountain SAR incidents are not known to cluster within a specific distance range. The distance band where the index has the largest peak z-score represented the mountain SAR incident neighborhood size where SAR incident frequency deviates the most from the mean. This research used this distance to define subsequent neighborhood relationships.

3.3.3 Hot Spot, Cluster, and Outlier Analysis

Mountain SAR incidents play out across a diverse topographic environment, and a single, global trend cannot capture local spatial relationships within the dataset. Two local spatial statistics were used in this research to investigate where mountain SAR incidents occur and in what local context: the Getis-Ord Gi* statistic and Anselin Local Moran's I.

This research applied the Gi* statistic to identify concentrations of mountain SAR incident hot spots that significantly differ from the rest of the study area. Hot spots are a useful tool for visual analysis, as they reveal statistically significant areas that should concern SAR organizations and policy makers. Hot spots are also easier to conceptualize and locate than individual incident points on a map, and they are more compelling than a simple density analysis since their significance can be measured. The Getis-Ord Gi* results lent themselves to a comparison of how sat-comm device activation hot spots compare to those based on incidents originating from other means of notification.

This research evaluated mountain SAR incident spatial clusters and outliers for significance using the Anselin Local Moran's I statistic. The neighborhood distance parameter was the same as that set for the Gi* statistic to support evaluation between the results. The probability a mountain SAR incident site is an outlier or belongs to a cluster is given by the p-value after running a set number of permutations of the Monte Carlo test to reject the null hypothesis that the attributes are randomly distributed. If the Anselin Local Moran's I values for the Monte Carlo permutations suggest less spatial clustering than the Anselin Local Moran's I values of actual mountain SAR incident distributions, then the actual distributions are registered as significant clusters. More permutations increase the precision of the pseudo p-value from the Monte Carlo permutations, but also require more processing time (Esri n.d.). Due to computational constraints, this research only ran 499 permutations, limiting the pseudo p-value threshold to $p = .002$. Because outliers may develop into a hot spot over time should more incidents occur in that area, they are worth investigating using the Anselin Local Moran's I statistic so SAR agencies may monitor for the evolution of future patterns.

3.4 Spatiotemporal Analysis of the CALOES Dataset

This research conducted spatiotemporal analysis on the CALOES mountain SAR incidents using the Emerging Hot Spot Analysis tool in ArcGIS Pro (Esri n.d.). This tool combines the Getis-Ord Gi* statistic with the Mann-Kendall trend test for a spatiotemporal consideration of mountain SAR incidents. Considering how the distribution of incidents changes over time allows SAR agencies to distinguish between older and more recent patterns which could reflect changes is outdoor recreation driven by sat-comm device usage.

For the Emerging Hot Spot Analysis tool to work, SAR incidents need to be structured by space and time. A space-time cube (STC) provides the format, with two dimensions measuring space and a third dimension measuring time. Figure 12 offers a visualization of the STC construct, adapted from Esri (n.d.). The area of analysis forms the base of the array, and layers representing a time series stack over the spatial base. Each slice of the time series represents one month of aggregated incidents due to the data's irregular start and end dates. While aggregating incidents by year would have been preferable to mitigate seasonal bias (see Aftergood and Flannigan 2022; Reddy et al. 2019; and Visner, Shirowzhan, and Pettit 2021), the Create Space Time Cube by Aggregating Points tool requires a minimum of ten time slices to run trend tests even though only four time slices are required to detect a trend. Time slices are defined by the last day of the month of the most recent month with complete SAR data. Hexagonal prisms match those used with the local statistics, although they are depicted as cubes in Figure 12 for ease of visualization.

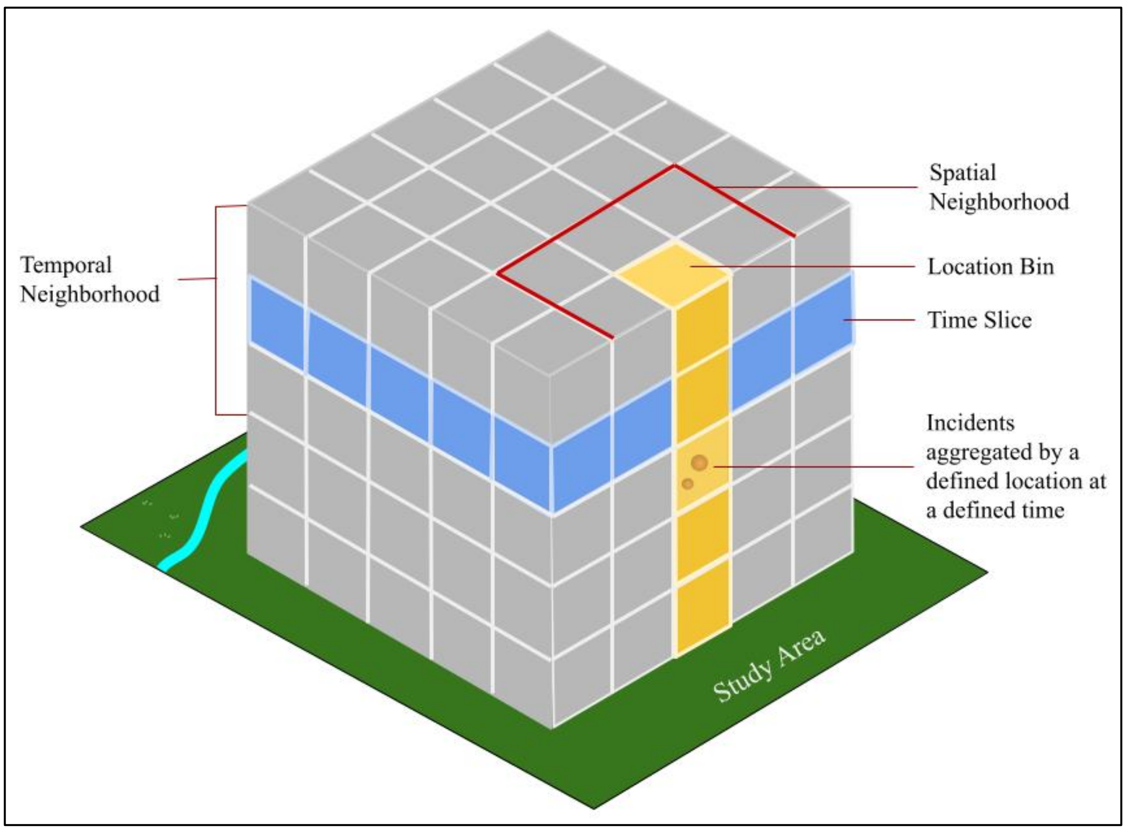

Figure 12. A graphical representation of a Space-Time Cube; adapted from Esri (n.d.)

The Emerging Hot Spot Analysis tool considers a location in the context of its spatial and temporal neighborhood. The global attribute mean describing SAR incident frequency (i.e., the $\bar{X}$

in (4) was adjusted to only consider attributes within the same temporal neighborhood, which is set at 12 months. To keep the Emerging Hot Spot results comparable to the purely spatial Gi* results, the spatial neighborhood fixed distance band is the same, despite potential biases associated with fewer incidents assessed per neighborhood per temporal period when running Emerging Hot Spot Analysis.

The Emerging Hot Spot Analysis tool's output is a time series of hot spots and cold spots based on the p-values and z-scores of the locations containing SAR incidents. The Emerging Hot Spot Analysis tool applies the Mann-Kendall trend test to the hot spot and cold spot time series to ascertain whether there is a positive or negative trend. The Mann-Kendall test is a non-parametric rank correlation test, meaning it does not need data to be normally distributed and is suitable for the right-skewed mountain SAR incident frequencies. Because the test looks for consistently increasing or decreasing trends over time, seasonal data would need to be considered by year, which is why the temporal neighborhoods are a twelve-month aggregate. The tool can assign one of eight trends: new, consecutive, intensifying, persistent, diminishing, sporadic, oscillating, and historical (Esri n.d.). In this manner, an analyst can identify areas that could be a consistent or growing concern to rescue teams, particularly owing to the use of sat-comm devices by outdoor recreationists.

3.5 Comparing the AFRCC and CALOES Datasets

The AFRCC PLB dataset augmented the CALOES SAR dataset in that it contains older recorded incidents–and additional, contemporary data points–that support or question the spatial patterns discovered amongst the CALOES SAR incidents. This research first examined the spatial and temporal similarities and differences between actual SAR missions from the two datasets through visual analysis and descriptive statistics to provide an overview of the spatial and temporal attributes of each dataset. This research then inspected the PLB activations from the AFRCC dataset in the context of the statistically significant spatial patterns of the CALOES dataset. Additionally, the subset of mountain SAR incidents from both datasets that were recorded as an accidental activation of a sat-comm device were reviewed and compared against actual SAR missions. Supplementing the spatial statistics with the visual analysis and descriptive statistics lent context to the results so rescue teams and organizations can demonstrate not just where mountain SAR incidents occur and how those locations might differ with sat-comm device usage, but they could begin to explore the impact of incident distributions on rescue operations.

3.5.1 Comparing Spatial Relationships and Attributes

This research applies visual analysis and descriptive statistics to mountain SAR data in order to evaluate how incident attributes could inform training and preparation plans for SAR teams as they adapt to the impacts of sat-comm device activations. Both methods are considered exploratory data analysis techniques as they do not test for significance but instead rely on interaction between the analyst and the data for interpretation. Visual analysis involves the visual inspection of representations like maps and GIS layers to draw conclusions (O'Sullivan and Unwin 2010). The visual analysis techniques used in this research include an inspection of incident locations, spatial relationships, and attributes by comparing SAR incidents against satellite imagery in a GIS. This research visually inspected AFRCC PLB activations to identify any that match a CALOES incident. This research used the Near tool to figure out where the AFRCC incidents lay in relation to the CALOES incident neighborhoods and to assess whether including the AFRCC data in future spatial statistical analysis could contribute to new – or reinforce current – mountain SAR hot spot, cluster, and outlier locations.

This research used descriptive statistics to compare incident counts and attributes over time for both the AFRCC and CALOES datasets. The results are presented in tabular or chart formats. This research examined incident elevation and temporal attributes at the incident-level. Considering the spatial and temporal attributes of incidents that derive from a sat-comm device activation against those originating with other means of notification gave insight into how sat-comm devices might be changing SAR dynamics.

3.5.2 Assessing Accidental Activations

The activation of a sat-comm device generates a SAR response until the activation can be confirmed as accidental or the incident is resolved. Accidental activations therefore pose a potential drain on resources if they occur in mountainous terrain and require the time and expenses associated with the deployment of specialist rescue teams. This research examined mountain SAR incidents determined to originate with an accidental device activation using the visual analysis and descriptive statistics described above, and then reviewed the results for how they might impact SAR organization planning and expectations.

3.6 Summary

This research leverages the benefits of GIS tools to explore how sat-comm device usage impacts the SAR environment. This research ran two point pattern analysis methods on actual mountain SAR incidents from the larger CALOES dataset, the results of which informed subsequent methods of spatial analysis. Creating an incident neighborhood structure supported local spatial statistical analysis to identify hot spots, clusters, and outliers. Additionally, incidents were organized by space as well as time in an STC and assessed for emerging hot spots. This research then evaluated the hot spots, clusters, outliers, and emerging hot spots attributed to incidents originating with a sat-comm device for similarities and differences against the sites associated with incidents originating from other means of SAR notification. The smaller AFRCC dataset was evaluated against the CALOES dataset for redundancies. This research then measured and visually assessed actual mountain SAR incidents unique to the AFRCC dataset in the context of the CALOES spatial analysis results to determine possible implications. Lastly, this research reviewed incident attributes and accidental sat-comm device activations using descriptive statistics to determine what sat-comm usage might mean for SAR team preparation.

Chapter 4 Results

The intent of this study is twofold: to explore the impact of satellite communication (sat-comm) devices on the search and rescue (SAR) landscape in California's High Sierras; and to present a methodology that could guide the efficient use of SAR resources and increase the safety margins for SAR rescue teams. In order to isolate mountain SAR incidents that met the definition of mountain SAR used in this study, the study area was restricted to within a five kilometer buffer of the High Sierra's wilderness areas, with a total area of 21,749.53 km^2. After data preparation and cleaning, 53 mountain SAR incidents represented the Air Force Rescue Coordination Center (AFRCC) dataset on PLB activations (eight of which were attributed to accidental activations), running from July 25, 2015, to July 17, 2022. The California Office of Emergency Services (CALOES) dataset was distilled to a total of 416 mountain SAR incidents (27 of which were due to the accidental activation of a sat-comm device) dated January 1, 2018, to July 27, 2022. After removing the accidental activations, roughly one-third of actual SAR incidents in the CALOES dataset were initiated with a sat-comm device, at 132 incidents. The remaining two-thirds started the SAR process through a different means of notification, at 257 incidents.

It is clear from a simple visual inspection of mountain SAR incident distributions that incidents do not have a random distribution across the Sierra Nevadas. Figure 13 presents maps of actual mountain SAR incidents and accidental activations from the AFRCC and CALOES datasets from 2018-2022 (AFRCC incidents pre-2018 were omitted from this figure so as to visually compare incidents across datasets from the same period). In Figure 13a and c, incidents appear concentrated along the eastern spine of the High Sierras, perhaps due to trail networks, the scenery, or the challenge of extreme recreation that can attract outdoor enthusiasts. The sat-comm device activations from both the AFRCC and CALOES incident datasets suggest positive spatial clustering as well as a higher proportion of spatial outliers (see Figure 13b), while mountain SAR incidents that begin with other means of notification have relatively fewer spatial outliers (see Figure 13a). Furthermore, sat-comm device activations appear distributed across a greater swath of the study area than incidents initiated by other means of notification, suggesting sat-comm devices could impact recreational behavior and rescue team requirements. These inferences, which were gathered from a simple assessment of points on maps, are supported by the results of spatial statistical analysis of the CALOES dataset. This research additionally explored how the spatial and temporal patterns could impact rescue team preparation through visual analysis and descriptive statistics of the AFRCC and CALOES data attributes and an evaluation of accidental sat-comm device activations.

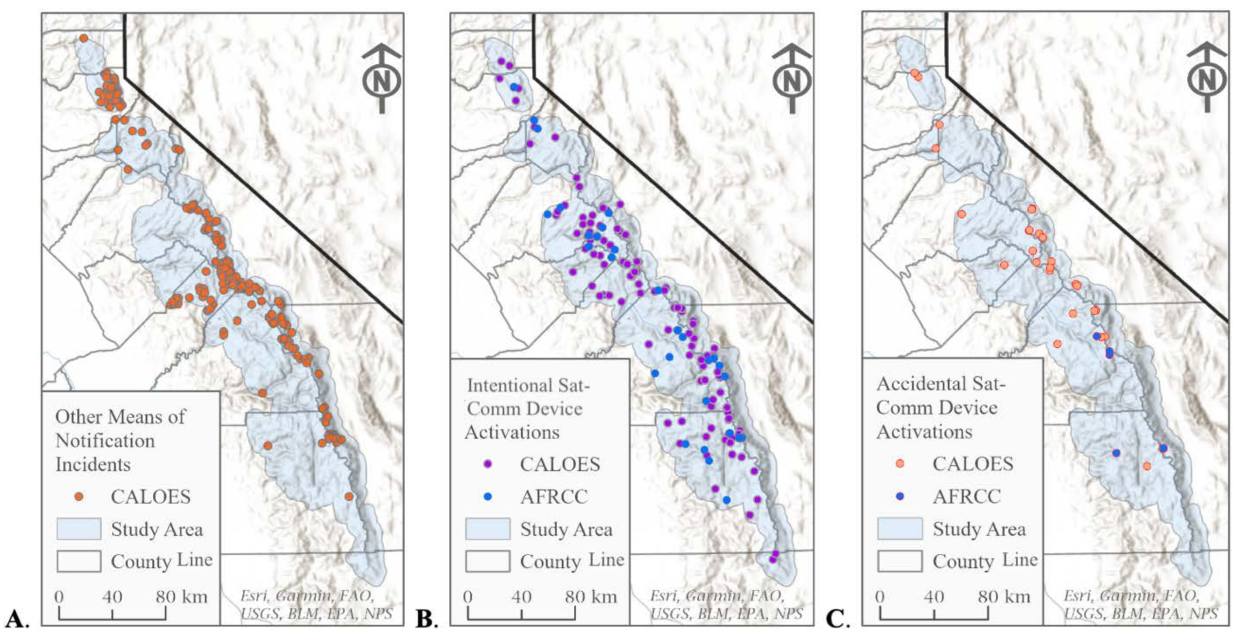

Figure 13. Distribution of SAR incidents by means of origination: (a) other means of notification, (b) intentional sat-comm activation, and (c) accidental sat-comm activation

4.1 Spatial Analysis of the CALOES Dataset

During data preparation, this research separated the CALOES mountain SAR incidents into three layers for spatial pattern analysis: all actual mountain SAR incidents; actual mountain

SAR incidents that originated with the activation of a sat-comm device; and actual mountain SAR incidents that are triggered by an 'other means of notification' (e.g., in-person notification, cell phone, etc.). This research did not consider accidental sat-comm device activations for statistical spatial analysis, as accidental activations are not necessarily driven by the same spatial relationships as actual SAR incidents and because the number of accidental activations reviewed in this study were too sparse. This research assessed mountain SAR incidents as both singular events and as aggregations within a neighborhood structure. Point pattern analysis consisted of average nearest neighbor calculations, a review of distances between neighboring points, and an exploration of kernel density distances. The resulting distances were judged by expert opinion to select a distance parameter that was small enough to reflect how SAR incidents interact over space but large enough to support reasonable computational processing times. This research then aggregated the mountain SAR incidents by a hexagonal grid whose cell-width matched the selected distance parameter and evaluated the aggregations to develop a neighborhood structure. The incidents within the neighborhood structure were assessed to determine how sat-comm devices impact the locations of incident hot spots, clusters, and outliers. Due to the sparse number of recorded PLB incidents from the AFRCC dataset within the study area, this study only ran spatial statistics on the CALOES dataset.

4.1.1 Point Pattern Analysis

The point pattern analysis results provided an initial insight into the spatial patterns of mountain SAR incidents. The nearest neighbor and kernel density estimates (KDE) point pattern analysis methods are a simple type of spatial analysis that do not consider topographic variability like sharp elevation changes or obstructions. While almost one-half of actual mountain SAR incidents occurred on the same date as another incident, only about one-eighth of these occurred within 250 m of another incident. These figures suggest it is unlikely a SAR incident impacted another occurring in the same location.

This research ran average nearest neighbor calculations on all three CALOES incident layers. The layer representing the totality of incidents regardless of notification method had a minimum bounding rectangle with an area of 30,669.64 km^2. To make the nearest neighbor ratio comparable across the notification methods, this area was set for the bounding rectangle of the other two layers. The average nearest neighbor results, presented in
Table 2, indicated significant spatial clustering for all three layers. The average nearest neighbor observed mean distance for the mountain SAR incidents originating from a sat-comm device activation is larger than that for the other means of notification incidents, suggesting the presence of outliers. Because the sat-comm layer also has a larger expected mean distance since it contained fewer incidents for the same bounding area, the nearest neighbor ratios for all three layers are relatively similar. The ratios range from 0.42 to 0.58, falling roughly equally between complete spatial randomness (i.e., a ratio of one) and complete spatial clustering (i.e., a ratio of zero). The layer of sat-comm device activations had the larger ratio of 0.58, while the layer of other means of notification had the smaller ratio of 0.42, suggesting the former has less clustering than the latter. The sat-comm device layer also resulted in a z-score closer to zero than the other two layers, suggesting less variation from the mean and hence less extreme clustering distances than the other two layers. The extremely low p-values indicate more significant clustering than could be expected due to random chance.

Table 2. Average nearest neighbor results

	Nearest Neighbor Ratio	Observed Mean Distance (m)	Expected Mean Distance (m)	z-score	p-value
All CALOES Actual SAR Incidents	0.50	2,227.63	4,439.66	-18.80	.000000
Sat-Comm Device Activations	0.58	4,446.48	7,621.45	-9.16	.000000
Other Means of Notification	0.42	2,277.72	5,462.08	-17.88	.000000

This research only calculated the minimum, average, and maximum distances between incidents for the layer representing all actual mountain SAR incidents so as to have the maximum number of inputs. The measurements between different numbers of neighbors are presented in Table 3. At 10 neighbors, the minimum distance began to exceed the 500 m used in subsequent analysis to represent a single location, so distance values beyond 10 neighbors are not included for inspection in the table. The average distance for all actual mountain SAR incidents to have at least one neighbor is 2,227.6 m, with the minimum distance between incidents at less than one meter and the maximum distance at almost 26 kilometers. At least one location within the dataset has 10 neighbors within a 600 m radius. However, the minimum distance from eight to nine nearest neighbors jumps about 300 m from just over 100 m to just over 400 m, suggesting most incidents that could be considered to share a location occur within roughly 100 m of each other. Furthermore, while some sites may have multiple incidents near each other, the average number of incidents do not, with the average number of incidents having only three neighbors within a five kilometer radius. Table 3 suggests there are limited, if any, interactions between incidents that impact subsequent incidents as well as the presence of several spatial outliers, as the average distances between incidents are relatively large. Instead, incidents occurring in proximity are likely location-specific rather than influenced by an incident nearby, with some sites containing more hazards or experiencing higher traffic than others.

Table 3. Distance relationships between actual SAR incidents in the CALOES dataset

Distance (meters)	Number of Neighbors									
	1	2	3	4	5	6	7	8	9	10
Minimum	0.088	38.88	47.67	60.94	67.79	94.66	95.35	**106.38**	**403.90**	**573.74**
Average	**2227.63**	**3909.32**	**4727.88**	5645.68	6354.99	7064.39	7696.88	8405.80	8951.71	9547.76
Maximum	25,926.46	37,246.16	37,556.37	45,874.96	48,106.98	67,244.65	68,099.67	79,925.45	84,268.22	89,541.62

This research next assessed actual mountain SAR incidents using KDE to determine the kernel size where incident densities best matched the study area's topography, which contains mountains, alpine lakes, meadows, and glacial valleys. This research evaluated the KDE values at 250 m, 500 m, and 1,000 m cell sizes using search distances of 1,000 m, 2,500 m, 5,000 m, and 10,000 m. The raster surface output of incident density estimates with the 500 m cell size provided the best resolution to represent incident density. The 2,500 m search distance offered the best depictions of incident clusters that followed topographic characteristics based on a visual assessment. The tool was run again using these settings for the features representing only intentional sat-comm device activations and incidents originating with other means of notification and were examined to check if the settings appropriately represented the smaller datasets. Figure 14 shows how the resulting density surface raster layers compare across the entire study area. The magnified area is just west of Whitney Portal on the Tulare-Inyo county border and represents a roughly three kilometer zone around the tallest peak within the continental United States. The density surface – and the smoothing effect of the kernel's quartic function – effectively conveys which areas have a high concentration of incidents and should be the focus of SAR agencies, which areas with a low incident density should be monitored for future trends or examined further for potentially hazardous conditions, and how the datasets representing methods of notification compare. It is worth noting in the magnified zone in Figure 14 that the incident clusters appear elongated, possibly pointing to the impact of visitor traffic along a trail network. The KDE results informed subsequent analyses involving incident aggregation schemes.

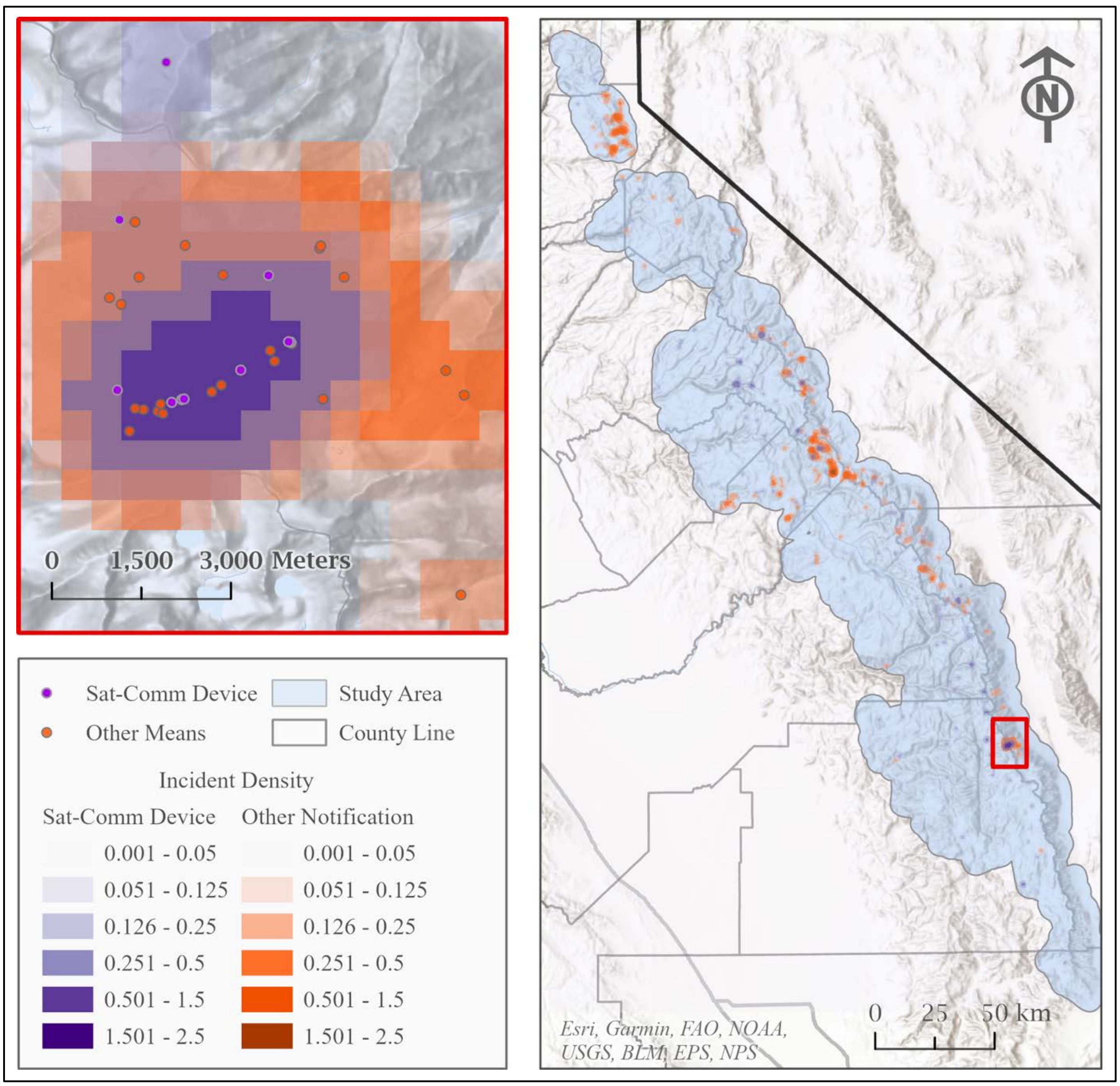

Figure 14. KDE results using a 500 m grid cell and a 2,500 m search radius

4.1.2 Incident Aggregation and Neighborhood Structure

This research aggregated mountain SAR incidents to support spatial statistics where the unit of analysis would represent the mountain SAR incident frequency per hexagon. After testing sizes for 250 m and 1,000 m, a hexagon with a width of 500 m was selected for a repeating grid. Five hundred meters effectively captured mountain SAR incidents within a single topographic location but was large enough to support reasonable computational processing times for the area of analysis. The grid of hexagons supported a neighborhood structure with near equal access to all neighbors due to hexagonal geometry. From a rescue team's perspective, 500 m is a fair distance to measure a single SAR site: should a helicopter be able to land or hover only in the middle of a hexagon, having rescue personnel move a person in a litter 250 m in any direction could be considered a maximum – albeit arduous – distance for most rescue teams of two or more people before driving a new landing or hover location. Figure 15 provides a snapshot of the relationship between the hexagons and mountain SAR incidents. Note how incidents within roughly 100 m of each other are generally within the same hexagonal cell, and those farther away may be in neighboring cells. It is also worth mentioning that these distances are based off a planar surface, and some incidents might have a greater slant range distance if separated by extreme changes in elevation. While a grid overlay is imperfect, since incidents are arbitrarily separated or grouped, the 500 m hexagonal grid effectively captures the local densities of incidents per cell to facilitate a comparison with neighboring cells.

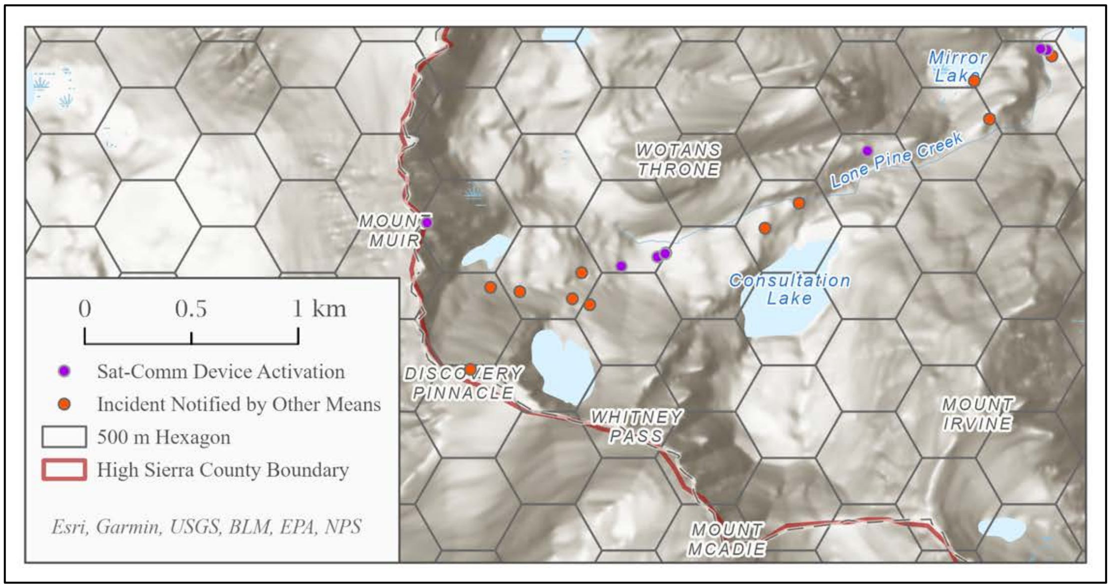

Figure 15. Mountain SAR incident distribution within the 500 m hexagonal grid; location is west of Whitney Portal on the border of Tulare and Inyo counties

This research aggregated each of the three CALOES layers of actual mountain SAR incidents by the hexagonal areal unit and tested each aggregated layer using the Global Moran's I statistic to explore which distances demonstrated statistically significant spatial autocorrelation. This research used the results to develop a neighborhood distance parameter for subsequent analysis. Ten distance bands were evaluated at 500 m, 1,000 m, and 2,000 m increments resulting in an exploration of spatial autocorrelation out to 18.5 km. All three layers had a significant z-score peak at 3,500 m, at which distance the mean hexagonal cell incident frequency deviated the most from the mean for the study area and suggests positive spatial autocorrelation. Looking at Figure 16, which depicts the results for increments of 1,000 m, other z-score peaks are also present in all three layers. This research disregarded the two peaks at 7,500 meters, as that would constitute a neighborhood structure that would be less useful for rescue agencies aiming to assess site-specific hazards and was not supported by the KDE results, which suggested 2,500 m was optimal for visualizing incident clusters.

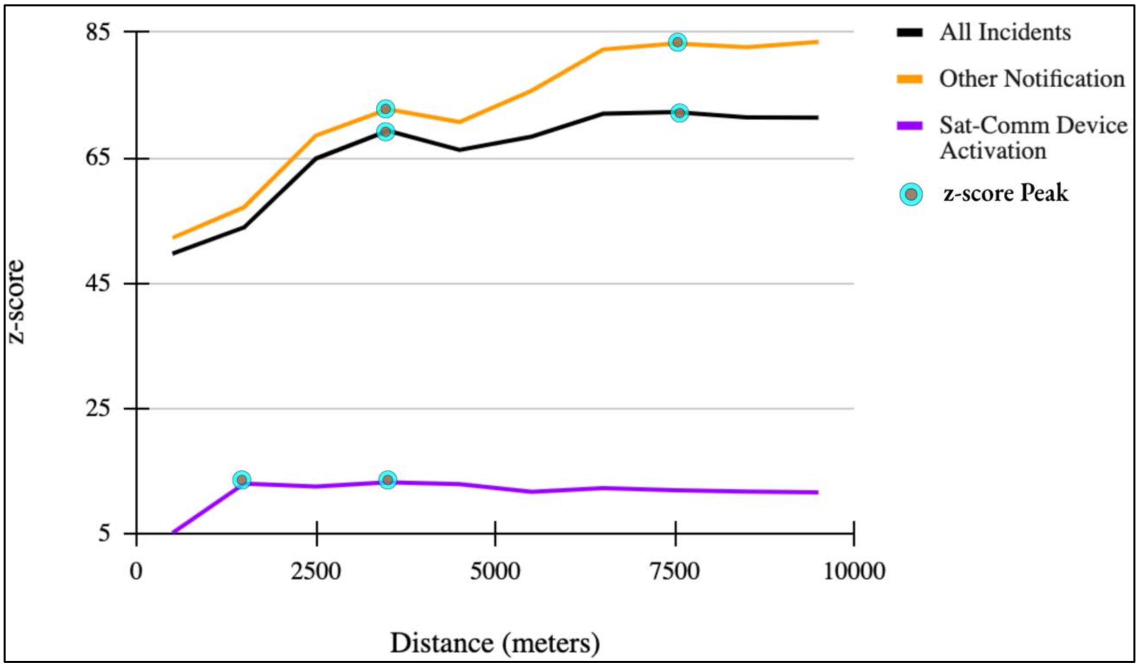

Figure 16. Global Moran's I distances for maximum spatial autocorrelation

In Figure 16, a notable peak is present at 1,500 m in the layer representing sat-comm device activations. At 1,500 m, the z-score is 12.98, compared to a z-score of 13.19 at 3,500 m. However, when running the global spatial statistic at increments of 500 m, which produces z-scores out to 5 km, only one z-score peak was present at 1,000 m with a z-score of 13.67. This research disregarded these z-score peaks at 1,000 m and 1,500 m for use as neighborhood sizes in subsequent analysis so as to facilitate comparison across all three CALOES layers. That said, a smaller spatial neighborhood might be a more accurate representation for the sparser sat-comm device activations layer, as larger neighborhood sizes might exaggerate the influence of a single sat-comm device activation on a location compared to the global mean.

Based on the Global Moran's I output and KDE results, this research set a neighborhood distance of 3,500 m for further spatial and spatiotemporal analysis. This distance makes sense from a topographic and SAR perspective: distances greater than 3.5 km might fail to capture the nuances of alpine meadows, cliff faces, and lakes and suggest false spatial associations; and half this distance is 1,750 m, which is roughly the distance a helicopter requires to set a safe, established approach to a landing or hover location, and incidents occurring within the final approach path typically pose similar challenges (e.g. vertical obstructions and vegetation) to a helicopter rescue team. The 3,500 m neighborhood fixed distance band allowed incident frequencies to be compared within a spatial neighborhood where they demonstrated significant spatial autocorrelation across the study area.

4.1.3 Hot Spot Analysis

With the actual mountain SAR incidents aggregated and a distance selected for defining the incident neighborhood, this research applied local spatial statistics to aid in the identification of incident hot spots, clusters, and outliers. Hot spots were identified using the Getis-Ord Gi* statistic. A hot spot is a neighborhood where the SAR incident frequency is significantly higher than that of the study area. However, hot spots do not necessarily equate to locations containing the highest number of incidents, but instead reveal the locations that significantly differ from the global mean. Incident outliers may appear as a hot spot location if a dataset is so sparse that even one incident can raise the neighborhood mean such that it is significantly greater than the global mean, as is the case with several locations originating with a sat-comm device activation. The global mean for all three CALOES layers has a low value, as over 99% of hexagons in the study area in all three layers contain no incidents.

The Hot Spot Analysis tool's results show hot spots of incidents that stem from a sat-comm device activation are in different locations than incidents that begin with other means of SAR notification, though there is a substantial area of overlap between the two layers. The portion of the study area considered a hot spot with a p-value of .01 or less stands at 5.10% for all actual mountain SAR incidents, 4.62% for incidents originating with a sat-comm device, and

5.21% for incidents originating with other means of notification. A comparison of the hot spots between the different methods of SAR response activation is depicted in Figure 17. Most of the sat-comm device hot spots and other means of notification hot spots exhibit unique distributions, suggesting intentional sat-comm device activations increase the demand for SAR services across a greater portion of the study area. However, as can be seen by the yellow areas in Figure 17, 13.21% of the hot spot locations with 99% confidence levels from the different methods of SAR notification overlap. This overlap between the different types of SAR notification is largely due to sat-comm device usage appearing in the same locations as other means of notification, rather than occurring nearby and expanding the size of significant neighborhoods. Thus, in addition to widening the distribution of SAR incident hot spots across the study area, these results suggest sat-comm device usage contributes to several hot spots alongside other means of notification where cell service or word-of-mouth relay are also possible.

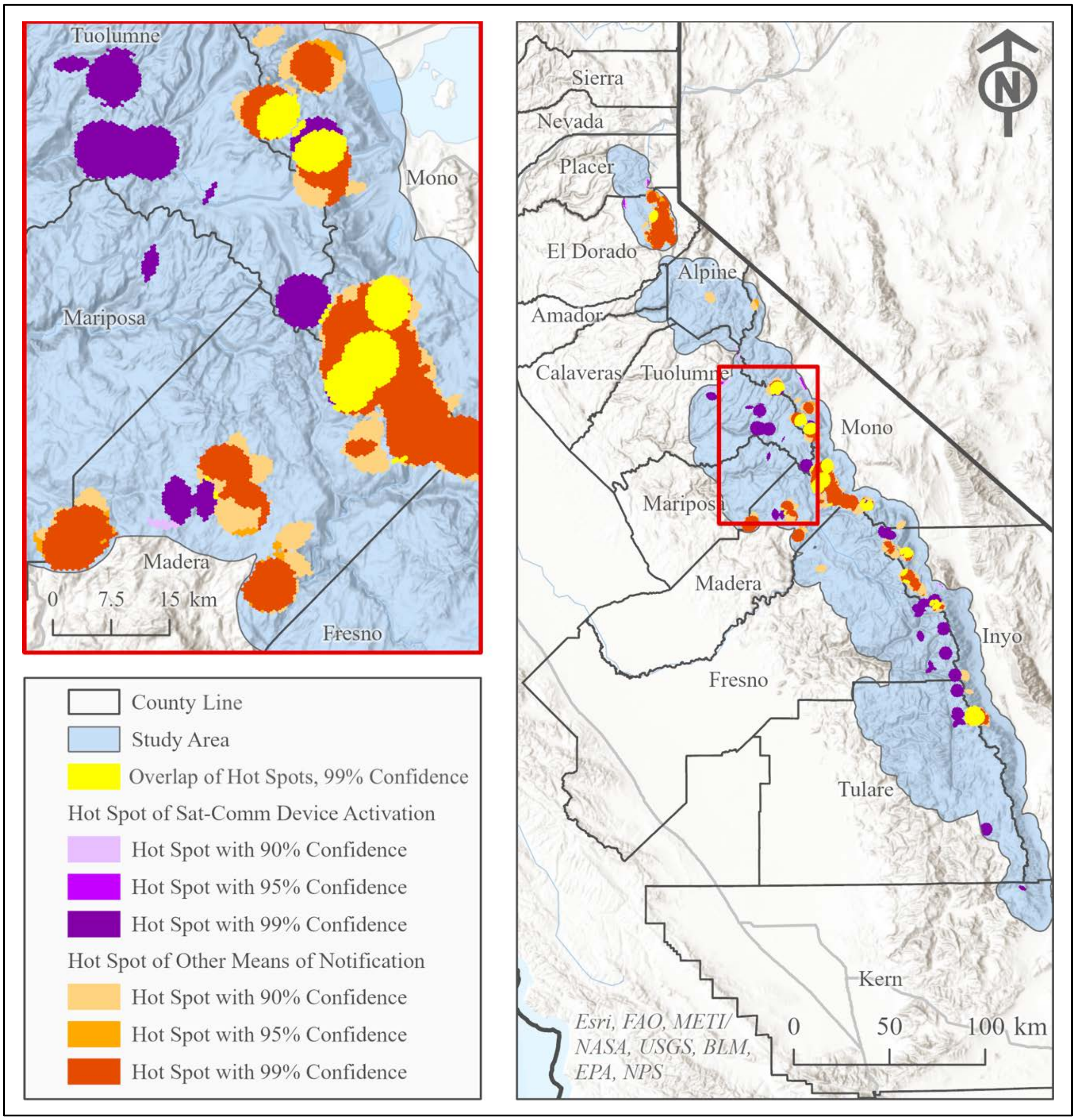

Figure 17. Mountain SAR incident hot spot distribution and overlap

4.1.4 Cluster and Outlier Analysis

While the Hot Spot Analysis tool, and the Getis-Ord Gi* static underpinning it, is useful for drawing attention to areas with multiple SAR incidents, the tool's results lack the level of detail to home-in on specific locations (i.e., the level of the 500 m hexagon) and to identify outliers. The Cluster and Outlier Analysis tool based off the Anselin Local Moran's I statistic categorizes locations as clusters and outliers at a finer resolution than the Gi* statistic, since each areal unit is assigned to a High-High cluster, Low-Low cluster, High-Low outlier, Low-High outlier or no significance category. Category labels describe the areal unit and neighborhood incident values respectively. The categorization makes Anselin Local Moran's I results easier to assess for site-specific spatial relationships that could set environmental expectations for rescue teams. The four categories of cluster and outlier relationships also helps SAR agencies anticipate the demand for SAR in a given neighborhood.

The graphical outputs of the two spatial statistics accessed through two GIS tools reveal their advantages and disadvantages. Figure 18 compares the spatial distribution of results based on the two types of local spatial statistics compared to point incidents. The distribution of significant neighborhoods appears similar in Figure 18b and c, since the 3,500 m neighborhood fixed distance band produces a similar spread of significance values. However, the Anselin Local Moran's I results (Figure 18c) are more nuanced and provide greater context to the neighborhoods. The Hot Spot Analysis tool based on the Getis-Ord Gi* statistic produces layers of hot spots that are easy to identify but appear equally relevant to SAR agencies, while the hot spots actually contain a range of incident counts, from two to upwards of seven. The Cluster and Outlier Analysis tool classified most of the hexagons within a neighborhood as Low-High outliers based on their Anselin Local Moran's index values, meaning they have lower incident frequency values than the mean but are in neighborhoods with a higher incident frequency than the mean. Because of the relative sparseness of the sat-comm device activations, even one incident raises the mean value for a neighborhood. The values at the center of the neighborhoods, which are generally marked as a High-High cluster or High-Low outlier site, allow SAR agencies to differentiate between areas that could be of greater concern than others.

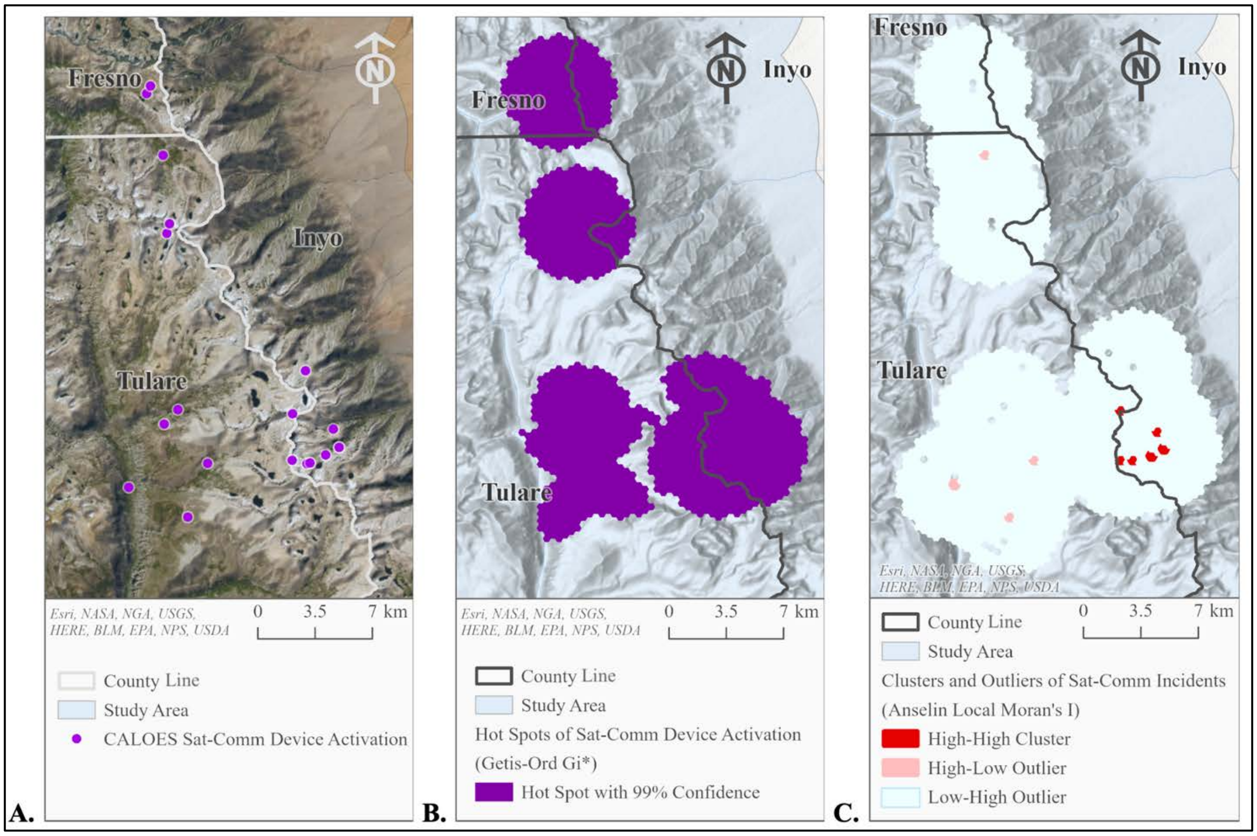

Figure 18. Results of local spatial statistics, including: (a) intentional sat-comm device activations as unique incidents, (b) hot spots identified using the Getis-Ord Gi* statistic, and (c) clusters and outliers defined using the Anselin Local Moran's I statistic

It is worth noting in Figure 18c that several hexagons in the center of a significant neighborhood are not considered significant, even though those are the only hexagons in the neighborhood containing incidents (reference Figure 18a). When values are too close to the mean, they may be considered insignificant using the Anselin Local Moran's I statistic, an issue Potter et al (2016) noted in their study on ecological phenomena when they elected to only run the Getis-Ord Gi* local spatial statistic. For this reason, SAR agencies who wish to examine cluster and outlier locations should consider the results carefully if they wish to weigh areas more seriously depending on if clusters or outliers are present, since they might misdiagnose SAR neighborhoods of interest to them.

A visual comparison of High-High cluster locations and High-Low outlier locations between the different types of notification method reveals the contrasting spatial distributions of the cluster and outlier categories. Figure 19a and b present the results for a visual comparison, with the map on the left showing the distribution of High-High clusters and High-Low outliers of sat-comm device activations, and the map on the right depicting the distribution based on other means of notification. No Low-Low clusters were present in any of the results. Since all Low-High outliers had an incident count of zero and served mostly to highlight neighborhoods containing significant values, they were excluded from a comparison of results. Looking at Figure 19a, it is apparent the layer of sat-comm device activations contains mostly High-Low outliers, at about 70% of all cluster and High-Low outlier sites. These results likely reflect the adoption of sat-comm devices as they increase in popularity compared to more established methods of communication, which could influence recreational behavior and decision making in remote areas lacking cell service or access to rescue service hubs. By contrast, Figure 19b has the opposite dynamic, with far more High-High clusters in the layer of other means of notification due to more incidents appearing within proximity to prior incidents and only about 20% of clusters and High-Low outliers designated as outliers. While the prior visual inspection of incidents and nearest neighbor distance measurements both suggested spatial outliers might play a larger role in the layer of sat-comm device activations than other means of notification, the Cluster and Outlier Analysis results provide measurable statistical significance of outlier versus cluster predominance, demonstrating the challenges to anticipating where future intentional sat-comm device activations may occur.

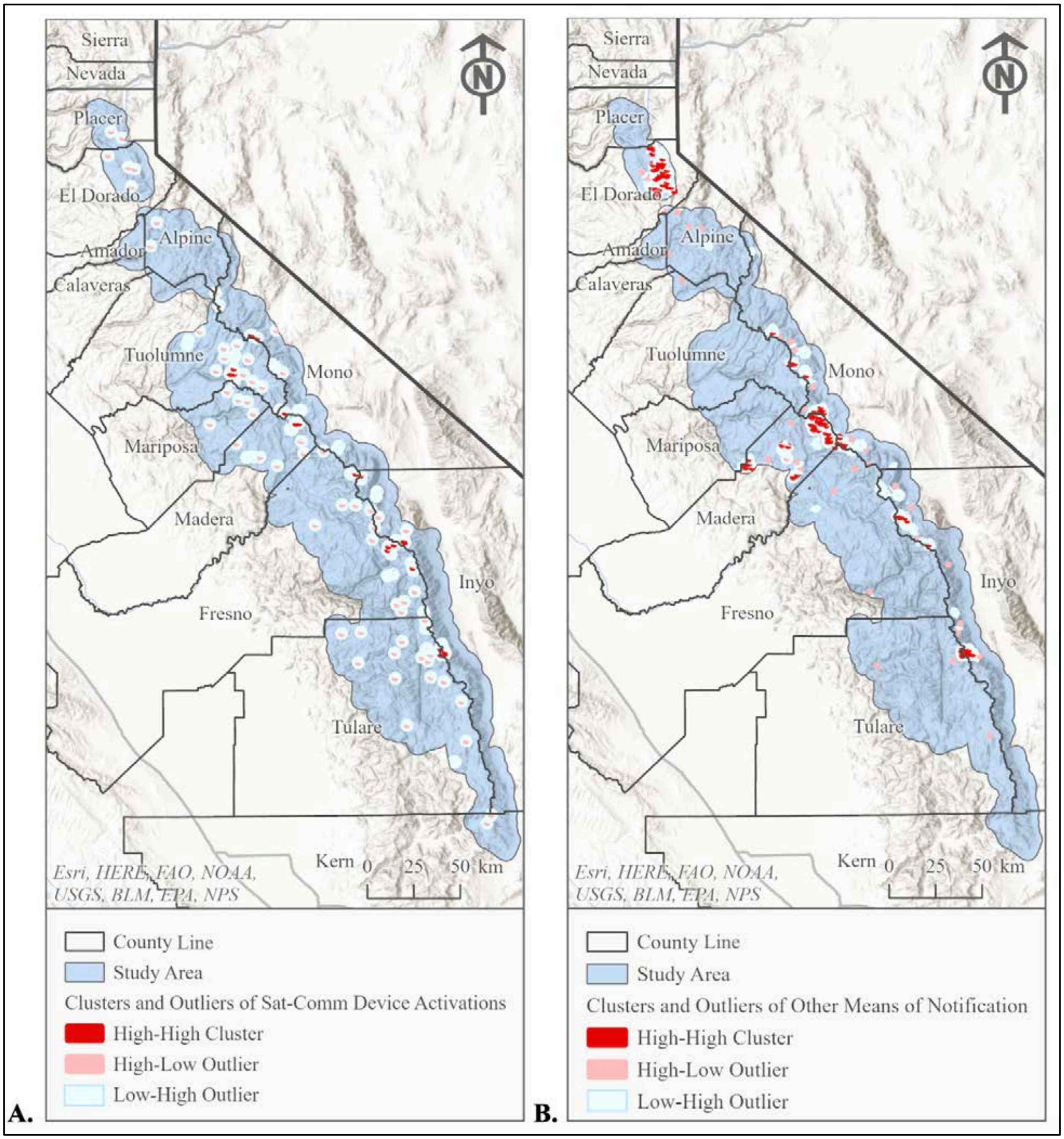

Figure 19. Anselin Local Moran's I results for (a) sat-comm device activations and (b) other means of notification

4.2 Spatiotemporal Analysis of the CALOES Dataset

In order to conduct statistical spatiotemporal analysis and detect emerging hot spots, this research aggregated CALOES mountain SAR incidents by time and space in a space-time cube

(STC) structure. Incidents were organized spatially by the same 500 m wide hexagonal grid as used with the local spatial statistics, but they were also binned by one-month intervals. In ArcGIS Pro, the Mann-Kendall trend test is run concurrently with STC creation (Esri n.d.); however, because the data are seasonal and the Mann-Kendall test does not consider periodicity, this research disregarded the STC trend results based off the one-month intervals produced by the Create Space Time Cube By Aggregating Points tool. The resulting STC had a total of 593,125 hexagon grid locations and 55 time-step intervals that could be grouped into spatial and temporal neighborhoods for analysis.

Prior to conducting spatiotemporal analysis on the STC, this research visualized the data over time without consideration given to spatial relationships. The results are presented as a line graph in Figure 20, where the number of sat-comm device activations are compared with other means of notification by month. The seasonal nature of the data is immediately apparent, with the summer months seeing far more SAR activity than winter months. The graph also indicates sat-comm device usage is supplementing and replacing other methods of communication since 2020, though there appears to be minimal sat-comm device usage recorded for 2022 at the time the CALOES dataset was requested. The results from the local spatial statistical analysis suggest the shift in method of SAR notification towards sat-comm devices is spatial as well as temporal, since sat-comm device activations occur in the same areas where other methods of notification are available. Conducting spatiotemporal analysis on incidents bounded within an STC allows SAR agencies to discern how these shifts occur over both time and space and further explore the role of sat-comm device activations on mountain SAR incident distribution.

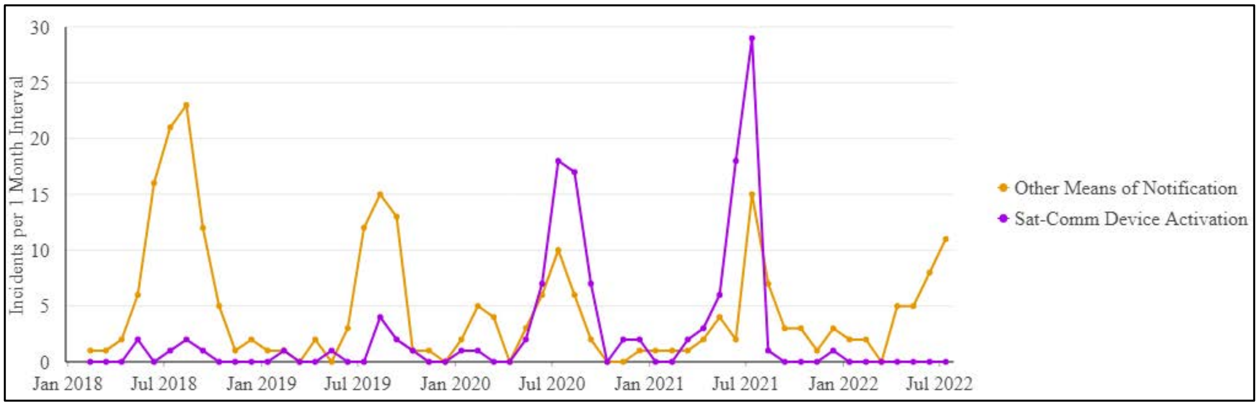

Figure 20. Incidents by notification method over time, CALOES dataset

Each of the three CALOES layers were the input for one STC, and this research tested all three STCs for emerging hot spot trends based on 3,500 m spatial neighborhoods and twelve-month temporal neighborhoods (to account for seasonal bias). The Getis-Ord Gi* statistic categorized locations within the spatiotemporal neighborhood as hot spots if they had high incident frequencies in a high incident-frequency neighborhood that significantly differed from what could be expected due to random chance. The Mann-Kendall test detected trends by comparing the Gi* z-score of a bin against previous bins to identify a constant increase or decrease in values over time. While more time intervals can provide trends with higher fidelity, a minimum of four intervals are required to detect a trend (which the four and a half years of CALOES incident data provided). Running the Emerging Hot Spot Analysis tool results in a two-dimensional layer where each areal unit is assigned a trend type.

Eight emerging hot spot trends are possible: new, consecutive, intensifying, persistent, diminishing, sporadic, oscillating, and historical (Esri n.d.). Two trends did not appear in any of the results: oscillating hot spots, which require a location to be considered a cold spot as well as a hot spot over time; and historical hot spots, where a location has been a hot spot for every time interval except the most recent one. Of the trend types, two mark emerging hot spots as relatively recent phenomena: new hot spots, which describe a location that is considered a hot spot for the first time during the most recent time interval (i.e., year), and consistent hot spots, which represent locations that have been a hot spot only for the last two years. The intensifying trend type is perhaps the most concerning to SAR agencies looking to put mitigation measures in place, as an intensifying hot spot marks where a location's neighborhood has been a hot spot for 90% of the time intervals and the Gi* z-score values have been increasing over time (i.e., the neighborhood's mean incident frequency is increasingly larger than the study area mean). The other trend types provide useful descriptions of hot spot patterns over time: a persistent hot spot is like an intensifying hot spot, but the Gi* z-scores are not increasing; a diminishing hot spot is a persistent hot spot with a significant decrease in Gi* z-score values over time; and sporadic hot spots represent locations that are a hot spot for the final year as well as during an earlier year. Visualizing the Emerging Hot Spot Analysis results on a map gives context to the distribution of hot spot trend types.

Like the purely spatial Hot Spot Analysis results, the significant neighborhoods from sat-comm device activations identified from the Emerging Hot Spot Analysis tool show some overlap with significant neighborhoods from other means of notification. The spatial overlap of several emerging hot spots suggests sat-comm device activations have shared neighborhoods with other means of notification for multiple years. However, the notification methods exhibit different spatial patterns of emerging hot spots when viewed in isolation. The emerging hot spots due to sat-comm device activations are smaller and sparser than the other means of notification emerging hot spots, reflecting the more recent usage of sat-comm devices and the smaller number of sat-comm device incidents aggregated per temporal neighborhood in an STC.

Figure 21 depicts the patterns of emerging hot spots for a section of the Sierras known at the Ritter Range west of Mammoth, CA, along the border of Madera, Fresno, and Inyo counties.

In Figure 21a, which presents the emerging hot spots of all actual mountain SAR incidents, both the emerging hot spot shapes and the trend types reflect the influences of the different methods of SAR notification. Figure 21b depicts the emerging hot spots resulting from the other means of notification STC. It shows how the other means of notification incidents exert the strongest influence on the shapes of the emerging hot spots in Figure 21a, since there are more incidents originating from other means of notification in the same neighborhoods over time than seen with sat-comm device activations. Figure 21b also contains all the persistent, intensifying, and diminishing trend types for the other means of notification emerging hot spots. Figure 21c shows the emerging hot spots from sat-comm device activations. The emerging hot spots are smaller, and the dominant trend type is consecutive, reflecting the more recent usage of sat-comm devices as a method of SAR notification. Sat-comm device activations influence the trend types in Figure 21a, since exploring sat-comm device activations and other means of notification in conjunction decreases the Gi* z-values for a spatial neighborhood by raising the study area mean for recent temporal neighborhoods. Comparing maps of emerging hot spots by notification method allows SAR agencies to consider the extent sat-comm device activations influence the spatial and temporal patterns of mountain SAR incidents, enabling a deeper examination of the underlying spatial and temporal relationships.

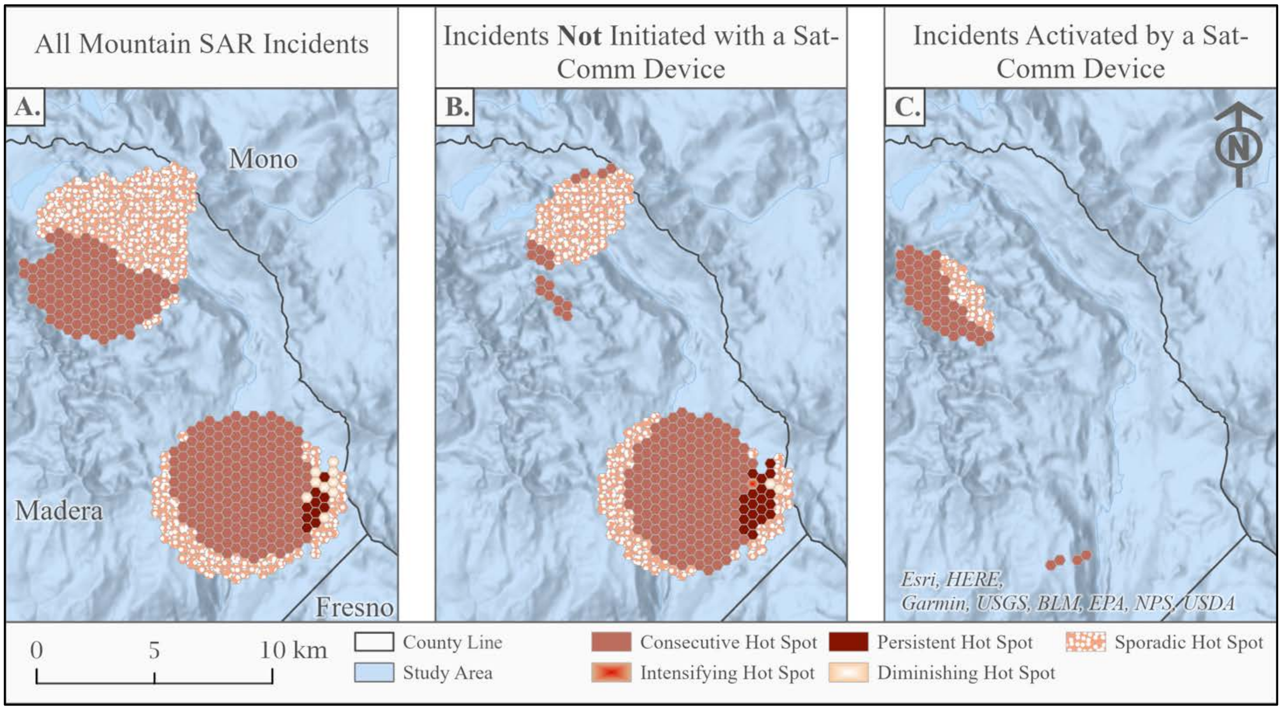

Figure 21. Emerging Hot Spot results on Ritter Range from (a) all actual mountain SAR incidents, (b) other means of notification, and (c) sat-comm device activations

Intensifying hot spots are concerning to SAR agencies, as those locations not only suggest the historical presence of SAR incident hot spots, but also that the numbers of incidents occurring in those neighborhoods are significantly increasing over time compared to the study area. Figure 22 presents the emerging hot spots identified around Mount Whitney, the tallest mountain within the continental United States. This area straddles the border between Tulare and Inyo counties, with ramifications for which county may be tasked with rescue responsibilities. Figure 22a depicts the entirety of intensifying hot spot locations for all actual mountain SAR incidents in the study area, representing 3.30% of hot spot trend types. Neither the other means of notification SAR incidents nor the sat-comm device activations (Figure 22b and c respectively) could capture this intensification trend when considered in isolation. The dominance of consecutive hot spots amongst sat-comm device activations added to the sporadic hot spots of the other means of notification incidents, serving to significantly increase the Gi* z-score values in the Whitney Portal area in more recent years. Creating an STC and running tests to detect emerging hot spots produces results that allow SAR agencies to identify areas of perpetual and increasing concern. Results similar to those depicted in Figure 22 can support decisions on how to manage resources and determine where mitigation measures should perhaps be concentrated.

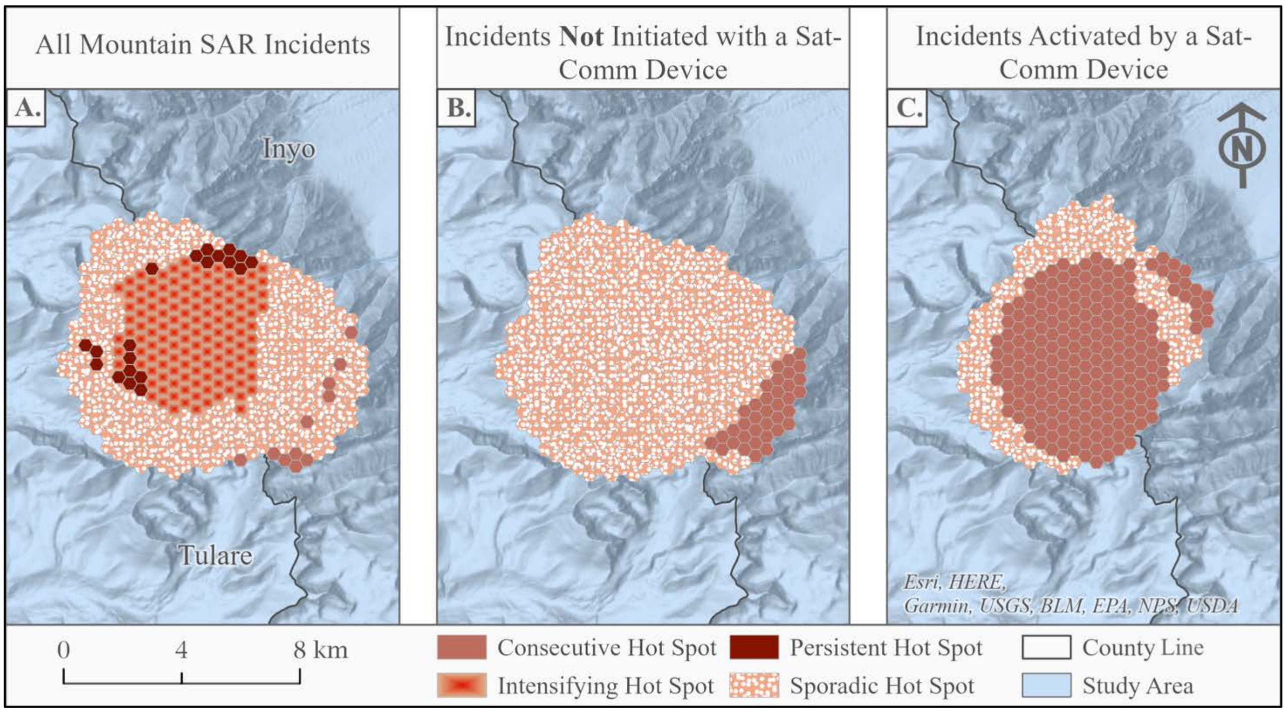

Figure 22. Emerging Hot Spot results near Mt. Whitney from (a) all actual mountain SAR incidents, (b) other means of notification, and (c) sat-comm device activations

Consecutive and sporadic trend types are the dominant categories across all CALOES mountain SAR incident layers. Table 4 gives a breakdown of the proportion of hot spot trend types per layer. Consecutive hot spots are the dominant trend type for sat-comm device activations. Sporadic hot spots are the dominant trend type for other means of notification. Consecutive and sporadic hot spots account for roughly 90% of mountain SAR incident locations. However, about 70% of sat-comm device activation hot spots are consecutive while about 20% are sporadic, while the reverse is true for other means of notification hot spots. Along with the prevalence of consecutive hot spots, sat-comm device locations have the highest percentage of new hot spots, at 8.45%. These results suggest sat-comm device usage is a recent phenomenon and that all mountain SAR incidents occur mainly in neighborhoods that have been a hot spot of at least two years of the four and a half years considered.

Table 4. Distribution of actual mountain SAR incidents per hot spot trend type

Hot Spot Trend Type	All Mountain SAR Incidents	Sat-Comm Device Activation	Other Means of Notification
New	2.62%	**8.45%**	3.93%
Intensifying	**3.30%**	-	0.034%
Diminishing	0.23%	-	0.068%
Consecutive	**46.09%**	**70.16%**	25.67%
Persistent	0.75%	-	0.68%
Sporadic	**47.02%**	21.39%	**69.62%**

4.3 Comparing the AFRCC and CALOES Datasets

This research compared the 45 intentional PLB activations from the AFRCC dataset against the 389 actual mountain SAR incidents from the CALOES dataset to check for redundancies. Only six of the recorded PLB activations possibly correspond to an incident in the CALOES dataset, all occurring within one day and one kilometer of each other. Two of the six were not categorized as either a PLB or SEND activation in the CALOES dataset, suggesting they were mislabeled in the CALOES dataset or possible represent separate incidents that took place in questionable spatial and temporal proximity to another one. Neither the time nor location of the 6 potential overlapping records are exact matches, but they are similar enough to raise questions. The time of day varies by an average of 7 hours and 50 minutes when comparing the CALOES local time to the AFRCC local time. However, the AFRCC stores PLB SAR incidents in Zulu time and date format, and the average difference between the AFRCC Zulu time and the CALOES local time is only 40 minutes, suggesting a possible miscommunication or misinterpretation of time format between the agencies. The average distance apart between the possibly redundant incidents is 358.07 m, and the average difference in elevation is 65.07 m. Since more information would be required to confirm the six PLB activations are duplicates across the datasets, they were not removed from the AFRCC dataset for subsequent analysis.

The PLB activations from the AFRCC dataset were next measured by their proximity to CALOES incidents in order to explore how the historical SAR incident datasets relate over space. This research evaluated distances between incidents based on the CALOES neighborhood structure used for spatial analysis, since the PLB activations represent contemporary and older incidents that could impact the results of future research should the two datasets be merged. Of the PLB activations representing actual SAR incidents, seven fell within 500 m of a CALOES-recorded sat-comm device activation. A further 27 PLB activations lay within the same neighborhood as a CALOES sat-comm device activation, of which 10 occurred before January 2018, 11 were in the same neighborhood as a sat-comm device activation cluster, and 16 were in the same neighborhood as a sat-comm device activation outlier. The average distance between a PLB activation and a CALOES sat-comm device activation is 3,735.88 m, and the median distance is 2,653.42 m. Two more PLB activations fell within 500 m of another means of notification incident from the CALOES dataset, and three PLB activations were within the same neighborhood as another means of notification incident. The average distance between a PLB activation and a CALOES other means of notification incident is 10,471.20 m, and the median distance is 6,465.72 m.

These proximity measurements imply the PLB activations since 2015 occur largely in the same neighborhoods as other sat-comm device activations recorded in the CALOES dataset, while they have a lesser degree of spatial overlap with incidents originating from other means of notification. If combined with the CALOES dataset, the PLB additions would likely increase the number of significant clusters of sat-comm device activations and increase the intensity of hot spots, while reducing the relative number of sat-comm device outliers. Additionally, because the AFRCC dataset includes data from three years prior to the CALOES dataset, comparing the datasets suggest sat-comm devices have potentially been used to initiate a SAR response in locations different than other methods of SAR notification for a longer period than the CALOES dataset can capture.

4.3.1 Attribute Comparison

The temporal and spatial attributes of the AFRCC and CALOES actual mountain SAR incidents were explored in order to provide context to SAR agencies and rescue teams. The temporal attributes examined were the month, the day of the week, and the time of day the SAR process started. For both datasets and all methods of SAR incident notification, the majority of SAR incidents occur from late spring through early autumn, starting in May and running through September. Figure 23 visualizes the results as data clocks. The data clock format reveals that the busiest month for SAR rescue teams varies by year, though is typically July or August. October through the end of January are historically the quietest months, with fewer than three actual mountain SAR incidents occurring per month during any year in either dataset. In the CALOES dataset, the proportion of incidents that occurred during the peak season and originated with a sat-comm device is 90.15%, while the proportion of peak-season incidents from other means of notification is 78.99%. Similar to the sat-comm device ratio in the CALOES dataset, the proportion of incidents that occur during the peak season from the AFRCC dataset stands at 91.11%. The higher percentage for sat-comm devices during the summer vice winter months could be attributed to a change in activity during the winter months, where the user might not expect to be either outside of cellular range or isolated from other people. Users also might not associate winter activities as risky and are instead caught off guard while conducting an activity they consider routine: a review of the available comments from CALOES incidents in the winter months suggest most SAR calls are the result of having a vehicle stuck in the snow or getting snowed in a building.

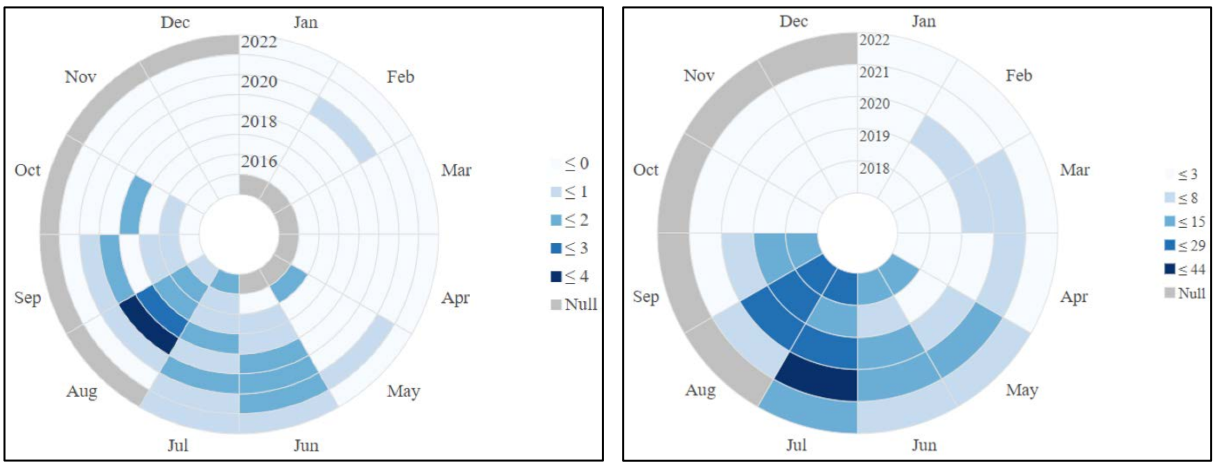

Figure 23. Data clocks of the AFRCC (left) and CALOES (right) datasets, 2018-2022

While the data clocks in Figure 23 provide a useful visual for capturing peak-season trends over time, an aggregation of mountain SAR incident solely by month and not broken up by year emphasizes the size of the demand during the summer season. Figure 24 presents the CALOES mountain SAR incidents by month and notification method as a bar graph. It must be noted in Figure 24 the ratios of peak months to off-season months do not include the second half of 2022 and therefore cannot capture the full seasonal impact of the 2022 case load. Even with those missing incidents, the spike in demand for SAR missions via the different notification methods is striking.

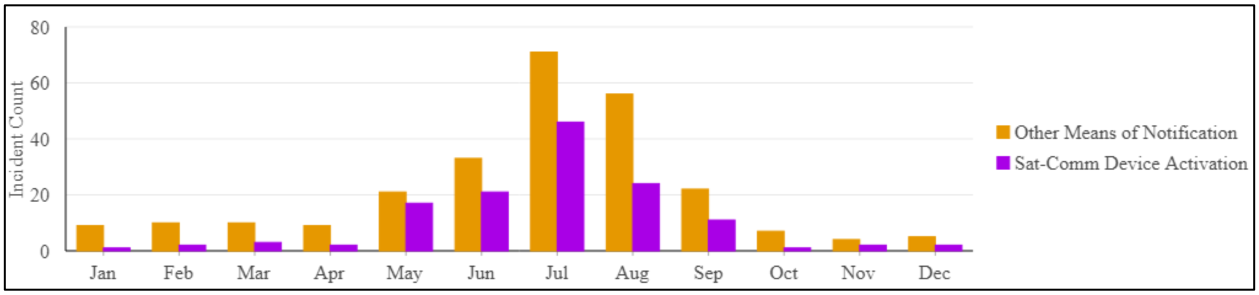

Figure 24. Incidents by month and method of notification, CALOES dataset

Like the monthly data, there is not an even spread of actual mountain SAR incidents throughout the course of the week. Most SAR incidents occur during the long-weekend days – i.e., Friday through Monday – while fewer tend to occur Tuesday through Thursday. The AFRCC incidents by day of the week are depicted as a graph in Figure 25. While almost 70% of incidents occur during long weekends, Wednesdays historically have the second highest number of incidents, at 15.56%, after Sunday, at 31.11%. Since the total number of PLB activations in the AFRCC dataset is relatively low, a few incidents can bias the conclusions drawn from a bar graph and more data would be required to accurately interpret incident spread by day of the week.

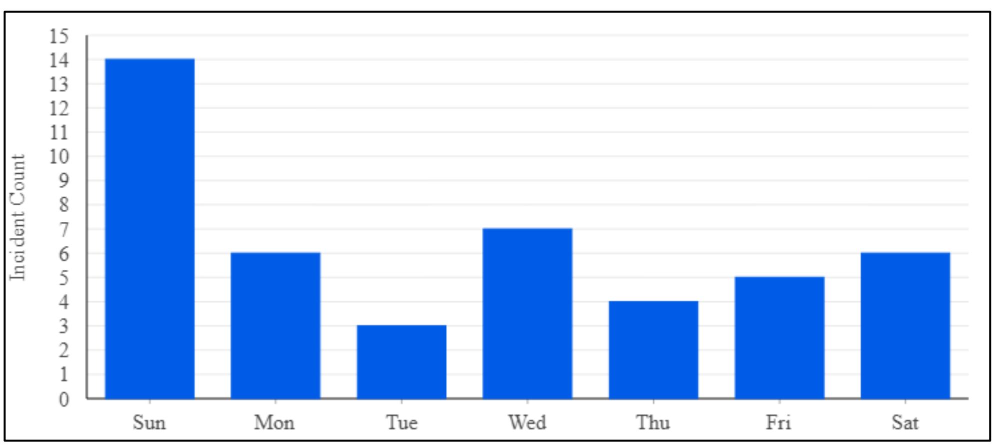

Figure 25. Incidents originating with a PLB activation per day of the week, AFRCC dataset

The CALOES incidents by day of the week and method of notification are also depicted as a bar graph in Figure 26. The percentage of incidents that occur during a long weekend for sat-comm device activations and other means of notification are 71.21% and 65.76% respectively. Saturdays and Sundays historically have the highest number of incidents that originate with another means of notification, while Sundays and Mondays have the highest number of incidents that begin with a sat-comm device activation. The relatively high percentage for all datasets and methods of notification favoring the long weekend days could likely be attributed to increased visitor traffic during those days.

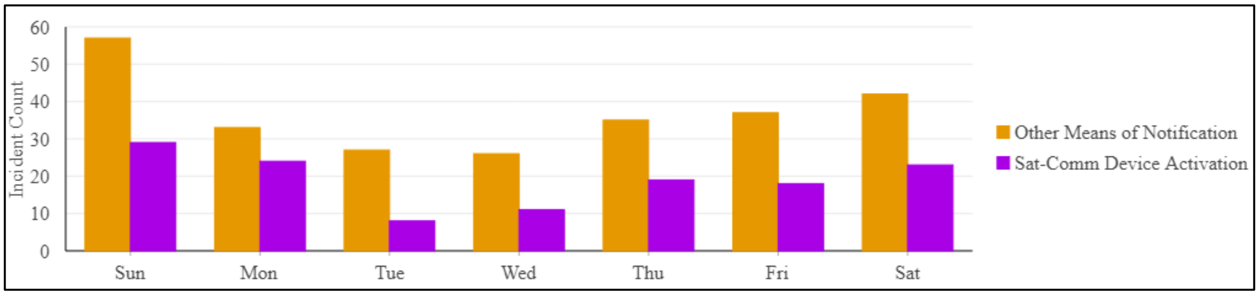

Figure 26. Incidents by day of the week and method of notification, CALOES dataset

This research reviewed actual mountain SAR incidents for when the notification occurred to consider implications for rescue team proficiency in day or night operations. Historically, the majority of PLB activations supporting an actual mountain SAR event occurred during the day, at 75.56%. Only one incident occurred within an hour to sunset, and the rest – at 22.22% – occurred at night. In contrast, most of the incidents recorded in the CALOES dataset took place at night. The predominance of night-time missions in the CALOES dataset applies to both sat-comm device activations and other means of notification, as can be seen from the bar graph in Figure 27. After including the mountain SAR incidents where the earliest recorded time of notification is within an hour of sunset, a total of 62.88% of rescues stemming from a sat-comm device activation and 71.60% of rescues originating from other means of notification likely required a rescue team to effect the rescue during hours of darkness. A minority of SAR incidents began during the hour prior to sunrise, possibly due to a lack of early morning recreational activity, or perhaps because of the renewed hope that inevitably rises with the dawn mitigates the desire by a subject to request a SAR response.

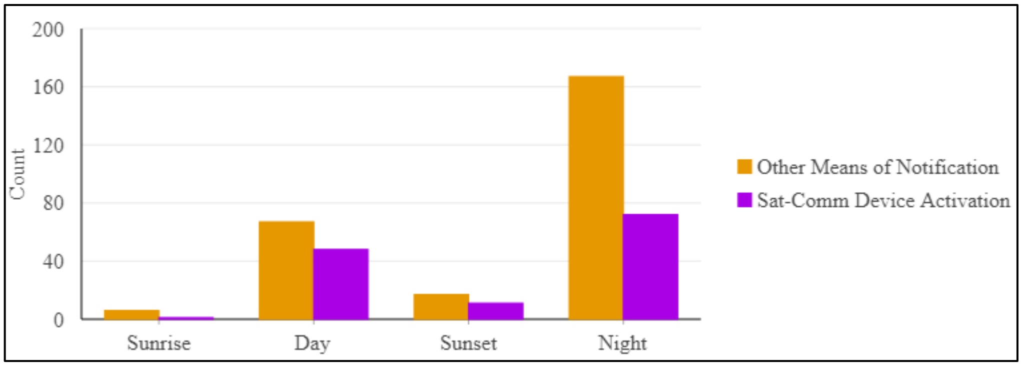

Figure 27. Incidents by time of day and method of notification, CALOES dataset

This research next assessed actual mountain SAR incidents by their elevation. Proportionally, incidents originating with a sat-comm device activation occur at higher elevations than other means of notification. The elevations of the intentional PLB activations from the AFRCC dataset are presented in Figure 28. Incidents were binned by 500 m intervals for ease of visualization. Mountain SAR incidents which occur above 6,000 ft (just under 2,000 m), can impact the ability of different helicopter models to perform a rescue, particularly in the summer months when 6,000 ft can "feel" like 10,000 ft to a helicopter's engines (see Fisher 2021 for a greater discussion on helicopter operations in California's mountains south of the High Sierras). In the AFRCC dataset, 88.89% of PLB activations supporting an actual mountain SAR incident occur above 2,000 m. Over half occur above 3,000 m (just under 10,000 ft). These results suggest the demand for SAR services increases with elevation.

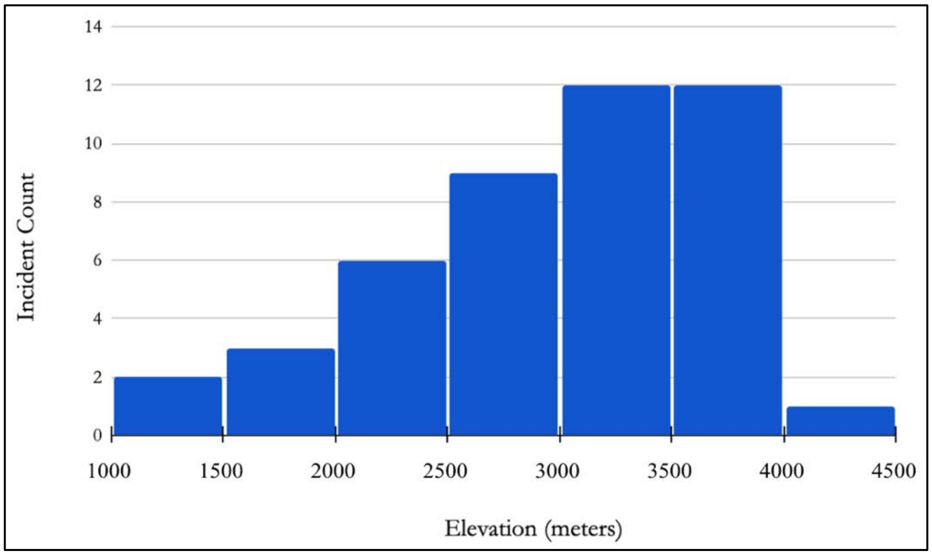

Figure 28. Incident elevations by PLB activation; AFRCC dataset

The elevations of the actual SAR incidents from the CALOES dataset are presented in Figure 29. The results reflect similar findings by Heggie and Amundson (2009), who determined in their study of US national parks that about a quarter of all SAR incidents in national parks were in mountainous terrain between 1,524-4,572 m. The relatively high elevation of all mountain SAR incidents reflects the underlying mountainous terrain, although the substantial number of incidents that occur at extreme elevations suggest SAR incidents are less likely in low-lying areas like foothills and the bottoms of canyons. Of the sat-comm device incidents, 89.39% occur above 2,000 m, while 91.05% of the incidents stemming from other means of notification occur above 2,000 m. After 2,000 m, however, incidents originating with other means of notification start to decrease, while sat-comm device usage starts to increase. This juxtaposition of increasing and decreasing notification methods over elevation could be due to the increased reliance by users on sat-comm devices to improve the perception of safety, even when experience levels do not match. This pattern could also be explained by experienced users carrying sat-comm devices (reference Boore and Bock 2013) and tackling challenges at higher elevation, at which point an accident occurs. Without more information on user behavior, rescue teams can only conclude from this research that sat-comm devices are playing an increasing role at higher elevations but cannot explain why.

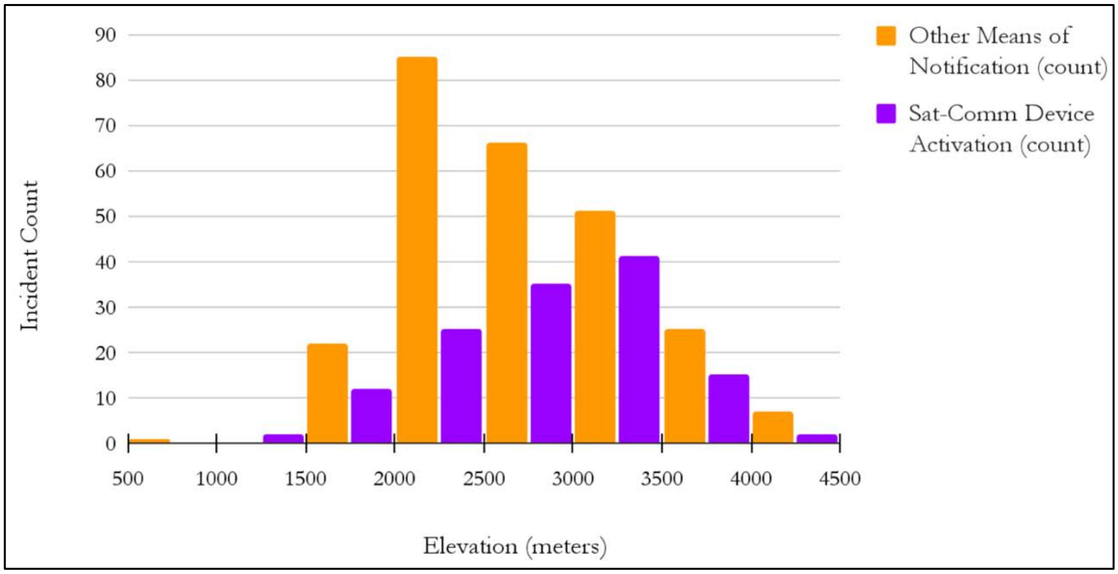

Figure 29. Incident elevations by method of notification, CALOES dataset

4.3.2 Accidental Activations

The accidental activation of a sat-com device could deplete mountain SAR resources and contribute to asset fatigue if the activation requires a rescue team to respond. Should the sat-comm device not have two-way messaging capabilities, or if the device's owner fails to catch the accidental activation and not actively monitor their device, then rescue teams will treat the activation as an actual incident until proven otherwise. There were a total of eight accidental activations of a PLB between January 2015 through July 2022 recorded in the AFRCC dataset for the study area. Five of these accidental activations occurred during the same time period as the CALOES dataset. The CALOES dataset contained a total of 27 accidental activations of a sat-comm device between January 2018 through July of 2022 in the study area. A comparison of the two datasets suggests only one accidental activation from each dataset could reference the same incident; however, as seen during the comparison of intentional activations described above, neither the earliest recorded time of notification nor geographic location were the same, leaving the dubious possibility that two separate incidents occurred within 400 m, one foot of elevation, and 14 hours of each other.

The temporal attributes of the accidental activations suggest the accidental activation of a sat-comm device could occur during any day of the week under day or night lighting conditions, and they occur most often during the summer months. Just under 90% of the accidental activations recorded in the CALOES dataset and 50% of those in the AFRCC dataset occurred during June through August, while 37.5% of the accidental activations in the AFRCC dataset occurred in the autumn months. Unlike actual mountain SAR incidents, which see fewer mid-week incidents, the CALOES dataset suggests accidental activations of sat-comm devices do not favor long weekends. Figure 30 presents a bar graph of incidents by day of the week. The results suggest a lower number of accidental activations historically occur on Saturday and Sunday. This is surprising, since outdoor recreation is typically higher during the weekends, and the increased number of visitors to wilderness areas during those dates would presumably increase the probability of an accidental activation. In contrast, all but one of the accidental PLB activations recorded in the AFRCC dataset occurred Friday through Sunday at two to three per day, with one incident occurring on a Tuesday. In the CALOES dataset, 59.26% of the accidental activations placed the earliest time of notification either within an hour of sunset or after sunset, while 62.5% of the accidental activations in the AFRCC dataset began during the day. These results suggest the accidental activation of sat-comm devices may place a burden on SAR resources, as the occur during the busy summer season, on all days of the week, day or night.

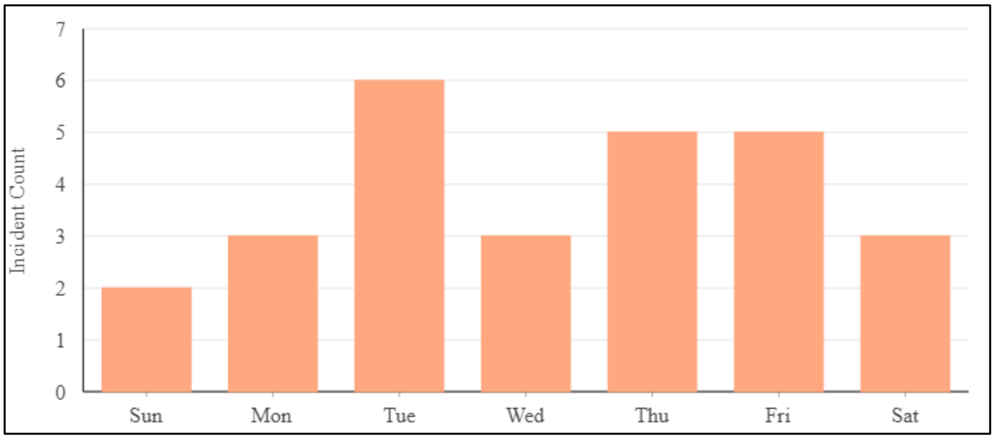

Figure 30. Accidental activations of a sat-comm device by day of the week, CALOES dataset

Like actual mountain SAR incidents originating from a sat-comm device, accidental sat-comm device activations occur in relatively inaccessible locations for rescue teams. Regarding elevation, all of the accidental PLB activations were above 2,000 m, while 85.18% of the accidental sat-comm device activations in the CALOES dataset occurred about 2,000 m. Using the distance between an incident and the area of analysis boundary as an accessibility metric, accidental activations and actual mountain SAR incidents can be compared to explore the challenges they may pose to rescue teams due a lack of infrastructure and challenging topography within wilderness areas. The results of the minimum, mean, and maximum distances of incidents to the study area boundary are presented in Table 5. On average, the accidental activations of sat-comm devices occur as far from the built environment as intentional distress calls. This result likely corresponds to the higher proportion of outliers found during the spatial statistical analysis of sat-comm device activations, indicating sat-comm device owners are venturing into remote areas removed from traditional SAR hot spot locations where they then intentionally call for rescue or accidentally activate their sat-comm device. SAR agencies should therefore expect to budget for the extra costs associated with accidental sat-comm device activations that may require extensive time or expense to verify a false alarm.

Table 5. Distances of sat-comm device activations from the area of analysis boundary

Distance (meters)	Sat-Comm Activations			
	Accidental (AFRCC)	Intentional (AFRCC)	Accidental (CALOES)	Intentional (CALOES)
Minimum	39.45	1,712.65	3,542.76	252.14
Mean	**13,873.53**	**15,179.06**	**11,835.38**	**11,177.72**
Maximum	26,810.77	30,135.48	27,627.11	33,114.79

Chapter 5 Discussion and Conclusions

This research conducted an exploratory spatial and temporal analysis of historical mountain search and rescue (SAR) incidents in order to examine how satellite communication (sat-comm) devices might impact traditional mountain SAR patterns. This study's methodology leveraged the capabilities of a geographic information system (GIS) to identify statistically significant spatial patterns over time. While aspatial statistical programs support most of the research on mountain SAR incidents to date (Boore and Bock 2013; Heggie and Amundson 2009; Kaufmann, Moser, and Lederer 2006), the tools available in a GIS can describe the distribution of incidents through simple visualizations as well as more complex statistical metrics, the products of which can help SAR organizations understand the operating environment and demands for their rescue teams. The methodology presented in this research could be tailored by overland SAR organizations to maintain an informed approach to their SAR resource and training plans. However, the output of this methodology is limited by the quality and quantity of historical incident records, and the results are only as good as the input used to generate them.

This chapter reviews the study's results, considers the limitations associated with the datasets and research methodology, and addresses possible research avenues that future works on mountain SAR spatial analysis could incorporate. Additionally, a section of this chapter proposes best practices for collecting and maintaining data by SAR agencies at large, as this research identified several deficiencies in the quality of mountain SAR datasets that could have lasting impacts on the SAR community's ability to analyze historical incidents and prepare for future SAR cases. The chapter concludes with a reflection on how this study advances the field of mountain SAR.

5.1 Project Findings

This study found sat-comm devices impact the spatial distribution of mountain SAR incidents in recent years, although sat-comm device activations exhibit similar temporal patterns to incidents originating with a traditional method of communication. An exploration of statistically significant hot spot, cluster, and outlier locations suggests sat-comm device activations exhibit a broader spatial distribution than SAR incidents stemming from other means of notification. Spatiotemporal analysis results emphasize the recent impact of sat-comm devices on the mountain SAR incident spatial patterns. An analysis of incident attributes reveals similar temporal patterns between sat-comm devices and other means of notification by week and month, although there is a clear increase in the number of mountain SAR incidents beginning with a sat-comm device over time. The attributes of accidental sat-comm device activations do not share these temporal trends, although they do suggest spatial similarity to intentional sat-comm device activations. Despite the benefits of improved positional accuracy that sat-comm devices provide to rescue teams, the introduction of portable sat-comm devices to outdoor recreation ultimately increase the burden placed on rescue teams by presenting a wider spatial distribution and the possibility of accidental activations unique to modern sat-comm devices.

5.1.1 Spatial Analysis Results

The results from both the Hot Spot Analysis tool, based on the Getis-Ord Gi* statistic, and the Cluster and Outlier Analysis tool, based on the Anselin Local Moran's I statistic, reveal sat-comm device activations contribute to higher incident frequencies in the same neighborhoods as other means of notification, as well as in new, more isolated locations spread out across the Sierra Nevada wilderness areas. Just over an eighth of mountain SAR incident hot spots attributed to sat-comm devices overlap with hot spots from other means of notification. Since most hot spots do not overlap, these results suggest different types of recreational behavior by sat-comm device owners. The lack of overlap might also be because there are no other viable ways to communicate in these locations other than with a sat-comm device; instead, overdue or missing person procedures would take effect and the mission focus would be a search. SAR missions classified as a search had been removed during the data preparation stage due to lack of precise coordinate information, and search areas were not explored in this study to explore whether the spatial relationship between sat-comm device activations and historical search areas over time.

The Hot Spot Analysis tool's results offer a visual product that facilitates rapid identification of neighborhoods of concern across the study area. Hot spot maps clearly communicate statistically significant neighborhoods of high mountain SAR incident frequency, which could be useful for determining resource allocation and the regional distribution of assets. Hot spots can also provide a means for future researchers to explore cross-jurisdictional relationships. For example, just under a sixth of the hexagons that contribute to a hot spot neighborhood are within 500 m of a county line in this study, a finding which highlights the importance of maintaining cross-jurisdictional datasets and communicating rescue team availability and capabilities. The Getis-Ord Gi* statistic, however, does not account for spatial outliers, which can present an increased burden to rescue teams due to their inaccessibility and the possible lack of familiarity by rescuers with outlier site hazards.

The Cluster and Outlier Analysis results highlighted the impact of spatial outliers on the sat-comm device activation distribution. A location marked as an outlier has an incident frequency above the global average but is surrounded by locations with low (i.e., no) incident counts. About 70% of locations with sat-comm device activations are considered outliers based on the Anselin Local Moran's I statistic, while just over 80% of locations with incidents from other means of notification belong to a cluster. These results indicate traditional methods of notification are more likely to be used repeatedly in a mountain SAR incident neighborhood, while sat-comm devices initiate the SAR process in new, remote locations, which could develop into clusters over time. Furthermore, these spatial patterns could suggest sat-comm devices are supplanting traditional methods of notification in addition to serving as the primary notification method in isolated areas.

5.1.2 Spatiotemporal Analysis Results

The Emerging Hot Spot Analysis tool based on the Getis-Ord Gi* local spatial statistic and Mann-Kendall trend test applied to an STC offer a novel approach for examining mountain SAR incidents. The tool's results suggest sat-comm device activations are essential to revealing locations that are exhibiting an intensification of mountain SAR incidents over time. Furthermore, sat-comm device activations demonstrate emerging hot spot patterns in more recent years, marked by the relatively higher proportions of new and consecutive trend types. As more mountain SAR incident records become available over time, SAR organizations should conduct further spatiotemporal analysis to observe whether sat-comm device incident outliers remain as outliers or develop into more emerging hot spots.

5.1.3 Attribute Analysis Results

The results of an exploration of mountain SAR incident attributes using descriptive statistics indicate little variation between the methods of notification other than elevation. The number of sat-comm device activations in both the AFRCC and CALOES datasets increased with an increase in elevation, while the number of incidents originating with other means of notification decreased above 2,000 m. Otherwise, while an increasing number of mountain SAR incidents rely on sat-comm devices to call for help through 2022, the weekly and monthly distribution of incidents does not show substantial variation between sat-comm device activations and other means of communication. Most mountain SAR incidents occur Friday through Monday during the summer months. PLB activations do not appear to favor long weekends, but the historical records from the AFRCC dataset contain relatively few incidents, making it difficult to capture temporal variation. Based on these findings, rescue teams should train for high-elevation rescues and anticipate increased demand Friday through Monday during the summer months.

5.1.4 Accidental Sat-Comm Device Activations

The results from visual analysis and descriptive statistics of accidental sat-comm device activations suggest they present a challenge for rescue teams. Accidental activations largely occur during the summer months, but they appear to occur at random throughout the week during day and night conditions. Like intentional sat-comm device activations, accidental activations mainly occur at high elevations above 2,000 m, and they occur at roughly equivalent distances from the study area boundary. SAR organizations should expect to budget for accidental activations that will likely occur at random in challenging, isolated locations.

5.2 Limitations

The most critical limitation in this research is data quality. The AFRCC and CALOES datasets suffer from omissions, redundancies, and mislabeling. The results can therefore only be considered representative of possible spatial and temporal patterns and cannot be treated as exact. The AFRCC does not store PLB activation reports in a database that can target attributes within the reports. This made dataset creation a laborious process of combing through seven years of national-scale records for location information to determine whether or not a record fell within the study area. Consequently, there is a chance records were missed and not included in the final product used for evaluation. It was also interesting to discover only a fifth of the AFRCC PLB activations possibly matched an incident in the CALOES data; ideally, 100% would match, since tasking flows from a national-level agency like AFRCC to the state and sheriff jurisdictions, and records would be kept at each agency executing the tasking. Of those sat-comm device activations that were a possible match, there appeared to be a mismatch in recorded incident start time, as the CALOES local time closely resembled the AFRCC Zulu time, which constitutes a seven- to eight-hour difference depending on daylight savings. Such discrepancies indicate a possible breakdown in communication as one agency hands off SAR responsibility to another. While not an issue encountered in this research, Durkee and Glynn-Linaris (2012) similarly emphasized the importance of relaying the basis of coordinate data when passing location information between agencies, as a mismatch of coordinate types could significantly alter the presumed location of a SAR incident.

In addition to missing these PLB activations, the CALOES dataset included multiple redundant entries as well as attribute inaccuracies. Redundant records are likely due to SAR cases handled by multiple rescue agencies when mutual aid is requested, which get combined into the single CALOES data repository when counties input their individual data. While the data preparation phase of this research involved extensive evaluation and cleaning in order to appropriately categorize incidents and remove duplicates, incidents that did not share identical times or coordinates would be overlooked for removal. Incidents that appeared near each other in time and space and shared similar attributes were potentially the same incident, but they had to be treated as isolated incidents due to insufficient attribute information for verification due to a lack of standardization when entering comments. Furthermore, during preparation of the

CALOES dataset, several recorded incidents were mislabeled as originating from a PLB activation when the comments stated a SEND had been employed. Additionally, several incidents had inaccurate coordinates – for example, the comments mentioned the response was to a hiking trail but the coordinates were in a lake – drawing into question all incidents which did not include comments that could be used to corroborate attribute descriptions. The data quality in both datasets would benefit from increased standardization at the organizational level and adding a quality control component for dataset evaluation and refinement.

Several limitations also exist with the research design and spatial analysis methods. In order to measure mountain SAR incident patterns over space, incidents required aggregation into areal units such that the areal units could have an attribute of incident frequency for use as a metric. Incident aggregation, however, generates several problems. The techniques an analyst employs to group spatially heterogenous data like SAR incidents into a grid can yield differing analytical results depending on the grid's parameters, otherwise known as the modifiable areal unit problem. For example, a large hexagon might contain more incidents than a small hexagon in the same location, which in turn might result in different locations being considered as contributing to a hot spot or being defined as an outlier.

Another problem associated with aggregation is computational processing demands. Aggregated data, particularly across a region as large as the Sierra Nevada wilderness areas, drive substantial processing requirements during spatial and temporal statistical analysis. One technique to mitigate this is to decrease the resolution of the areal unit (i.e., make the areal unit have a larger surface area), although resolution needs to be balanced with an accurate representation of the spatial data in a digital space. The 500 m hexagon grid effectively captured local topographic variation, preserved incident scene specificity, and supported reasonable processing times. However, even the 500 m hexagon at this study's scale of analysis exceeded the computational processing capabilities of the ArcGIS Pro 2.9 Local Cluster and Outlier Analysis tool, which would have lent a temporal consideration when identifying spatial clusters and outliers using the Anselin Local Moran's I statistic and would have complemented the results of the Emerging Hot Spot Analysis tool that uses the Getis-Ord Gi* and Mann-Kendall trend test combination.

Lastly, researcher bias could pose limitations on the research design and interpretation of results. The author of this study is an expert in helicopter SAR and military SAR operations, a perspective which creates a bias towards distances that are compatible with an airborne perspective. For example, the 500 m hexagon represents a single site of SAR incidents. This size of hexagon makes sense for a medium-sized helicopter crew that requires space for landing and has multiple crew members or SAR ground team passengers who could take turns carrying injured subjects to the helicopter. However, for a SAR hiking party or technical rescue team, an incident half a click away from another one might not seem like they are in comparable locations. Parameter selection is often subjective in the spatial sciences and guided by expert opinion, but these decisions must be acknowledged and tailored to answer the research questions at hand.

5.3 Recommendations

This study recommends future actions for two groups: spatial analysts and SAR agencies. While this research presents methods to explore the impact of sat-comm device activations on mountain SAR incidents, future research should continue to explore ways to advance the spatial analysis methodology of mountain SAR incidents, as well as consider the role of SAR asset accessibility and subject behavior. The onus is on SAR agencies to develop and retain quality incident records to support meaningful research, and this study recommends SAR agencies focus resources to standardize, collect, and share mountain SAR incident records.

5.3.1 Recommendations for Future Research

While this study demonstrates techniques to determine locations worth the attention of SAR agencies and rescue teams, future studies could expand upon the accessibility of incident locations or hot spots. Accessibility analysis would require a deeper knowledge of the number and types of available rescue assets – be they different models of helicopters, off-road vehicles, or foot traffic – and points of entry and exit for those assets. For example, helicopters would require considerations for medical handover sites and refuel locations, as well as identifying potential landing sites or hover-only locations in wilderness areas based on ground cover, slope, and elevation. SAR ground vehicles, hiking teams, and climbing teams would benefit from mapped roads and trail networks. Accessibility analysis would allow a comparison of jurisdictions based on numbers of SAR incidents and available SAR assets in order to inform an appropriate distribution of resources and take note of any gaps in coverage.

Another way to support SAR policy in addition to the spatial analysis of mountain SAR incidents would be to determine the causal factors of the observed spatial patterns through correlation analysis or regression techniques. Indices representing weather conditions, topographic complexity, and demographics could all be used to determine what might cause certain types of SAR incidents, and whether sat-comm devices are involved in those types of SAR incidents. Such analysis would, however, require a breakdown of SAR incidents by activity (e.g., hiking, technical, swimming, etc.), by severity of outcome (i.e., self-recovered through death), or another category against which potential causal factors could be assessed. Attribute gaps and inconsistencies in the CALOES dataset hindered such analysis herein, but correlation analysis could enhance future research if the intent is to support mitigation measures so as to reduce SAR team operating costs. Results are more meaningful if it can be determined not only whether the number of incidents are increasing or decreasing in specific areas, but what types of activities the subjects are engaged in that are driving those patterns since they might require different specialty teams (e.g., technical rope training or OHV equipment). Similarly, a severity scale would indicate whether the types of incidents that are occurring require a greater or reduced rescue team footprint and medical support, which implications for operating costs.

Future behavioral studies of sat-comm device owners would benefit from having additional information on demographics, as well as perhaps a comparison against comparable technologies like cellular devices. Behaviors and demographics that correlate with sat-comm device activations could provide insights to rescue teams responding to mountain SAR incidents as well as other types of emergency situations, from car accidents to wildfires to flooding. While private companies that create and support SEND products are not willing to share consumer information, SAR agencies could consider including demographic and subject behavioral data in their rescue reports. Non-satellite capable cell phones were once a new communications technology altering the SAR notification landscape, and making note of whether a SAR case began via cellular network could make an interesting comparison to the newer sat-comm capability. Future researchers could also incorporate cellular network coverage areas into their GIS analysis. Such layers are already available for comparison to SAR incident sites on SARTopo, an online mapping tool that facilitates merging custom layers with environmental and topographic layers (CalTopo 2021). Understanding user behavior would be beneficial should rescue centers become overwhelmed with cases as satellite connectivity grows, driving SAR agencies to evaluate mitigation measures to control operating costs.

Lastly, as SAR agencies collect more SAR incident data over time, future research should revisit the methods presented in this study once there are enough inputs for statistically significant trend analysis. Due to the main dataset used in this analysis only spanning four and a half years, and the supporting dataset only seven years, there were not enough years of data to compare layers in using the Mann-Kendall trend statistic, which requires a minimum of ten years to run in ArcGIS Pro 2.9. Since mountain SAR data, like wildfire data, is highly seasonal, incidents would need to be grouped by year for trend tests unless seasonal variation can be accounted for. Trend analysis is a useful measure for SAR agencies aiming to anticipate the trajectory of SAR cases and their attributes, and being able to present trend data could help SAR agencies make decisions about resource allocation at the county and state level.

5.3.2 Recommendations for SAR Agencies

SAR agencies have a responsibility to improve their operations and mitigate the hazards faced by rescue teams tasked to respond to a case. This responsibility requires an adequate understanding of available technologies and the willingness to set the standard for SAR documentation and record keeping. SAR agencies at all levels of responsibility should maintain secure digital records in a format that can be integrated with geographic and statistical software. Rescue teams or emergency response coordinators (e.g., watch-floor personnel and duty officers) should be provided with clear, standardized guidance on what information to collect during, and keep after, a SAR case that can maximize post-mission analysis. SAR agencies responsible for maintaining SAR incident records should incorporate a quality control component, be it a technical specialist or software service, that can corroborate incident report entries, catch redundancies, and follow-up with subdivisions for the timely incorporation of records. In this way, mountain SAR agencies can build a foundation for adapting and improving the SAR process.

5.4 Conclusion

This study gives an overview of the implications of sat-comm device usage on mountain SAR operations and provides methodology that SAR agencies may adopt to advance their policies and improve SAR safety margins. Ultimately mountain SAR incidents depend on the number of personnel partaking in outdoor recreation: without visitors, SAR in wilderness areas would be a moot point. However, the Sierra Nevadas continue to draw high numbers of visitors who all hold the potential to require assistance. With the advent of emergency satellite communications capabilities on cellular phones, there is an increased likelihood people will use satellites to call for help from any location able to connect to the satellite infrastructure. Understanding how sat-comm technology is currently affecting SAR operations is therefore necessary for anticipating future operations and demands on SAR resources. Not every SAR case can be a guaranteed success. However, research like this that increases the odds to save even one life makes the time and energy spent on preparation and analysis worthwhile.

In an effort to improve the accessibility of this research, its results, and its recommendations, a StoryMap version of this thesis may be found at: https://storymaps.arcgis.com/stories/7889bc805a1a4eeb87e34e5edcd7cab7.

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