ANALYZING WEATHER OBSERVATION DATA TO IMPROVE EMERGENCY SERVICES PILOT RISK ASSESSMENT IN MARGINAL WEATHER CONDITIONS

by

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Dedicated to my parents, brother, sister, and my wonderful fiancée, for their unwavering support and encouragement as I pursue my education and career goals.

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LIST OF ACRONYMS

1P1	Plymouth Municipal Airport
5G	5^{th} Generation
AGL	Above Ground Level
AIRMET	Air Mission Meteorological Information Report
AMDAR	Aircraft Meteorological Data Relay
ASOS	Automated Surface Observation Station
ATC	Air Traffic Control
AWC	Aviation Weather Center
AWOS	Automated Weather Observation Station
CAP	Civil Air Patrol
DR	Disaster Response
EFB	Electronic Flight Bag
ELT	Emergency Locating Transmitter
EMS	Emergency Medical Services
ES	Emergency Services
GA	General Aviation
HEMS	Helicopter Emergency Medical Services Tool
IFR	Instrument Flight Rules
IMC	Instrument Meteorological Conditions
KBAK	Lebanon Municipal Airport
KBUR	Bob Hope Airport
KNN	K^{th} Nearest Neighbor
KPTV	Porterville Municipal Airport

KSBP	San Luis County Regional Airport
LOA	Low-Altitude Operations
METAR	Meteorological Terminal Aerodrome Report
ML	Machine Learning
MVFR	Marginal Visual Flight Rules
NM	Nautical Mile
NTSB	National Transportation and Safety Board
PEGASAS	Partnership to Enhance General Aviation Safety, Accessibility, and Sustainability
PIC	Pilot in Command
PIREP	Pilot Weather Report
SAR	Search and Rescue
SDT	Signal Detection Theory
SIGMET	Significant Meteorological Information Report
SPECI METAR	Special Meteorological Terminal Aerodrome Report
STEREO	Scalable Traffic Management for Emergency Response Operations
TAF	Terminal Aerodrome Forecast
VFR	Visual Flight Rules

DISCLAIMER

The FAA has in part sponsored this project and other projects which were foundational to this research through the Partnership to Enhance General Aviation Safety, Accessibility, and Sustainability (PEGASAS) Projects 33 and 34. However, it neither endorses nor rejects the findings of this research. The presentation of this information is in the interest of invoking technical community comment on the results and conclusions of the research. The findings and conclusions presented here are those of the author, and do not represent official positions of any government agency.

ABSTRACT

Emergency services (ES) pilots operate in a dynamic, high-risk team environment, as a subset of general aviation (GA) operations. The time constraints associated with ES operations means that ES pilots must make flight decisions quickly and often with limited or incomplete information (Worm, 1999). Due to the nature of ES operations, the consequences of an incorrect flight decision can be severe, including loss of life. ES operations are often initiated by extreme weather events, and ES pilots are frequently required to fly on the boundary between marginal visual flight rules (MVFR) weather conditions and instrument meteorological conditions (IMC). Unfortunately, an unintended transition into IMC is the leading cause of fatal accidents in GA operations (Ayiei et al., 2020). Mission objectives dictate that most ES pilots fly below 1,500' above ground level (AGL) for extended periods of time, and low-altitude flight in hazardous weather can reduce a pilot's outside visual reference, thus leading to spatial disorientation, loss of control, or controlled flight into terrain. To mitigate this problem, ES pilots must be able to accurately assess weather conditions before and during flight. However, the current method of presenting meteorological aerodrome reports (METARs) on weather displays can be misleading to pilots. Weather conditions in the areas between weather observation stations can be different than what is reported by the METAR observations at those stations. This can cause current or forecasted weather conditions *between* weather stations to be incompletely represented. However, pilots are given no obvious indication of how incompletely represented weather conditions can affect weather-related risk. This research demonstrates that a K^{th} Nearest Neighbor (KNN) analysis can be used to identify areas where the variability of conditions between weather stations (and thus weather-related risk) is incompletely represented by METAR observations. In addition, it is shown that areas where there is an increased risk of an unintended transition from MVFR to IMC can be identified among areas with incompletely represented conditions and depicted to pilots on aviation weather displays. Machine learning tactics are proposed as a way to consider additional inputs in future KNN analyses, and several emerging technologies are proposed as mediums to collect additional weather observations. The ability for an ES pilot to more accurately assess weather-related risk in MVFR conditions using the proposed technologies is evaluated, the benefits to ES pilots and the GA community are discussed, and the requirements and limitations of the study are examined.

1. INTRODUCTION

Emergency Services (ES) pilots operate in team-based and high-risk settings, as a subset of general aviation (GA) operations, to provide emergency services to the public. Successful completion of ES mission objectives can mitigate the negative effects of a disaster, help individuals and communities in need, and save lives. However, due to the time-sensitive nature of ES operations, decisions are often made quickly and on incomplete or delayed information (Worm, 1999). These decisions include preflight and inflight decisions made by ES pilots. Due to the life-saving nature associated with the successful completion of objectives, the penalty for an incorrect decision during ES operations is high. Furthermore, because ES operations often occur in the aftermath of extreme weather events, ES pilots are often presented with meteorological conditions that are more hazardous than other GA operations.

The objective of ES missions can include search and rescue (SAR) of missing persons or aircraft, providing natural disaster relief through aerial photography and disaster response (DR), air emergency medical services (EMS), and delivering lifesaving and time-sensitive supplies to an effected area. To support these mission objectives, it is common for ES pilots to fly below 1,500’ AGL for extended periods of time. These low-altitude operations (LAO) present significant hazards when flying in marginal weather or near rapidly varying terrain. Sudden changes in weather can quickly cause marginal visual flight rules (MVFR) conditions to change into instrument meteorological conditions (IMC), and an unintended transition into IMC is the leading cause of fatal aviation accidents, including controlled flight into terrain (Ayiei et al., 2020). To mitigate this problem, it is critical that ES pilots can accurately assess weather conditions and are alerted to areas where there is an increased risk of transitioning into IMC.

Obtaining weather information using standard meteorological aerodrome report (METAR) data or other Aviation Weather Center (AWC) reports can be misleading. To begin, METAR observations are only taken at airports containing an automated weather observation station (AWOS) or an automated surface observation station (ASOS). Many geographical areas across the United States have rapidly varying terrain or have significant distance between weather stations. The dataset of weather observation stations in these areas is often geographically sparse and does not contain enough datapoints to completely represent weather conditions in topographically distinct areas between weather observation stations. This can cause weather conditions between weather stations to be incompletely represented by METAR observations on weather displays. Furthermore, METAR data is reported to the AWC at a regular cadence of once per hour. Thus, if weather conditions in the vicinity of an airport degrade quicker than weather observations are reported, these changes in conditions may not be depicted on a weather display. Essentially, the weather conditions reported by a METAR observation at a weather observation station may be different than the actual weather conditions in the surrounding area. However, that METAR observation may be the nearest available representation of those weather conditions on an aviation weather display. Because the METAR observation differs from the weather conditions in the vicinity, those weather conditions in the vicinity may not be correctly represented on the weather display (this research refers to this as an *incomplete representation* of those weather conditions in the vicinity). As a critical note: This research does not seek to investigate the accuracy of singular METAR observation datapoints, but instead investigates how well those METAR observations represent weather conditions in the areas between weather stations. To avoid confusion between the nomenclature used in this document and in existing aviation literature, the terminology *incomplete representation* will be used to discuss this problem.

Actual weather conditions between weather stations are never perfectly represented, and therefore weather conditions between weather stations are always somewhat incompletely represented and uncertain. However, the completeness of weather condition representation is further diminished when weather data is old, is generated via a geographically sparse weather observation dataset, or when terrain features or weather conditions create significant variability between stations (such as a mountain range between two airports both located in shallow valleys). If weather conditions are incompletely represented on a weather display, then hazardous weather may be present, but not represented on that display. This causes weather conditions, and their associated risks, to be uncertain. ES pilots performing weather assessment over areas where weather conditions are uncertain or incompletely represented by METAR observations are more likely to incorrectly assess weather-related risk. Particularly during LAO and in marginal weather conditions, an error in weather assessment can be dangerous and can lead to an unintended transition into IMC, controlled flight into terrain, or otherwise flying in weather conditions that the pilot would not have knowingly flown into. Furthermore, an ES aircraft accident would compromise the original mission objective, potentially making the downed ES aircraft itself the subject of an additional search, rescue, and equipment recovery mission. Pilots already have problems with accurately and reliably interpreting presented weather data in the cockpit (Wiggins, 2014). Not alerting pilots that weather conditions may be incompletely represented, or that unrepresented weather conditions may contain severe weather-related risks, can cause weather assessment to be more difficult and increases the chances that a decision-error will be made.

It is critical that ES pilots can accurately assess if weather conditions are suitable for flight; Identifying weather-related hazards can reduce the risk of a severe or fatal aviation accident occurring and flying when weather is appropriate enables mission success. Currently, weather displays do not obviously indicate to pilots where weather conditions may be incompletely represented. Hazardous weather conditions, including IMC, may exist near a weather observation station but may not be represented by that weather station's METAR observation. This is especially dangerous to ES pilots evaluating if MVFR conditions are suitable for low-altitude flight, as an error in weather assessment at low-altitudes is more likely to result in an unintended transition into IMC, controlled flight into terrain, and a severe or fatal aviation accident. Furthermore, ES operations often take place in remote locations, where the METAR observation dataset does not contain enough weather observations to completely represent weather conditions in that area. Fortunately, the advancement of several technologies is expanding how, where, and when weather observations can be collected. For instance, aircraft with aircraft meteorological data relay (AMDAR) capabilities have become increasingly more prevalent in recent years (FAA, 2021). Such aircraft have the necessary on-board equipment to provide autonomous reporting of atmospheric flight conditions to the National Weather Service (FAA, 2021). In addition, the FAA's Partnership to Enhance General Aviation Safety, Accessibility, and Sustainability (PEGASAS) team is currently developing technologies to autonomously transform pilot radio communications into pilot weather reports (PIREPs), with the goal of significantly increasing the number of PIREPs submitted by 2035 (FAA, 2021). Finally, drone technology is quickly advancing, and it has been shown that drones can effectively be used to collect atmospheric weather information (Ciobanu, n.d.).

Giving ES pilots large amounts of raw weather data, however, would be ineffective. ES pilots do not have the time nor the mental capacity to perform an in-depth risk assessment involving weather observation station data, AMDAR reports, PIREPs, and drone data prior to making a flight decision. Existing weather data presentations depict weather data in a relatively succinct format. However, weather displays do not indicate how uncertain or incompletely represented weather conditions can influence weather-related risks. Opportunely, previous studies have shown that machine learning (ML) can be used to analyze large amounts of weather data (McGovern et al., 2017). One study, completed by the PEGASAS team, compared 10-years of weather data from 64 FAA-certified weather stations in California to find regions where METAR data was more varied between weather stations (Johnson et al., 2021). Because of the extensive work required to perform such an analysis, visibility was the only weather parameter used in comparing weather station data (Johnson et al., 2021). Though the study did not use ML, it provides a methodology upon which ML could be built. It was found that if weather station data within a region had greater differences, then weather conditions between weather stations were more variable. If an area has large variations in weather conditions, then it is more likely that the weather conditions reported by a METAR observation differ from the weather conditions in the surrounding area (the weather conditions in the surrounding area are incompletely represented by the METAR observation).

By identifying areas between weather stations where weather conditions may be incompletely represented, then with further analysis, areas where unrepresented instrument meteorological conditions (IMC) are more likely to exist can be identified. If IMC are physically present but are not shown by a nearby METAR on a weather display, then a pilot would have higher chance of unintentionally transitioning into IMC if flying through that area: The pilot's evaluation of the weather conditions was based on the METAR, but the METAR did not completely represent the weather conditions in the surrounding area and did not show that IMC were present. If areas between weather stations where unrepresented IMC may exist were identified, then these areas could be depicted to pilots on weather displays, and pilots could be warned of areas where there is a higher risk of an MVFR to IMC transition.

Depicting high-risk MVFR to IMC transition areas on weather displays would be beneficial to all pilots in the GA community. A pilot using such displays would have an improved ability to identify hazardous weather and make safer and more informed weather-related flight decisions. For most of the GA community, the risk of an unintended transition into IMC can be minimized by avoiding flight in marginal weather altogether. This is not the case for ES pilots, who frequently perform LAO in MVFR conditions, and have great pressure to fly under such circumstances. For ES flights with the direct mission objective of saving lives, such as search and rescue, cancelling a flight due to weather has severe consequences effecting more than the pilot and aircrew. In such circumstances, identifying that there is an increased risk of transitioning into IMC may not be sufficient evidence to cancel a flight. However, if an ES pilot were given a set of local, low-altitude, real-time weather observations, in combination with a presentation that depicts areas where the risk of an MVFR to IMC transition is high, the pilot could make much more informed flight decisions. Successful SAR flying in marginal weather could result in saving lives, but equally as important, successfully *not flying* when conditions are too hazardous could prevent additional aviation accidents or casualties.

2. REVIEW OF LITERATURE

From 1995 to 2015, weather-related disasters claimed the lives of over 600,000 people, and left an additional 4.1 billion individuals injured, homeless, or otherwise in need of emergency services (Shaw, 2015). From 2000 to 2013, the Coast Guard alone averaged over 65,000 hours of search and rescue services per year, with a total of over 549,000 people assisted and over 68,000 lives saved (BTS, 2019). This does not include the 33,544 lives saved during Hurricane Katrina (BTS, 2019). These various natural disasters caused the loss of $3.24 Billion in property value and claimed the lives of 9,900 individuals (BTS, 2019). To mitigate injury and prevent casualties, it is critical that ES operations can respond immediately and execute missions quickly. During Coast Guard SAR operations from 2000 to 2013, 71% of casualties occurred prior to the Coast Guard being notified, and 59% fewer casualties occurred following notification (BTS, 2019). Rapid ES disaster response can also mitigate property loss and reduce the effects of a disaster. When the 150-mile-long River Raisin in Monroe, Michigan flooded, the Civil Air Patrol (CAP) used aerial photography to coordinate emergency responses and redirect traffic along auxiliary county roads (Solomon, 2009). The effort was largely successful due to the rapidity of the response: The Cessna-172 conducting the photo reconnaissance took off just 30 minutes after being notified and completed all observations within the next hour (Solomon, 2009).

In the United States, SAR responses are conducted by several teams, including the National Guard, Coast Guard, the Civil Air Patrol, the Federal Emergency Management Agency, state or local police, firefighters, and by volunteers from several organizations (Rossier, 1998). In general, ES pilots are mostly non-military pilots with only private pilot or higher training, and operate as a subset of GA (Pokodner et al., 2020). ES pilots perform various aerial search patterns depending on the terrain, mission requirements, and weather of the operational environment (Rossier, 1998). There are 857 operations bases around the U.S. that house 1,211 fixed-wing and rotary aircraft used for ES operations (Fiorino, 2010). Since 1998, there has been an increase of aviation accidents, causing an expansion of ES, including air medical transport (Elias, 2006). These accidents have been attributed to operational factors including decision-making in deteriorating weather (Elias, 2006) and inadvertent flight into IMC (Fiorino, 2010). However, the rise of ES services in response to aviation accidents is not without its own risks.

From 2001 to 2004, the rate of fatal helicopter air ambulance accidents increased compared to the period from 1993 to 2000 (Elias, 2006). Air ambulance services using helicopters and fixed-wing aircraft have both increased, with 54% of operations being from hospital to hospital, 33% being on-scene responses, and the remaining 13% being from transporting organs, medical supplies, or specialty medical staff (Fiorino, 2010). Each year, the United States transports 500,000 ill or injured patients in emergency services aircraft (Fiorino, 2010).

There is extremely high pressure for ES pilots to fly during an ES operation, including in hazardous weather conditions. In EMS aerial operations, the National Transportation and Safety Board (NTSB) found that pilots felt pressured to continue or begin flight in marginal weather conditions to maintain good relationships with hospital administration (Elias, 2006). In regions with several competing air-EMS providers, the external pressure to fly was greater, as pilots did not want to diminish the reputation of their air-EMS provider and potentially limit future flight opportunities (Elias, 2006). In 1988, the NTSB found that when ES management operates in a location distant from pilots, it can cause pilots to overemphasize completing mission objectives and can "compromise sound judgement in regard to flight safety" (Elias, 2006, p. 11). It was also found that EMS personnel can put pressure on pilots to fly in marginal weather conditions, partially due to a "lack of understanding of weather-related considerations, genuine zeal to get a job done, or even competition between EMS programs" (Elias, 2006, p. 12). ES helicopter pilots also cited that the pressure to speed up operational response time was a significant factor affecting mission safety (Elias, 2006).

Aerial operations, such as SAR, that have the direct mission objective of rescuing or saving lives are particularly time-critical (Chenji et al., 2012). Today, most aircraft and rotorcraft have an Emergency Locating Transmitter (ELT) on board, which automatically produces a signal on an emergency frequency if sensors determine that the aircraft or rotorcraft has been in an accident. These emergency radio frequencies are monitored by local ES teams. If an ELT signal is detected, the search and rescue process begins immediately (Rossier, 1998). A SAR can also be initiated by an unexpected or sudden loss of communication with aircraft from Air Traffic Control (ATC) (Rossier, 1998), by an aircraft not closing a flight plan within 30 minutes of their estimated time of arrival, or if an aircraft that is expected to be handed off to a flight service station fails to make radio or radar contact (FAA, 2021). Unfortunately, in SAR, it can take anywhere from 45 seconds to 2.5 hours for an ELT signal to be triangulated to produce a geographic location (Rossier, 1998). Triangulation time increases in locations with dynamic and rapidly varying terrain (CAP, 2004).

Other SAR operations, such as a search for a missing person on-foot, do not provide an ELT to notify ES teams of location. Instead, they must rely on the last known reported location of the person. Unfortunately, many people delay reporting a missing person, and the first 48 hours is the most critical to safely returning missing individuals ("What to Do if Your Child Goes Missing," n.d.). Adverse weather and variable terrain can further inhibit an ES response. Aerial SAR in mountainous terrain is often only performed in the daytime to avoid accidental controlled flight into terrain (Rossier, 1998). Regardless of the reason for a delay in initiating or continuing SAR, ES response teams are often required to make up for lost time from the start of an operation.

The use of unmanned aircraft systems in ES operations is becoming increasingly more popular in SAR, hurricane response, and wildland firefighting (Tabor, 2021). NASA's Scalable Traffic Management for Emergency Response Operations (STEREO) program is working to use drones to reduce response times in ES operations (Tabor, 2021). Along with taking aerial observations, STEREO proposed the use of drones as a medium to collect and transmit ES aircraft position data to improve aircraft and ground team coordination during an ES operation (Shirt et al., 2017; Tabor, 2021). This technology was proved as feasible during a U.S. forestry training exercise in Phoenix, AZ (Chowdhury et al., 2017; Tabor, 2021). The maturation of ad-hoc Wi-Fi network technology has enabled drones to be used in places in which cellular networks are otherwise inaccessible (Tabor, 2021). This is of particular benefit to ES operations, which can be carried out in remote environments that are sometimes outside of the range of standard network coverage. Drones have also been used for earthquake disaster response (DR) in Haiti and the Dominican Republic (Cohen, 2014), typhoon DR in Haiyan (Greenwood, 2015), and tsunami DR in Fukushima, Japan (Pamintuan-Lamorena, 2014).

Drone swarms are becoming increasingly more prevalent in non-military applications as well (Shirt et al., 2017). Drone swarms can provide wider coverage areas, with higher data resolution, and are being proposed to be used for search and rescue (Shirt et al., 2017). One of the issues with large drone swarms is that efficiently controlling maneuvers becomes increasingly more difficult as the size of the swarm increases (Sunil et al., 2020). Due to the volume of drone-to-drone and drone-to-base communication, any large drone swarm will require significant data transmission to operate (Sunil et al., 2020). Fortunately, the development and expanded use of 5G networks provides the necessary bandwidth to command and control drone swarms (Sunil et al., 2020).

2.1 Weather Variables

ES pilot certification requirements vary based on the organization. For example, in CAP, mission pilots are not required to hold an IFR certificate and there is no additional requirement for ES pilots to complete formal weather-related training beyond that which is taught in private pilot instruction (CAP, 2017). However, air EMS pilots require more than 2,000 hours of experience in both IFR and VFR conditions ("What do EMS Pilots Do," n.d.). Regardless, ES pilots operate as a subset of GA, and all ES pilots are subject to the same weather-related risks as other GA pilots. Even if an ES pilot has their IFR certificate, they are not immune to the dangers of incorrect weather assessment or an unintended transition into IMC. Even for an IFR pilot, an unintended transition into IMC poses two types of risk. There is an environmental risk associated with now flying without a visual reference available; and there is a cognitive risk associated with quickly trying to transition from flight under visual flight rules to flight under instrument flight rules.

During private pilot training, about nine hours are dedicated to weather-related instruction (Ahlstrom et al., 2016). Pilots tend to overestimate their knowledge of weather and often lack the skills to operate in many weather conditions (Ahlstrom et al., 2016). Decision errors derived from in-flight planning or weather are considered pilot error, and contribute to 60-80% of all GA accidents (Ayiei et al., 2020). Historically, most aviation weather fatalities occur in the early morning and evening. Fatalities also occur more frequently between October and April in North America (Fultz & Ashley, 2016). Working around inclement weather, ES pilots can assist with hurricane or blizzard victims, disaster relief, and emergency response (Rossier, 1998). However, even with today's technology and available satellite data, weather is still major source of risk due to pilot error and aircraft performance in adverse conditions (Fultz & Ashley, 2016). "The most common weather citations for aviation accidents are wind, visibility, low ceiling, and high-density altitude" (Fultz & Ashley, 2016, p. 292). Figure 1 shows aviation fatalities and percentages for fatal accidents from 1982 to 2013 (Fultz & Ashley, 2016). It can be seen that GA has significantly more fatalities than commercial, air taxi, and agriculture applications. Since visibility, wind, precipitation, and icing are more prominent in causing aviation accidents (Fultz & Ashley, 2016), these parameters are expanded on below.

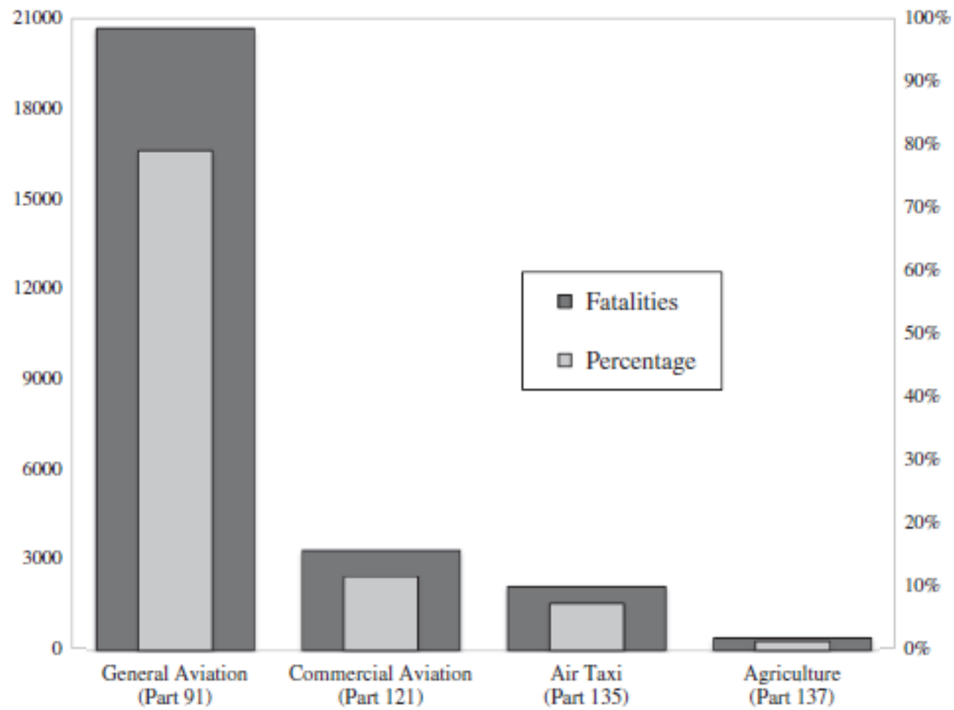

Figure 1. U.S. aviation fatalities between 1982 and 2013 from "Fatal weather-related general aviation accidents in the United States" by Fultz, 2016

2.1.1 Visibility and Cloud Coverage

Visual flight rules (VFR) pilots must use their visual field to navigate and fly aircraft, and are required to maintain minimum visibility and cloud clearances during the entire flight (Ahlstrom et al., 2016). Alternatively, instrument flight rules (IFR) pilots use their cockpit instruments to navigate through weather that does not meet visual criteria, allowing them to fly through clouds, fog, or other weather not within the VFR domain. If weather conditions do not meet VFR criteria, they are referred to as instrument meteorological conditions (IMC).

In ES and GA, VFR pilots flying into IMC is the leading cause of accidents. Accidental transition into IMC is more prevalent in flights at low altitudes, in unfamiliar regions with rough terrain, in inclement weather, and in low visibility conditions (Fiorino, 2010), all of which are ripe domains for ES operations. The NTSB reports that two-thirds of accidents that occur in IMC will be fatal (Ayiei et al., 2020). From 1990 to 1997, the NTSB observed that of 14,000 accidents, fatalities were the highest (11%) in accidents caused by unintentional transition into IMC (Ayiei et al., 2020). Past studies have shown that pilots continuing from VFR to IMC had higher confidence and skill ratings, yet made mistakes early in the decision-making process and incorrectly judged visibility (Ayiei et al., 2020).

2.1.2 Wind

Wind was the most cited weather hazard during weather accidents from 1982 to 2013 at 50% (Fultz & Ashley, 2016). While wind was prevalent in these accidents, only 7.8% ended in fatalities (Fultz & Ashley, 2016). 40% of non-fatal accidents had crosswinds as a contributing factor of the accident and fatal events consisted of gusts at 31%, tailwinds at 26%, and high winds at 22% (Fultz & Ashley, 2016).

2.1.3 Precipitation and Icing

ES pilots have additional pressure over other GA pilots to operate in conditions that are conducive to icing. If an aircraft should face icing conditions, Aviation Safety Magazine recommends flying VFR over IFR (Burnside, 2010). Private pilot instruction also recommends flying below the clouds if icing is inadvertently encountered. However, reducing altitude may not be possible during low-altitude ES operations. This makes ice and precipitation a greater risk factor for ES pilots.

2.1.4 Terrain Variables

Dramatic changes in terrain can cause weather to have more variability and be more unpredictable. Unfortunately, an ES response is more likely to be initiated over such terrain, as a dynamic landscape is a contributing factor in aircraft accidents and in people getting lost or stranded (Macwan et al., 2011). The combination of variable terrain and reduced visibility can delay an ES operation. For example, it is common to wait for improved visibility or until daylight to fly ES aerial operations in mountainous terrain (Rossier, 1998).

Mountains present particularly volatile and unstable air columns called mountain waves. In mountain waves, wind passing over a mountain peak can cause significant updrafts and downdrafts, as well as high turbulence close to the ground (SSA, n.d.). As shown in Figure 2, areas of circulating turbulence cause wind directions near the surface to oscillate between blowing towards and away from the mountain. This presents dynamic and powerful wind conditions that have variable behavior on a very small geographic scale. Because of phenomenon like this, states that have mountains have a higher accident rate of 15.3 accidents per 100,000 flight hours (Aguiar et al., 2017). Flying over mountains or high-elevation terrain makes navigation difficult because of rapidly declining visibility, gusty winds, and terrain avoidance (Aguiar et al., 2017). Past studies have shown a 68% increase in fatal accidents specifically in the mountainous area of the Colorado Rockies, as opposed to the rest of the state (Aguiar et al., 2017).

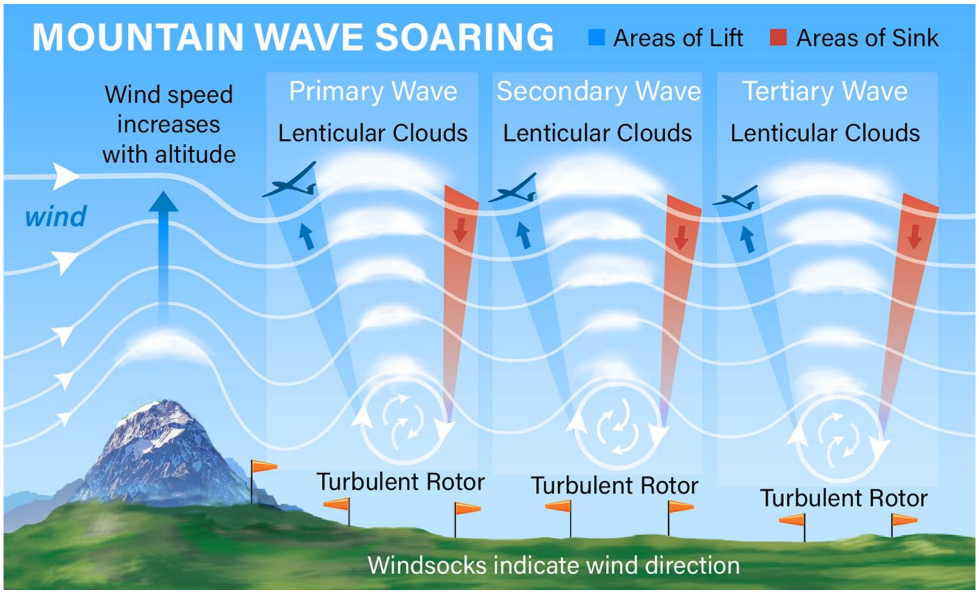

Figure 2. Mountain wave effects from “Lift Sources” by SSA, n.d.

2.2 Weather Reports

ES pilots use the same weather data presentation resources as other GA pilots to make flight decisions. The Aviation Weather Center (AWC) is the official medium to present pilot weather data. Although there are several additional weather data presentation sources which pilots can access, this research focuses only on those sources officially recognized by the AWC. Different types of weather measurements, forecasts, and observations exist on the AWC website. Pilots can choose to use none, some of, or all of these weather sources to help them make flight decisions. The more frequently used measurements, forecasts, and observations are detailed below.

2.2.1 Meteorological Terminal Aerodrome Reports

A meteorological terminal aerodrome report (METAR) is a weather report which measures the current atmospheric conditions at an airfield. Data from these observations are uploaded to the AWC to be distributed to pilots (Skybrary, 2019a). A METAR typically consists of wind speed in knots, wind direction, visibility in statute miles, precipitation, sky cover with cloud-altitude, temperature, dewpoint, atmospheric pressure, and other supplemental information (Skybrary, 2019a). METAR weather stations take atmospheric measurements at a regular cadence of once per hour. However, if weather has significantly changed within the hour period, a SPECI METAR can be issued to take a measurement outside of the regular cadence (Skybrary, 2019a). However, if changing conditions between weather stations do not cause the weather conditions in the vicinity of a METAR station to significantly change, a SPECI METAR will not be issued. METARs are available to pilots online via AWC and are broadcast over the radio in traditional alphanumeric code format, which allows pilots to access METAR data mid-flight without the use of an electronic flight bag (EFB).

METAR data can be classified into four different categories: VFR, MVFR, IFR, and low IFR. On a visual depiction map, weather stations reporting VFR, MVFR, IFR, and low IFR are depicted as green, blue, red, and purple dots, respectively. Table 1 details how each category is determined.

Table 1. Flight categories and depiction on a visual depiction map

Category	Visibility	Cloud Ceiling	Depiction on Map
VFR	5 statute miles or greater	3,000’ AGL or greater	Green dot
MVFR	3 - 5 statute miles	1,000 - 3,000’ AGL	Blue dot
IFR	1 - 3 statute miles	500 - 1,000’ AGL	Red dot
Low IFR	Less than 1 statute mile	Less than 500’ AGL	Purple dot

2.2.2 Terminal Aerodrome Forecasts

Terminal aerodrome forecasts (TAFs) are presented similar to a METAR, except that presented weather data is a forecast instead of a current atmospheric measurement. Forecasts include surface wind speed and direction, visibility, cloud coverage, and any expected significant changes in weather for a specified date and time (Skybrary, 2019b). Unlike METARs, TAFs are not broadcast over the radio and must be obtained through the AWC or internet enabled EFB systems. TAFs are updated every 6 hours, and small changes in weather conditions are often not depicted on TAFs.

2.2.3 Radar

Radar measures the intensity of nearby convective weather by measuring the movement of precipitation and the density of that precipitation in the weather system. Precipitation can include rain, hail, snow, and ice (Skybrary, 2016).

2.2.4 Pilot Reports

A pilot weather report (PIREP) is a pilot reported measurement of weather phenomenon experienced during flight. Pilots can give reports of icing, turbulence, volcanic ash, wind shear, other weather phenomenon, or any otherwise important remarks (CFINotebook). Figure 3 displays the PIREP metrics reported in PIREPs from 2003 to 2008 (Casner, 2010).

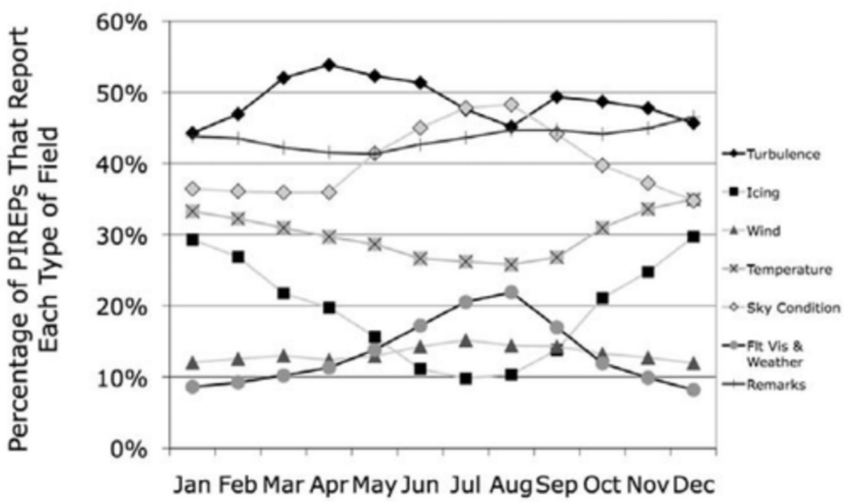

Figure 3. Percentage of PIREPs that report each type of field from “Why Don't Pilots Submit More Pilot Weather Reports (PIREPs)?” by Casner, 2010

PIREPs offer aviation meteorologists an opportunity to confirm if weather predictions are accurate by giving a “three-dimensional look at the atmosphere” (Johnson & Pokodner, 2020, para. 5). However, because PIREP data is primarily generated via pilot interpretation, the severity of weather conditions is subject to pilot perception and descriptive report. PIREPs are also the best opportunity for pilots to get current weather observations at locations other than airports. From 2003 to 2008, approximately 4,700,000 PIREPs were submitted in the United States, averaging only 1 PIREP per hour, per 42,156 square miles (Casner, 2010). Considering that weather systems can have significant geographic variations, both in surface location and in altitude, and significant temporal variation within an hour (Casner, 2010), a single PIREP over such a large area does not provide sufficient weather information to ES pilots making time-critical, high-risk decisions.

After surveying 189 pilots, it was found that a lack of familiarity with the PIREP submission process played a role in the lack of PIREP submissions (Casner, 2010). The research also indicated that reporting PIREPs in plain language, as opposed to standard PIREP submission format, would be beneficial (Casner, 2010). In fact, 44% of PIREPs already use this type of language through the remarks section (Casner, 2010). Pilots in the study overwhelmingly agreed that PIREPs are a critical resource for weather-based flight planning and in-flight awareness (Casner, 2010). The research found that in-cockpit PIREP submission assistance technology would be beneficial in encouraging pilots to submit more PIREPs (Casner, 2010).

2.2.5 Air Mission Meteorological Information & Significant Meteorological Information

Air mission meteorological information reports (AIRMETs) are issued notifications regarding factors that could affect the safety of flights in a particular area. Extreme or hazardous weather is not included in AIRMETs but is included in significant meteorological information reports (SIGMETs). Notifications can include IFR conditions, turbulence, terrain obscuration, or icing levels. AIRMETs come in three types, Sierra (mountain obscuration or cloud ceilings less than 1000' AGL), Tango (moderate turbulence or sustained surface winds of greater than 30 knots), and Zulu (moderate icing and freezing levels) (Fritts, 2020). SIGMETs are like AIRMETs, except that SIGMETs indicate more hazardous weather. This can include severe icing, severe turbulence, dust storms, and volcanic ash (Fritts, 2020).

2.2.6 Helicopter Emergency Medical Services (HEMS) Tool

The AWC developed a tool for helicopter emergency medical services (HEMS) pilots which estimates areas of VFR, MVFR, IFR, or low IFR conditions based on observed weather data. This tool is useful to ES pilots but can be misleading in its depiction of weather conditions. Areas of VFR, MVFR, IFR, and low IFR conditions are estimated using radar data, METARs, and other weather reports. As shown in Figure 4, these estimates can be incorrect. In the Figure 4 example, low-IFR conditions observed at a weather station are located in areas estimated to be "VFR". Similarly, VFR conditions observed at a weather station are located in areas estimated to be "marginal". The condition estimations in the HEMS tool were never intended to be error-free, but the inconsistency in risk presentation from the weather observations can be misleading and can cause an error in weather dissemination and evaluation. In fact, one accident report states that an incorrect dissemination of the HEMS tool presentation was a contributing factor in a fatal EMS helicopter accident (NTSB, 2020). Depicting areas where weather-related risk is increased due to incomplete weather condition representation would be a beneficial addition to a weather presentation such as this.

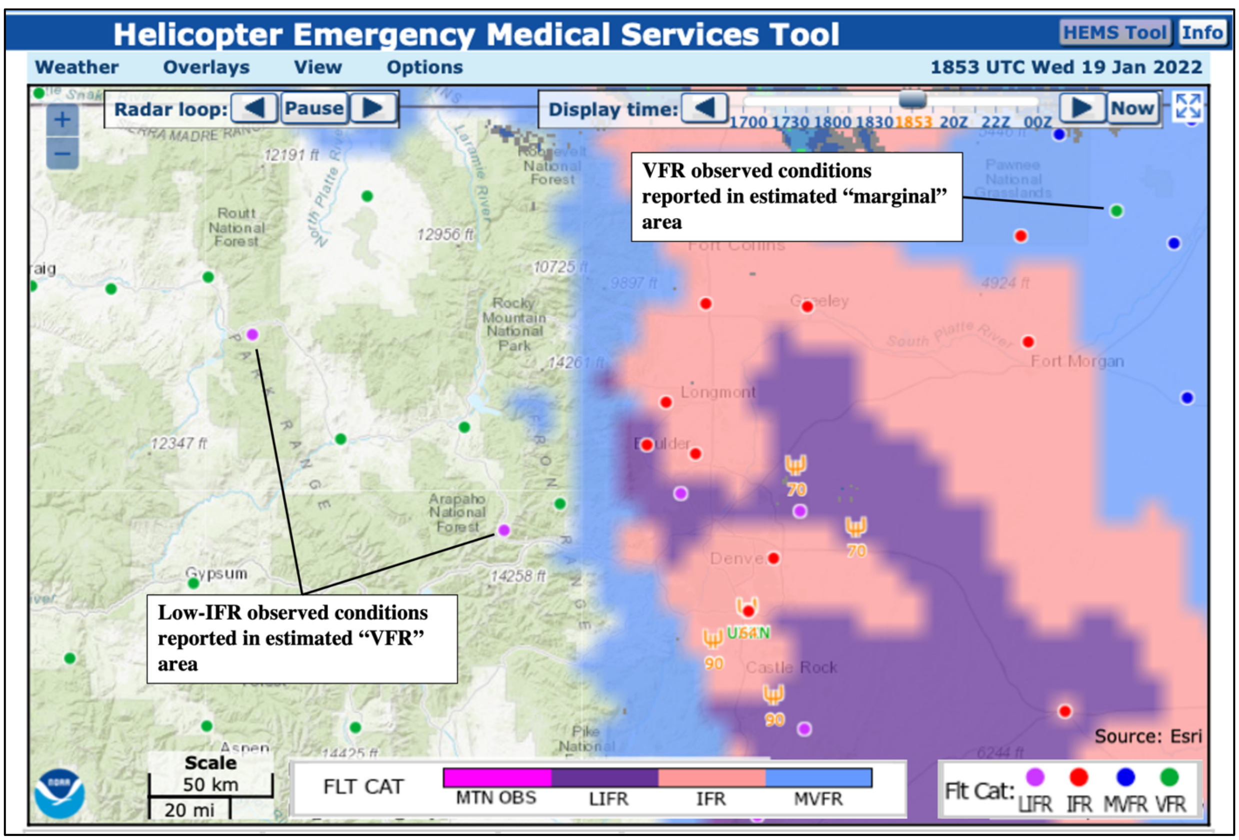

Figure 4. Errors in condition estimation on the Helicopter Emergency Medical Services (HEMS) tool can be misleading to pilots. HEMS graphic generated via AWC

2.3 Pilot Variables & Human Factors

The NTSB examined ES safety issues from 1978 to 1986 and found 59 accidents in which improvements needed to be made in weather forecasting, personal training, and operations management (NTSB, 2006). When the NTSB recommended 19 safety modifications after 1986, the following 15 years from 1990 to 2005 showed that a significant number of accidents continued to occur in ES (NTSB, 2006).

Improving aviation situational awareness is one way that an ES pilot can mitigate accidents or problems during operations. There are four pillars to aviation situational awareness including position, terrain, traffic, and weather (Spirkovska & Lodha, 2003). Situational awareness for weather has attributed to over 30% of accidents and 15% of fatal accidents in GA (Spirkovska & Lodha, 2003). This could be due to issues with retaining and absorbing weather information needed to make well-informed and safe flight decisions (Spirkovska & Lodha, 2003). Another possible cause is difficulty in tracking weather changes during the flight and inability to multitask (Spirkovska & Lodha, 2003). Due to lack of experience, ability to correctly interpret weather conditions, fatigue, and workload, pilots are sometimes unable to recognize transitions from MVFR to IMC (Ayiei et al., 2020). Pilots flying from MVRF into IMC can experience spatial disorientation and can lead to flying at altitudes in which the pilot cannot recover from a loss of aircraft control (Ayiei et al., 2020).

In Knecht (2008), pilots were asked open-ended Likert Scale questions about adverse weather. The VFR and IFR pilots were asked questions that determined which weather factors mentally dominated a four-hour flight (Knecht, 2008). The ranking of preflight factors included storms (83%), ice (48%), cloud ceiling (46%), visibility (57%), and wind (52%) (Knecht, 2008). In-flight factors were storms (81%), ice (42%), cloud ceiling (41%), and visibility (49%) (Knecht, 2008).

ES pilots are often presented with time-critical weather-related decisions (Walmsley & Gilbey, 2020). In making such decisions, pilots tend to rely on past information and experiences to inform their decision to continue flight or to deviate around adverse or declining weather (Walmsley & Gilbey, 2020). This is inherently risky, as a pilot's use of past information and cognitive heuristics can lead to accidents (Walmsley & Gilbey, 2019).

Weather data can be displayed via an in-cockpit weather display or on an EFB (Ahlstrom, 2015). On such displays, weather symbology can show different characters and colors for similar weather conditions. Previous studies showed that pilots using graphical precipitation weather displays had increased situational awareness when making flight decisions (Ahlstrom, 2015).

2.4 Machine Learning in Weather Analysis and Prediction

Machine learning has previously been considered as a method to analyze and predict weather, and advances in the field of ML are expanding the potential applications of a ML algorithm (Han et al., 2021). There are competing ideas as to which ML model is best suited for weather analysis, including artificial neural networks, numerical weather approaches, or direct sensing or hybrid approaches (Han et al., 2021). Regardless of the method taken, previous studies have shown that ML can be used to predict and analyze weather. For example, one study was successful in producing accurate, long-term weather predictions that incorporate seasonal weather trends (Han et al., 2021). The Amazon Forecast Index, a historical data-based ML software that predicts product demand, offers a weather index option that predicts weather over shipping routes to avoid supply chain disruption (Amazon, 2021). Another study was able to accurately predict hail using a series of randomly generated decision trees, as shown in Figure 5 (McGovern et al., 2017). This hail analysis exemplifies how many weather parameters must be considered to accurately predict just one weather variable (hail), and how a deep analysis must be condensed into a format that is easily disseminated by pilots. It is just as critical that pilots are informed of what is causing bad weather, so that they can be aware of what changes in weather to look for during weather condition evaluation.

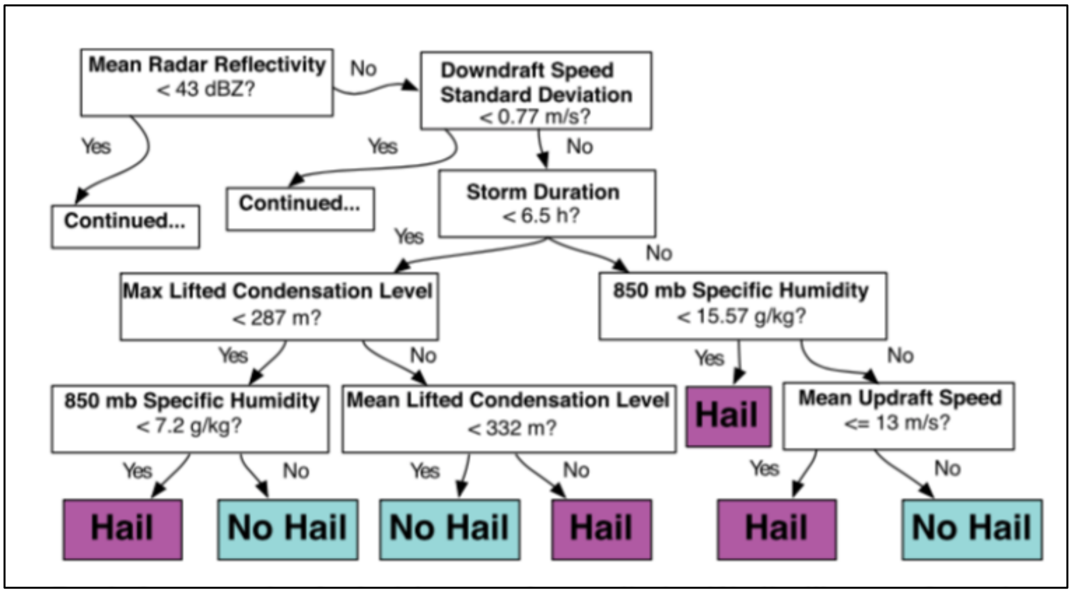

Figure 5. Hail Prediction Model from "Using Artificial Intelligence to Improve Real-Time Decision-Making for High-Impact Weather" by McGovern et al., 2017

2.5 Machine Learning in Piloting and Other Critical Applications

Several industries, including aviation, are using ML to help people make critical decisions, more accurately, and in less time (Briganti & Le Moine, 2020). In the medical industry, advanced ML tactics have been employed to detect atrial fibrillation, cardiovascular risk, as well as to help diagnose medical conditions within the fields of pulmonary medicine, endocrinology, nephrology, gastroenterology, and neurology (Briganti & Le Moine, 2020). ML is also being considered as a means to help pilots solve multivariable problems in the air, provide crew with more refined and optimized interfaces, and perform flight-assistive functions such as displaying safe flight paths, object tracking and recognition, and filtering and displaying only critical information during an emergency (Kulida & Lebedev, 2020). One study found that a ML-informed in-cockpit display is "very important, especially in landing conditions with poor visibility, as well as in low-altitude flight" (Kulida & Lebedev, 2020, pg. 2). The study went on to develop a prototype system that produced flight paths which avoided hazardous, mountainous terrain in the area surrounding Elizovo airport in Russia (Kulida & Lebedev, 2020). In both the medical and the aviation communities, ML is becoming increasingly more trusted to be used for critical task decisions.

The FAA's PEGASAS team has already begun to integrate ML to autonomously transform informal pilot radio communications into standardized PIREPs (Pokodner et al., 2020). This ML-based speech recognition technology was identified by the FAA as a critical technology to improve and modernize the PIREP submission process (FAA, 2021). The GA community accounts for a majority of weather-related accidents (McGovern et al., 2017; Pokodner et al., 2020), and GA pilots struggle with properly interpreting presented weather information and with accurate weather assessment. Increasing the number of PIREPs available is one way to mitigate this problem, as the additional data provided by PIREPs would help to represent actual weather conditions more completely on weather displays.

To develop the hands-minimized PIREP submission software, the PEGASAS team collected 252 PIREP recordings from pilot participants (Pokodner et al., 2020). Each participant was given several in-flight weather scenarios and could choose whether or not to submit a PIREP for each scenario. If the participant chose to submit a PIREP, the PIREP was recorded, the audio was transcribed, and the transcribed message was then translated into a standard PIREP format (Pokodner et al., 2020). This process is demonstrated in Figure 6. A ML-algorithm was trained using this process and was able to autonomously translate voice recordings into standard PIREPs with relative accuracy (Pokodner et al., 2020).

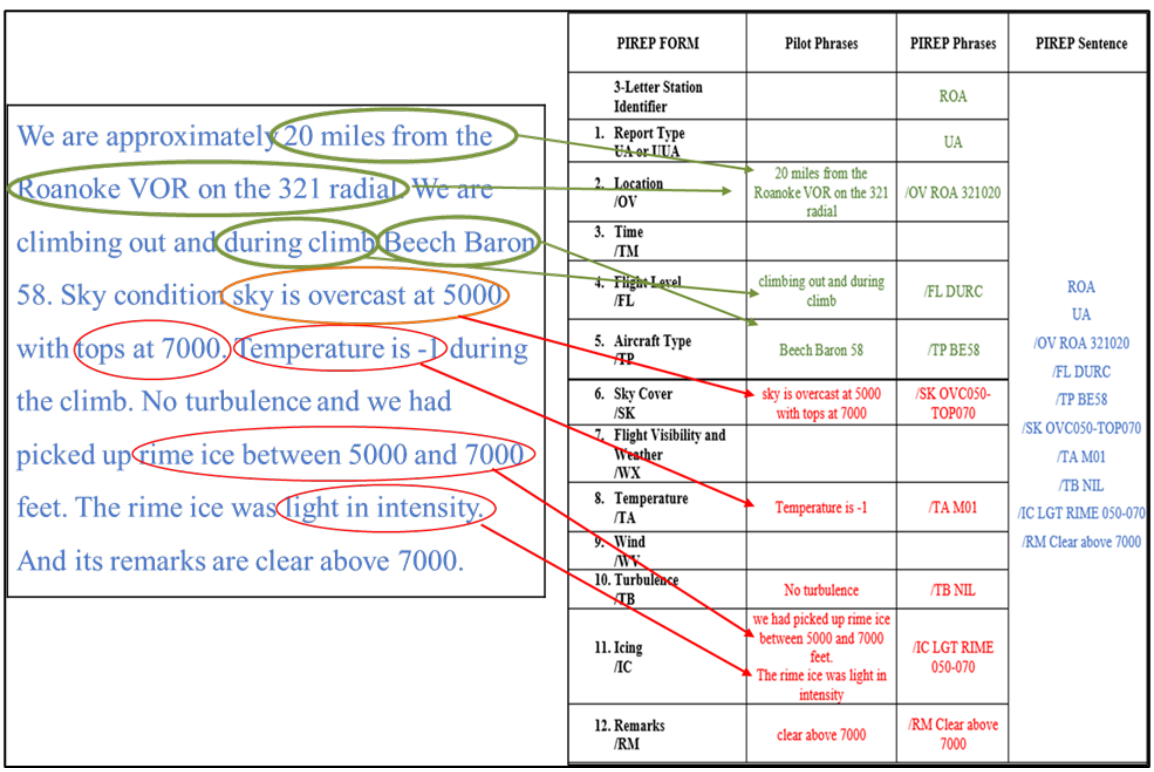

Figure 6. Sample of an icing PIREP transcription translated to a PIREP sentence from "PEGASAS Project 33 - Augmented Weather Interfaces Project (AWIP)" by Pokodner et al., 2020

In a separate analysis, the PEGASAS team demonstrated that regions with more variable weather conditions can be identified by evaluating differences in METAR data between weather stations. The PEGASAS team showed this is feasible by examining 10-years of METAR data at 5-minute increments from 64 FAA-certified weather stations in California (Johnson et al., 2021). To perform the analysis, weather stations were divided into regions and the visibility observations reported by weather stations within each region were compared. Regions with greater differences in visibility observations had more variation in reported weather conditions, and there was therefore greater variability in weather conditions between weather stations (Johnson et al., 2021). In the PEGASAS study, weather stations with large differences in weather observation data were known as having low correlation.

The PEGASAS regional weather data correlation analysis successfully demonstrated that areas between weather stations where weather conditions have greater variation can be identified by comparing METAR data. For simplicity, the analysis used only visibility as an input parameter in analyses. Figure 7 shows the monthly correlation parameters for weather stations within the California central valley region (Johnson et al., 2021). Although the initial study did not use ML software, it demonstrated a methodology upon which ML can be built. It should be noted that although METAR data is reported and distributed to pilots hourly via the AWC, METAR observations can be taken more frequently. In this case, observations were taken at 5-minute increments and were stored outside of the AWC domain to be used in the PEGASAS analysis.

Year [a]	Average Monthly Pairwise Correlations												Average Monthly Correlations (M_1) [d]	Standard Deviation (SD_1) [e]
	Jan	Feb	Mar	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC		
2010	11%	19%	47%	50%	66%	91%	MD	97%	90%	37%	22%	15%	50%	0.32
2011	15%	44%	31%	61%	67%	78%	94%	92%	84%*	52%	19%	20%	52%	0.29
2012	16%	40%	45%	55%	85%	95%	81%*	83%	81%	70%	28%	11%	55%	0.29
2013	13%	40%	57%	63%	71%	84%	69%	88%	75%	71%	12%	16%	55%	0.28
2014	13%	22%	65%	71%	64%	84%	83%*	86%*	74%	62%	37%	23%	52%	0.25
2015	14%	36%	46%	59%	70%	87%*	88%	90%	77%	64%	21%	18%	53%	0.28
2016	14%	36%	46%	59%	70%	87%*	88%	90%	77%	64%	21%	18%	53%	0.28
2017	7%	10%	57%	74%*	37%	73%	89%*	85%	85%	91%	43%	22%	51%	0.32
2018	1%	20%	33%	69%	75%	MD	91%*	46%	95%*	70%	67%	17%	44%	0.28
2019 [b]	29%	46%	28%	54%	58%	90%*	MD	MD	MD	MD	86%	5%	44%	0.26
M_2 [f]	13%	31%	46%	60%	66%	84%	85%	84%	80%	65%	36%	17%		
SD_2 [g]	0.07	0.12	0.12	0.07	0.13	0.08	0.11	0.16	0.06	0.15	0.24	0.05		

Note. a The central valley region has seven locations, however KDLO and KO32 were not included in the analysis for having huge amounts of missing data. b. KVIS was also not included in the analysis for having missing data. c. MD indicates complete Missing Data for the particular month. d M_1 indicates the average monthly correlation for each individual year. e SD_1 indicated the standard deviation for each year. f M_2, indicates the average monthly correlation for each month for years 2010 to 2019. g SD_2 indicates the standard deviation for each month for years 2010 to 2019. * also indicates missing data.

Figure 7. California central valley region monthly average correlation values from "PEGASAS Project 33 - Augmented Weather Interfaces Project (AWIP)" by Johnson et al., 2021

3. PROBLEM STATEMENT

3.1 Case Study & Example ES Operation

In December of 1996, a Learjet with two pilots flew an ILS approach to runway 18 of Lebanon Municipal Airport (KLEB), located in Vermont (NTSB, 1996). Weather observations at that time reported IFR daytime flight conditions; an overcast cloud layer at 1,200’ AGL, wind at 5 knots, and 5 statute miles of visibility (NTSB, 1996). Terrain surrounding KLEB is mountainous, with several sparsely inhabited forests. After missing an instrument approach for runway 18, the pilots received clearance to circle back for another approach on runway 25. Nine minutes later, the pilots misidentified their position and started their descent too early, leading the aircraft to descend directly into the surrounding mountainous terrain (NTSB, 1996). After several failed attempts to contact the aircraft and after losing radar contact, ATC declared an emergency missing aircraft (NTSB, 1996; Rossier, 1998).

Shortly after declaring the emergency, CAP, the National Guard, state police officers, and several volunteers were enacted to begin a search and rescue for the missing aircraft (Rossier, 1998). CAP aircraft were assigned to fly half-mile-wide grid search patterns at 1,000’ AGL, National Guard helicopters began flying contour searches at 500’ AGL, and A-10s were used to fly search patterns at 2,000’ AGL (Rossier, 1998). Aircraft from six different states participated in the search (Rossier, 1998). In the end, after two weeks of searching, the SAR was called off with no indication of the Learjet or the two missing pilots (Rossier, 1998). It was not until two years later that the aircraft wreckage was found on private property 17 nm away from the airport (NTSB, 1996).

The NTSB accident investigation found that factors contributing to the accident included becoming lost or disoriented, misjudging navaid signals, prematurely descending, and misreading IFR procedures (NTSB, 1996). The low ceilings and IFR conditions contributed to the pilot’s spatial disorientation and ultimately led to the accident. These were experienced, commercially rated pilots, with over 6,317 hours of total combined flight time (NTSB, 1996). For comparison, CAP mission pilots require just 500 hours of pilot in command (PIC) time (CAP, 2017) and EMS pilots require 2,000 hours (“What do EMS Pilots Do”). While the pilots of the Learjet had the opportunity to postpone the flight due to the inclement weather, the ES aircraft assigned to the

SAR did not have such an option. Weather conditions were marginal during the SAR, and flying in the marginal weather meant the possibility of rescuing the two pilots before the quickly approaching cold weather set in. Due to the nature of the SAR operation, these ES aircraft were flying low-altitude flight profiles near terrain with mountain peaks greater than 3,000' high. During the two-week SAR operation, ES pilots had a significant risk of accidental controlled flight into terrain. This was exacerbated by deteriorating weather conditions. On several occasions, SAR aircraft were grounded due to weather-related concerns (Rossier, 1998).

Figure 8 shows the Learjet accident location relative to KLEB. The accident location is designated by the blue waypoint located at 43.826° N, 72.000° W, and is 17 nm from KLEB. Distance rings at 5-nm radial increments were plotted around KLEB and are shown in black. FAA-certified weather observation stations are shown by a yellow dot. As a note, the ES pilots would not have been flying along the blue line shown in Figure 8, as they did not know where the downed aircraft was located. Instead, they would have been flying their various search patterns as described above. An example of a grid search pattern is shown by an orange line in Figure 8.

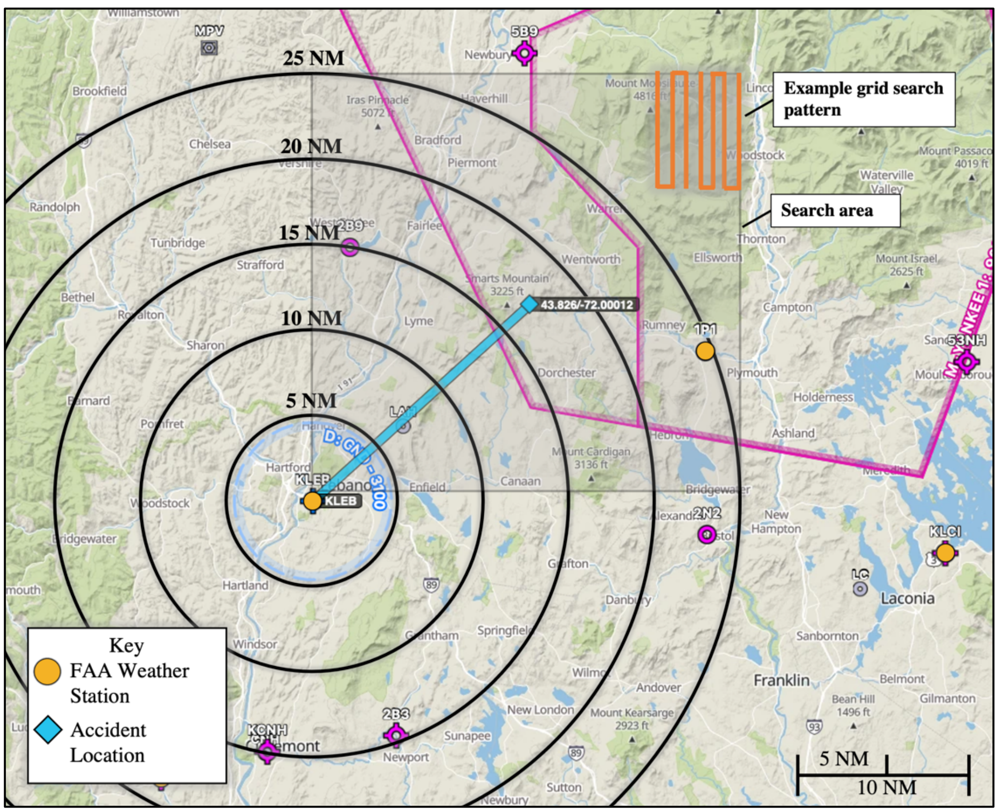

Figure 8. Learjet accident location relative to Lebanon Municipal Airport (KLEB). Visual depiction map created using ForeFlight

The relative direction of the Learjet was known to ATC prior to the aircraft going missing. In this case, ATC knew that the Learjet was northeast of the airport and attempting to follow a published IFR approach. Therefore, search tactics would have been directed to focus on the northeast quadrant of the local airspace. This is shown by the faded grey square in Figure 8. Notably, within this 25-nm by 25-nm search area, only two FAA weather observation stations exist; an ASOS at KLEB and an AWOS at Plymouth Municipal Airport (1P1).

The SAR operation to find the Learjet was frequently paused due to weather (Rossier, 1998). The small number of weather observation stations in the search area meant that weather conditions between weather stations and in the surrounding area may not have been completely represented by METAR observations on weather displays. This would have caused weather conditions in the area to be uncertain. Even if METAR observations at KLEB and 1P1 were both depicting MVFR conditions, pilots would have had little indication if the area near, for example, Bradford (the northwest quadrant of the search area) had similar conditions. Moreover, if KLEB was reporting MVFR and 1P1 was reporting IFR, the actual weather conditions in the search area would have been more uncertain and would be on the boundary between flyable and unflyable. If the degree of uncertainty in weather assessment were not so large, and the penalty for an incorrect flight decision were not so high for the ES pilots, it is reasonable to assume that the operation would not have been paused so frequently by weather-related concerns.

Incomplete weather condition representation and uncertainty issues identified in the SAR near KLEB are not isolated to this operation. ES operations are frequently performed in remote areas with few weather observation stations available. Thus, it is common that ES pilots are required to assess weather-related risk in areas where conditions may be incompletely represented. There are three common issues pertaining to ES pilots assessing weather-related risk during ES operations. They are as follows:

i. ES operational areas often do not contain enough weather observation station datapoints to depict topographically distinct areas between weather observation stations, and METAR observations presented on weather displays can be up to an hour old. This can cause weather conditions between weather stations to be uncertain or incompletely represented on weather displays.

ii. Weather displays do not indicate how incompletely represented weather conditions between weather stations can affect weather-related risk. Pilots who are unaware of these risks have a diminished ability to identify weather that is unsuitable for flight.

iii. ES pilots more frequently fly low-altitude flight profiles, near variable terrain, and in dynamic weather which fluctuates between MVFR and IFR conditions. An error in weather assessment under these circumstances, due to incomplete weather information, is more likely to result in an unintended transition into IMC, controlled flight into terrain, or even a fatal aviation accident.

Making flight decisions when weather conditions are uncertain can be dangerous, especially for pilots performing LAO near dynamic terrain. If the ES pilots from the SAR near KLEB had additional low-altitude weather observations from within the search area, weather conditions would have been more completely represented, and weather condition uncertainty would have been reduced. Furthermore, if the ES pilots' weather displays depicted and alerted pilots to areas where there was a higher risk of a transition into IMC, the pilots could have more correctly identified weather-related risk in areas where weather conditions were the most uncertain. A pilot who is more capable of identifying risk would be better equipped to decide when marginal weather is suitable for flight, and when it is not. This means that additional time could have been spent in the air looking for the wreckage and flight in hazardous weather would be avoided. Although the Learjet pilots did not survive this accident, there are plenty of other ES operations in which downed or missing aircraft yield survivors. When cold or harsh weather is approaching, flying in appropriate marginal weather could mean the difference between rescuing an accident survivor and delays of weeks or months before finding the remains of an accident victim.

The decision to fly in marginal weather is more difficult than the decision to fly in very calm or very hazardous weather. In marginal weather, small changes in atmospheric conditions can turn previously flyable weather into IMC or weather that is unsuitable for flight. These small changes in conditions are often not depicted in aviation weather displays, especially when considering that data may be geographically sparse or that data may be old, and conditions degraded. This can cause instrument conditions to be present, but not represented by nearby METAR observations on a weather display; A pilot flying through an area with unrepresented IMC would be more likely to get into a weather-related accident. Therefore, if weather conditions in the vicinity of a weather station are incompletely represented on a weather display, then it may not be obvious that IMC exists, and it would be difficult to correctly assess the weather-related risks associated with flight through that area.

Because weather condition misrepresentation is partially caused by geographic sparsity in the dataset, an idealized solution might include more sensor coverage (more weather observation stations) providing weather information to more completely represent weather conditions in the areas between weather stations. This would reduce weather condition uncertainty and mitigate the chances of an unintended transition into IMC. However, the cost and time associated with constructing and maintaining this many weather stations make the idea logistically and financially impossible. Furthermore, applying this concept across the area of the United States is even more infeasible. But what if areas where there is a high risk of transitioning from MVFR to IMC could be depicted on weather displays without using a closely packed array of weather stations? And, what if there were a cheaper and more flexible option to gather weather observations? To examine these possibilities, the impact of incomplete representation of weather conditions in the areas between weather stations can be characterized in greater depth.

3.2 Incompletely Represented Weather Conditions Between Weather Observation Stations

To estimate weather conditions along a flight path, a pilot must examine weather observations at nearby weather stations and geographically interpolate weather conditions between those stations. There are several factors that can make this interpolation more difficult, including increased distance between weather stations, the rapidity at which conditions are changing, more dynamic terrain, and closer proximity to large bodies of water or mountains. Because all weather stations have some distance between them, weather conditions between stations are never perfectly represented by METAR observations. This causes weather conditions between stations to always be somewhat uncertain. However, increased distance between stations, older weather observation data, and larger variations in weather conditions near weather stations can each cause METAR observations to not completely represent weather conditions in the vicinity of a weather station: If weather conditions between weather stations are incompletely represented by METAR observations (especially when terrain or other features exist between those stations), then weather conditions in the areas between stations are also more uncertain to pilots performing weather assessment. Again, for most GA pilots, weather condition uncertainty can be managed by implementing larger safety margins in weather-based flight decisions. This means that a GA pilot observing marginal weather over a flight profile can decide not to fly: the risk of a weather-related accident outweighs the reward of the GA pilot flying. However, lives are dependent on successfully flying ES operations, even in MVFR conditions. For the ES pilot, the risk-reward balance in much more in favor of flying. ES operations often occur in remote locations, where weather observation stations are sparse. Therefore, ES pilots often cannot see detailed, current weather conditions at the site of operations and must be able to geographically interpolate weather conditions across a much wider area. This is problematic, as interpolation over a spatial plane is difficult, particularly when datapoints are scarce. One study found that "spatial interpolation in those parts of a region with few climate data was not accurate and precise when compared to other areas with more climate data" (Bhowmik & Costa, 2014, para. 2).

In Figure 9, a visual depiction map with a flight profile from San Luis County Airport (KSBP) to Porterville Municipal Airport (KPTV) demonstrates how dynamic terrain and large distances between weather stations can cause actual weather conditions between stations to be uncertain. Both airports are located in California. Conditions near the flight path vary greatly, and are being reported as VFR, MVFR, and low IFR. There are several factors that indicate that actual weather conditions in Figure 9 may be more complex than what is being represented in the Figure. Terrain between the two airports is mountainous, with peaks ranging from 3,000' to 5,000'. There are no weather stations directly between the airports, and KSBP is located near the coast. These factors indicate that weather conditions between the weather observation stations may be considerably different than what is being reported by the METAR observations at those stations. Therefore, there is a risk that the weather conditions between observation stations are being incompletely represented. This causes pilot assessment of weather conditions along the flight path to be uncertain and increases the chances that an error will be made during weather assessment. Consider how difficult it would be to geographically interpolate weather conditions across the flight path, or in the area contained by the black box, as shown in Figure 9. Are conditions VFR, MVFR, or are the IFR and unflyable? Does the low IFR weather reported at Atascadero indicate IFR conditions are present on the flight path, or do the VFR conditions observed at Delano indicate that conditions are suitable for flight? How will conditions change in the hour it takes to fly the route? How do weather conditions at the peak of the mountains differ from those reported on the ground at the airports? Most GA pilots can alleviate weather-related concerns by choosing instead to fly on a day where weather conditions are not MVFR and are not on the boundary of being unsuitable for flight. Here, uncertain weather conditions have a less impactful influence on risk. For example, if each weather station in Figure 9 were reporting VFR, the weather-related "safety margin" in the risk assessment would be greater. However, it is critical that ES pilots fly if weather conditions are suitable, even in MVFR conditions. ES pilots must be able to accurately assess weather-related risk in marginal conditions, including over areas where conditions may be incompletely represented and are more uncertain.

Figure 9. Terrain and varying METAR observations cause weather conditions to be uncertain between KSBP and KPTV. Visual depiction map created using ForeFlight

Weather conditions change over time and METAR data is uploaded once per hour to the AWC. As METAR observations approach being an hour old, it is more likely that actual conditions differ from what is being reported on weather displays. Similarly, it is more likely that weather conditions between weather stations are incompletely represented by METARs on weather displays as METAR data ages. Performing weather assessment using old data is problematic. It has been shown that delayed information flow can negatively influence a decision-maker's performance (Caldwell, 1997). Similar to how greater distances between weather stations can cause weather conditions between stations to be uncertain, older data can introduce addition uncertainty into a pilot's assessment of weather conditions. As shown by a long history of research, including the Beer Distribution Game (Sterman, 1989), humans are notoriously deficient at accounting for information delay in a dynamic decision-making process.

Weather condition assessment is complicated by how conditions vary in time and space. Consider the hail prediction model shown in Figure 5; The single variable of hail has a multitude of factors influencing if hail was to be expected or not. Now consider that hail is just one of many weather variables that a pilot must consider when making a decision to fly. Each weather variable changes with time and varies in severity over geographic space. Furthermore, consider that small changes in these variables can turn MVFR conditions into IMC or unflyable conditions. Identifying these small changes on a weather display is difficult. If weather stations have large distances between them, or if weather observation data is old, the difficulty of identifying these changes in weather-related risk is increased. This is problematic for a pilot evaluating risk in MVFR conditions. It would be easy to incorrectly assess risk if weather conditions between stations are incompletely represented by METAR observations, especially if unrepresented IMC exists in the area.

3.3 Cognitive Bias in ES Pilot Decision-Making

GA pilots are often deficient in disseminating presented weather data (Beringer & Ball, 2003; Wiggins, 2014), and such deficiencies are exacerbated when risk is not obvious due to incompletely represented weather conditions. In a weather data presentation simulation, qualified pilots showed significant variance when estimating turbulence intensity based on radar displays (Wiggins, 2014). Another study found that variations in weather symbology presentation, including how METARs, SIGMETs, and lightning strikes were presented within weather displays, can affect a pilot's perception of weather (Ahlstrom, 2015). While clearly and concisely presented weather information can better a pilot's ability to interpret data (McAdaragh, 2002), uncertainties in presented data can cause pilots given the same data to arrive at different conclusions about weather conditions (Beringer & Ball, 2003; Wiggins, 2014).

A variety of theories exist as to why pilots presented with the same data may arrive at different conclusions. Event-based anchoring refers to the decision-making process in which previous experiences influence a decision-maker's cognitive bias. This is related to recognition-primed decision-making, in which a bias is reinforced when that bias leads to a correct decision in a previous situation (Patterson et al., 2009). A cognitive bias speeds up the decision-making process and can reduce cognitive load. While this is advantageous for efficient decision-making, this can also lead to an incorrect, and sometimes fatal, flight decision for pilots.

Relying on a cognitive bias to correctly disseminate weather data is problematic. Researchers found that pilots often place more emphasis on weather data obtained earlier in a flight, and do not properly adjust to changing weather conditions (Walmsley & Gilbey, 2016). The researchers indicated that pilots who were exposed to an initial good forecast felt confident in continuing a simulated flight, whereas pilots exposed to an initial bad forecast tended to divert their flights even when it was unnecessary (Walmsley & Gilbey, 2016). A pilot's cognitive decision bias must consider the effects of incomplete weather condition representation, so that risk can be more accurately assessed. The most severe weather-related risks are associated with an unintended transition into IMC; a pilot who can identify areas where there is a high risk of an IMC transition would have developed a cognitive bias that can more accurately consider these risks.

3.4 Pilot Risk Analysis in ES Operations

ES pilots experience additional factors that make accurate risk analysis more critical than in other GA applications. ES operations are focused on specific, high-risk, and time-sensitive task accomplishment. In general, high-risk team performance settings have little availability for error, and there is a high penalty for failure to complete objectives (Caldwell, 1997). People's lives, property, and well-being are highly dependent on the successful completion of ES operations. Depending on the scale of the response, ES operations may require the coordination of numerous aircraft and ground teams, with each team containing multiple individuals and multiple modes of communication. As the size and complexity of the response increases, as does the need for effective and efficient teamwork, and larger teams can lead to lower cohesion and less response flexibility (Salas et al., 2017). ES decisions are often made using incomplete or delayed information (Worm, 1999), and information delay limits an operator's ability to effectively respond to a dynamic and time-critical situation (Caldwell, 2014). Making a decision correctly and quickly becomes increasingly more important in multi-agent, dynamic, time-sensitive, team settings such as ES operations, as small errors may have serious, unforeseen, and irreversible consequences (Worm, 1999).

Flying low-altitude flight profiles for extended periods of time, near rapidly varying terrain, and in marginal weather, presents significant risk and leaves little room for pilot strategic replanning in the event of human error or mechanical plane performance issues. Such flight profiles leave the pilot, aircrew, and aircraft operating at the boundary of the operational envelope; temporally, operationally, and in crew capability. Longer periods of time in the air and less time to rest between flights can lead to an increased chance of human error and degraded crew performance. These problems are exacerbated by flying in marginal weather, and ES pilot are more likely to fly in such conditions.

ES pilots have a higher overall workload due to having additional tasks and responsibilities. While this is necessary for ES task accomplishment, a higher workload can also negatively affect overall team performance (Caldwell & Garrett, 2010). In addition, circumstances yielding life or death outcomes can evoke decision makers to be more likely to take risks (Wang, 1996), and the FAA found that the more important a flight is, the more a pilot is susceptible to compromising their personal weather minimums (FAA, n.d.).

The time-sensitivity of tasks, uncertainty of event information, criticality of mission success, and the high-risk team performance setting makes correct pilot decision making more critical in ES operations. Yet, the high cognitive workload, increased chances of unfavorable weather, high external pressure to fly, and the life-saving potential of ES operations leaves ES pilots more likely to fly in hazardous weather. ES pilot decision-making is too critical to be complicated by unnecessary risk. While certain risk factors stemming from the operational constraints of ES missions cannot be changed, improving weather-related risk assessment would better the chances of ES operational mission success.

3.5 ES Pilot Decision-Making & Signal Detection Theory

Signal Detection Theory (SDT) is a model that depicts decision making under uncertainty (Lerman et al., 2010), and can be used to examine how ES pilots make flight decisions in marginal weather using a weather display that incompletely represents weather conditions. Depicting flight decisions using SDT can demonstrate the effect that weather condition uncertainty can have on the ES pilot decision-making process. SDT identifies a decision maker's ability to detect a signal from background noise. In this case, the ES pilot is the decision maker and detecting unflyable weather is the signal. A decision maker's level of sensitivity corresponds to how well they can identify that a signal is either absent or present: Sensitivity is the ES pilot's ability to identify when weather is not suitable for flight. Figure 10 shows sensitivity (d') as the distance between the peak of the noise curve and the peak of the signal curve. A higher sensitivity is represented by a greater d' distance; having a higher sensitivity means there is less of a chance that noise will be misdiagnosed as a signal. For an ES pilot, a higher sensitivity means it is easier to make the correct decision to fly in marginal weather, as well as not to fly when conditions may be worse than what is represented on weather displays by METAR observations. The line of criterion represents the boundary that separates the decision-maker's response that a signal is either present or absent.

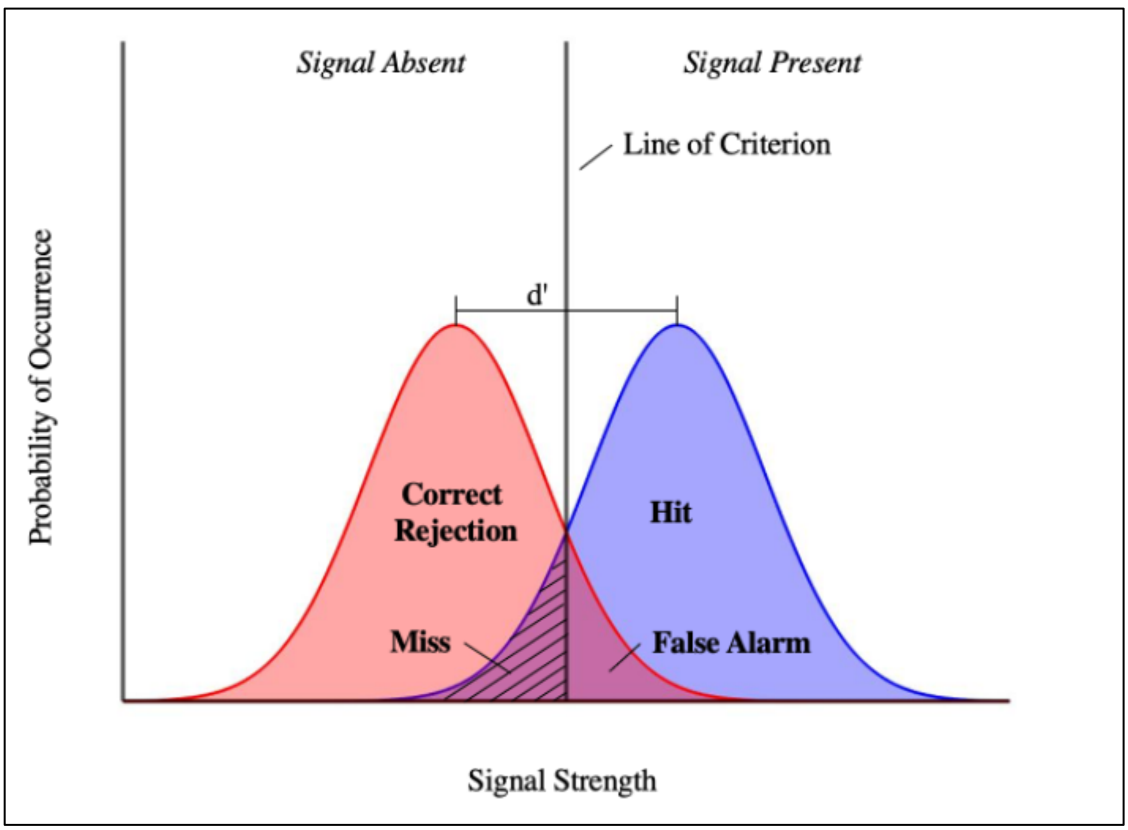

Figure 10. Signal Detection Theory curves with no bias, adapted from Lerman et al., 2010

As shown in Figure 11, decision makers have a bias (ß), which influences whether they are more likely to determine that a signal is absent (a conservative bias), or that a signal is present (a liberal bias). High external pressure to fly leaves ES pilots with a conservative decision bias, meaning that pilots are more likely to determine the unflyable weather signal is absent and that weather is suitable for flight. In a completely unbiased decision maker, the line of criterion is equidistant from the peak of the signal and noise curves. In a conservatively biased decision maker, the line is closer to the peak of the signal curve. The opposite is true for a liberal bias.

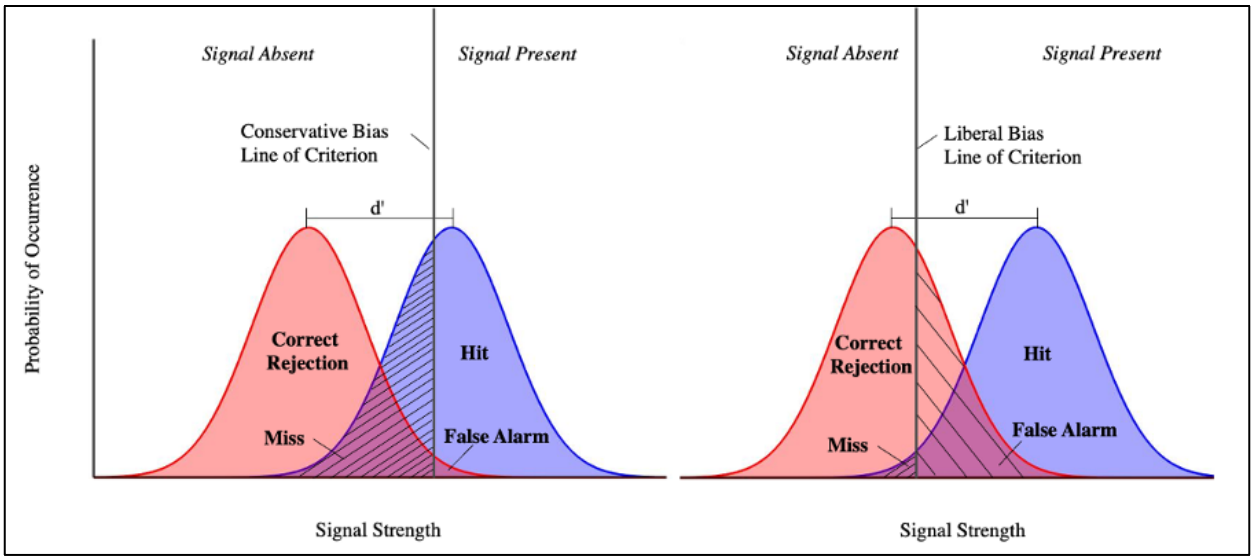

Figure 11. Signal Detection Theory curves with a conservative bias (left) and liberal bias (right), adapted from Lerman et al., 2010

Bias is influenced by the severity of the consequences for detecting or failing to detect a signal, as well as prior experience (Lerman et al., 2010). If failure to detect the signal presents a catastrophic consequence, then the decision maker will likely have a liberal bias. A liberally biased decision maker would rather determine a signal is present and be incorrect, than to incorrectly determine a signal is not present. Without indicating how risk is affected by incompletely represented or uncertain weather conditions, an ES pilot's decision bias is incorrectly calibrated. This type of incorrect calibration could produce the following error: a flight decision made using a weather display that perfectly (completely) represents conditions between weather stations would use the same criteria and bias as a flight decision made using a display where weather conditions between stations are hazardous and incompletely represented. A correct decision in the first scenario would be incorrect in the second.

Sensitivity is affected by factors that “change the amount of ambiguity in the stimulus situation” (Lerman et al., 2010, para. 6). Signal sensitivity is more easily visualized from the perspective of a pilot evaluating preflight weather conditions. A day with clear skies, 10 statute-miles of visibility, and no wind would have no “unflyable weather” signal. In essence, the weather is very clearly suitable for flight, and the pilot’s decision to fly is not difficult. The same is true for a pilot deciding to fly on a day with hurricane-force winds and IFR visibility. Here, it is obvious that weather conditions are unsuitable for flight, and the pilot’s decision is equally as easy to make. The pilot’s sensitivity to correctly assess the unflyable weather signal in both situations is high. The signal gets much more difficult to assess in circumstances where the reported (or observed) weather conditions are marginal, but nearby weather conditions are incompletely represented. Here, small changes in actual weather conditions can turn safe MVFR weather conditions into conditions that are no longer suitable for flight. If weather conditions are incompletely represented on a weather display, then these small changes in weather conditions may not be shown, making it difficult or impossible for the pilot to identify that weather is now unsuitable for flight. Thus, the pilot’s sensitivity to detect or assess the unflyable weather signal is further reduced.

Excluding ES pilots, the GA community generally flies in weather conditions where the unflyable weather signal is easy to assess (VFR conditions). There is no need for a GA pilot to risk flying in uncertain weather with so little reward. However, ES pilots are often required to fly in weather conditions or circumstances which cause the unflyable weather signal to be difficult to detect. This includes flight in marginal weather and in areas where weather conditions between weather stations are incompletely represented. Therefore, the ES pilot’s ability to assess weather-related risk, and to detect unflyable weather, is reduced.

There are four possible outcomes generated in SDT. The hit and correct rejection outcomes represent a correct decision, while the false alarm, also known as a Type I error, and miss or Type II error, represent an incorrect decision. Table 2 further details the outcomes of the SDT model and describes their relevance towards an ES pilot’s weather-related decision-making. For ES pilots, a correct “go” decision (correct rejection) is equally as important as a correct “no-go” decision (hit). Similarly, an incorrect “go” decision (miss, Type II error) can be just as harmful as an incorrect “no-go” decision (false alarm, Type I error). For the remainder of the GA community, there is little consequence for an incorrect "no-go" decision (Type I error), and little additional benefit for a correct "go" decision (correct rejection) in marginal weather.

Table 2. Signal Detection Theory outcomes for an ES pilot assessing weather for flight

SDT Outcome	Description	Relevance Towards ES Pilots
Decision-Maker: ES pilot **Signal:** Weather conditions that are unsuitable for flight		
Hit	There was a signal present, and the decision-maker detected the signal.	Non-flyable weather was detected, and **the correct "no-go" decision was made.**
Correct Rejection	There was not a signal present, and the decision-maker correctly identified the absence of a signal.	The pilot determined the weather was flyable and **the correct "go" decision was made.**
False Alarm (Type I Error)	There was not a signal present, but the decision-maker incorrectly identified that a signal was present.	The pilot incorrectly determined the weather was not suitable for flight and **the incorrect "no-go" decision was made.**
Miss (Type II Error)	There was a signal present, but the decision-maker failed to detect the signal.	The pilot incorrectly determined the weather was suitable for flight and **the incorrect "go" decision was made.**

A pilot assessing weather-related risk near weather stations reporting MVFR conditions must consider that (unreported) conditions in the vicinity may be IMC, but these IMC may not be represented on a weather display. A pilot who has successfully flown in marginal weather before would have a decision bias calibrated to accept that MVFR reported weather conditions are suitable for flight. Current weather displays do not provide pilots with an indication that unrepresented weather conditions may contain severe weather-related risks, nor do they indicate that weather conditions may be incompletely represented. Thus, if the same pilot were presented with another situation containing MVFR reported weather conditions, the weather display may look the same, but nearby conditions in the vicinity may be IMC and unflyable. The cognitive decision bias derived from the first scenario would provide an incorrect flight decision in the second. This would have caused an incorrect "go" decision to be made (Type II Error) and could have resulted in an unintended transition into IMC or an aviation accident. The opposite could also be true. A pilot who has correctly decided not to fly given MVFR reported conditions would be more biased to reject MVFR conditions as suitable for flight. If MVFR were being reported by a METAR and nearby conditions were being represented completely by the METAR observation, then conditions in the vicinity would have been MVFR and flyable. Thus, the pilot who rejects these conditions as suitable for flight would be making an incorrect “no-go” decision (Type I Error).

As previously noted, weather conditions in the vicinity of a weather station are more likely to be incompletely represented by a METAR observation if conditions in the vicinity are largely varied. Figure 12 shows the decision-making process for an ES pilot deciding whether or not to fly and demonstrates that, when weather conditions between weather stations have large variations, they may be incompletely represented by METAR observations. This can cause an ES pilot to decide to takeoff in weather that is unsuitable for flight (Type II Error), or to not fly when they could have (Type I Error).

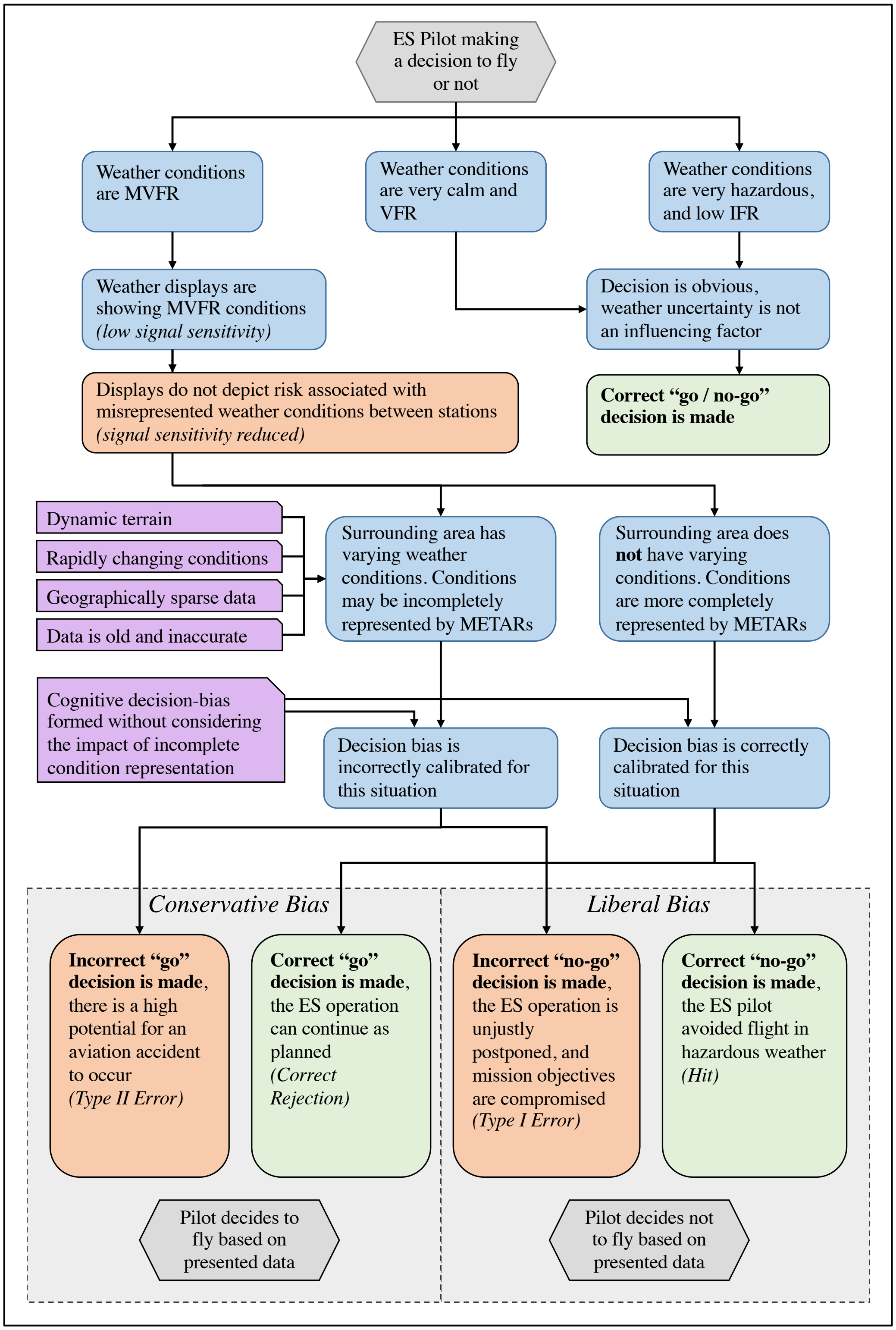

Figure 12. ES pilot flight decision diagram and SDT

4. METHODS

Incompletely represented weather conditions between weather stations can cause risk assessment to be difficult for pilots, leading to Type I and Type II errors. Though weather-related risk cannot be removed entirely from ES operations, improving an ES pilot's ability to identify weather-related risk would help ES pilots make safer and, when appropriate, more cautious flight decisions. The most severe consequences for an incorrect flight decision occur following an unintended transition into IMC, where the likelihood of aircraft accidents is higher. By depicting areas between weather stations where there is a high risk of transitioning from MVFR to IMC, Type I and Type II errors can be minimized where uncertainty about weather conditions is high.

To identify areas where there is a higher risk of a transition from MVFR into IMC, a method must first be established to identify where weather conditions between weather stations are likely to be incompletely represented on weather displays. If hazardous weather, including IMC, exists in these areas, then it may not be shown on a weather display, and the risks associated with that hazardous weather would not be obvious to a pilot. This research uses a K^{th} nearest neighbor (KNN) analysis, based off the methodology from the PEGASAS regional weather data correlation study, to numerically identify areas between weather stations where weather conditions have more variation. If weather conditions in the vicinity of a weather station have more variation, then the METAR observation at that station is more likely to incompletely represent those nearby weather conditions. The KNN analysis was performed on a small test set of 15 METAR observation stations in California. The intent of the analysis was to demonstrate the feasibility of the methodology using a real weather observation dataset. Once these areas have been identified, further evaluation can be used to determine areas where there is a higher risk of transitioning from MVFR and into IMC. This process is further detailed later.

4.1 Identifying Areas Where Weather Conditions are More Likely to be Incompletely Represented Using a KNN Analysis

The PEGASAS regional weather data correlation analysis demonstrated that variable weather conditions across a region can be identified by comparing weather station data. In the PEGASAS analysis, average monthly weather station variation trends were assessed over regions containing several weather observation stations. The KNN analysis used in this research assesses the completeness of weather condition representation between stations by comparing METAR observations. Weather condition representation is assessed over smaller geographic areas compared to those used in the PEGASAS study. In addition, the KNN analysis evaluates weather observations at a single instant in time, instead of evaluating average monthly trends.

The KNN analysis measures the distance, known as *KNN-distance*, between a selected point and its *K* nearest neighbors. Weather stations were given an *incomplete weather condition representation score* based on how well reported METAR observations represent nearby weather conditions. A higher incomplete weather condition representation score indicates that conditions in the area surrounding a weather station are more variable, and therefore the METAR observation at that station is more likely to incompletely represent weather conditions in the surrounding area. For this analysis, *K* was chosen to be three, meaning that a weather station's score was calculated by comparing its own observation to those of its three nearest neighbors. The *nearest neighbors* were the three closest weather stations to the station being evaluated, as measured by the KNN-distance. The KNN-distance is not simply a measure of geographic distance between weather stations; in some cases, geographic distance may not recognize differences in climate zones or intervening terrain variations between stations. Instead, KNN-distance was a function of similarity in a weather station's observed conditions and relative geographic distance from one station to its nearest neighbors. The method to calculate KNN-distance is further detailed below.

The KNN analysis demonstrates the process to gather, classify, and analyze weather observation data to numerically identify areas where weather conditions between stations are more likely to be incompletely represented by METAR data. For simplicity, and to more easily visually depict how incomplete representation is communicated to pilots, the KNN method considered only visual depiction status and geographic distance between weather stations as input parameters. The observation stations used in the analysis are shown on a visual depiction map in Figure 13. Each weather station was given a weather condition score based on the reported condition on the visual depiction map. VFR conditions were given a score of 1, MVFR a score of 2, IFR a score of 3, and low IFR a score of 4. As a note, an example flight profile from KBUR to KSBD is later examined to identify the applications of these technologies. This shown by the cyan line.

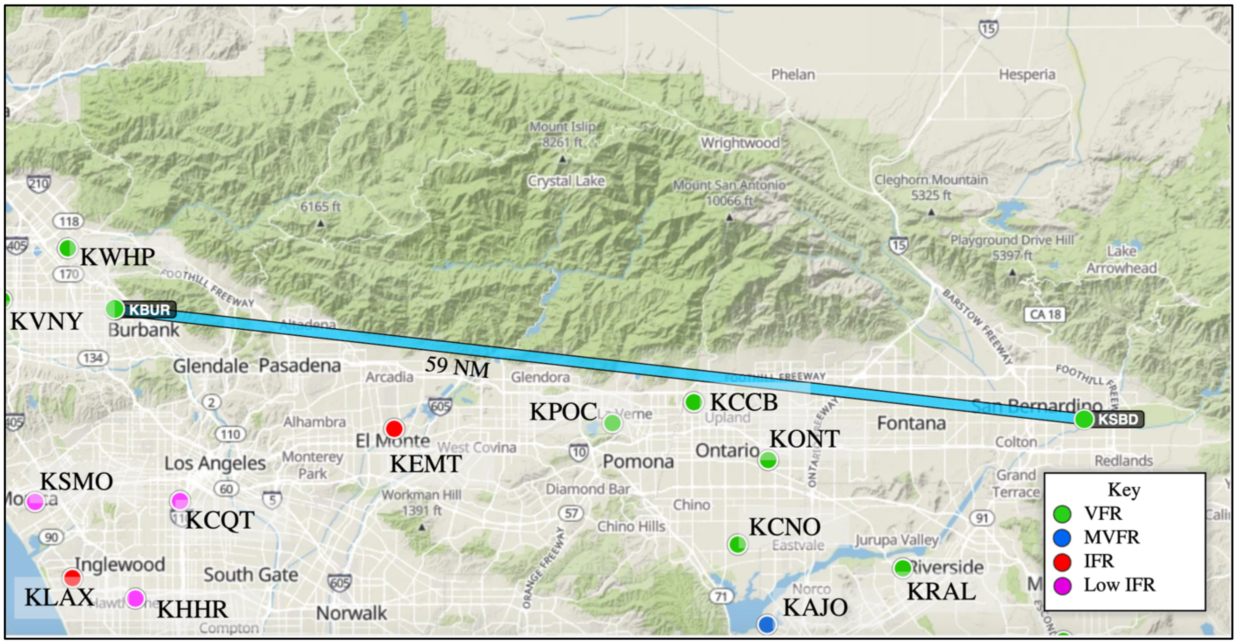

Figure 13. California weather stations used in the KNN analysis. Visual depiction map created using ForeFlight

Next, 15 scatter plots were created, one for each weather station. For each scatter plot, one station was chosen to be evaluated to determine if nearby weather conditions had large amounts of variation. The station chosen to be evaluated is referred to as the *station of evaluation*. The amount of variation in weather conditions between weather stations was evaluated by comparing METAR data and distances between the station of evaluation and its nearest neighbors. The scatter plot coordinates were generated as follows: the geographic distance from each point to the station of evaluation was represented on the x-axis, and the numerical score representing weather condition was on the y-axis. Two of the 15 scatter plots created are shown in Figure 14, one with respect to KWHP and one with respect to KEMT. On each plot, the station of evaluation is shown as an orange dot.

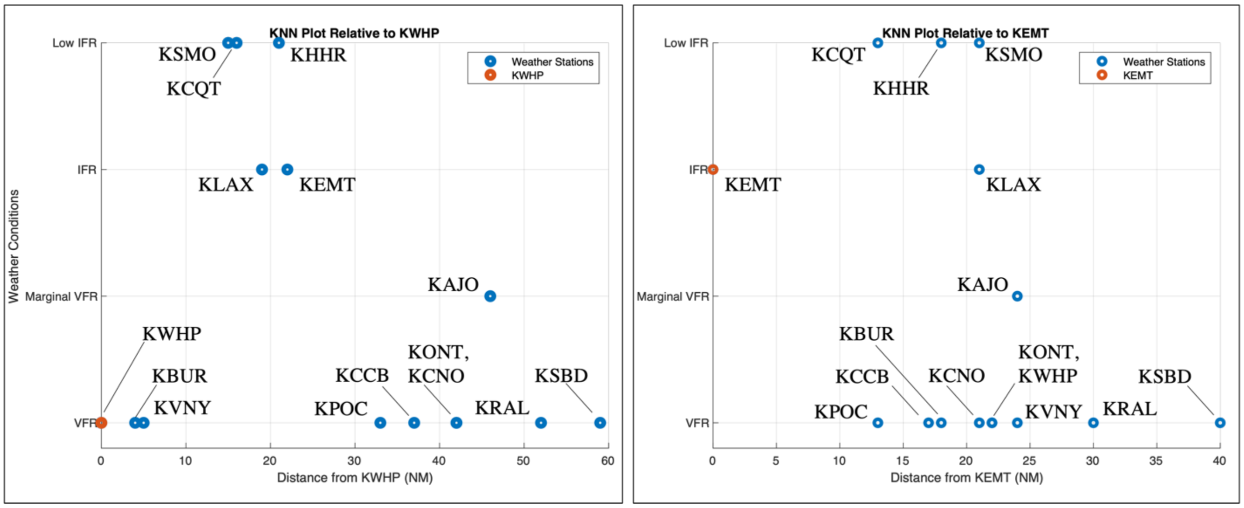

Figure 14. Scatter plot of distances from the *station of evaluation* (shown by an orange dot) vs. weather conditions observed. Distances are relative to KWHP (left) and relative to KEMT (right)

Using the scatter plots, the KNN analysis was performed to evaluate if weather conditions between the station of evaluation and nearby weather stations had large variations. If weather conditions surrounding the station of evaluation were largely varied, then it is likely that the METAR observation at that station does not completely represent weather conditions in the surrounding area. Figure 15 shows how the KNN-distance is calculated using the relative geographic distance from the station of evaluation and the weather condition score: Relative geographic distance is the x-component of the KNN-distance and the difference (Δ) in weather station score is the y-component. For the KNN method to more accurately predict where conditions between weather stations were more variable, the x-axis and y-axis had to be scaled such that KNN-distance was more heavily dependent on the difference in weather condition score than on relative geographic distance. To do this, both the x-axis and y-axis were normalized, and an empirically derived distance-coefficient (γ) was multiplied to the relative geographic distance. Equation 1 shows how the KNN-distance was calculated using the distance-coefficient.

$$KNN\ distance = \sqrt{(\Delta\ weather\ condition\ score)^2 + (\gamma * relative\ distance)^2} \qquad (1)$$

$$*\ Weather\ condition\ score\ and\ relative\ distance\ are\ normalized\ in\ the\ equation$$

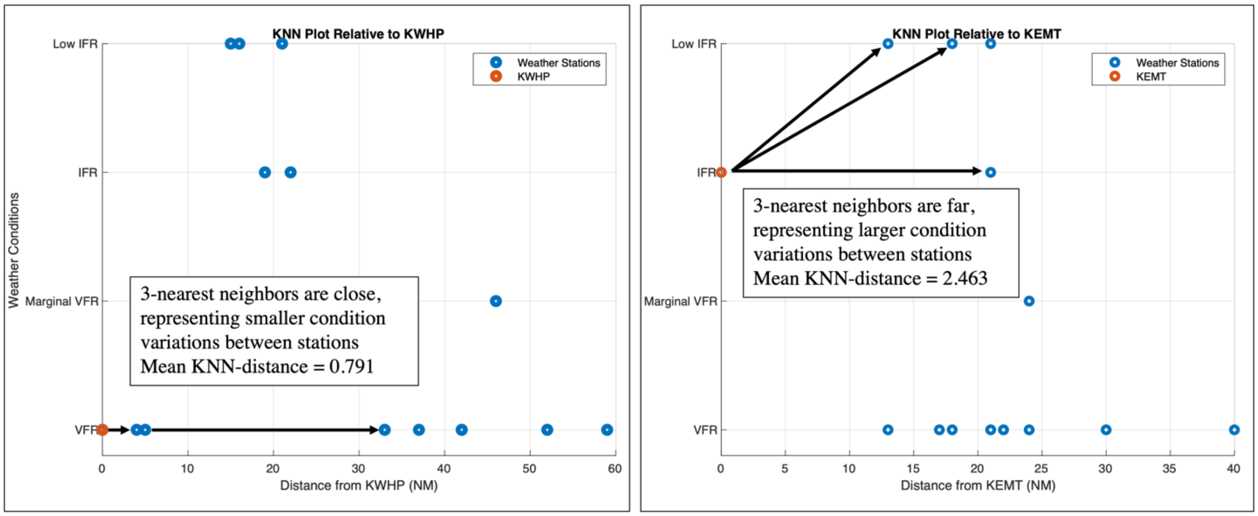

Figure 15. Mean KNN-distance depiction relative to KWHP (left) and relative to KEMT (right). Distances used in KNN-distance calculations were scaled according to equation 1

The mean KNN-distance was calculated for each of the 15 weather stations, producing an weather condition incompleteness representation score for each. A high score indicates that weather conditions in the vicinity of the station of evaluation are more likely to be incompletely represented by the station's METAR observation. The 15 scores were normalized and compared, and are shown in Figure 16. In Figure 16, those weather stations whose nearby observations differ from their own have a higher score. For example, KEMT has a high weather condition incompleteness representation score. This is justified in Figure 13; KEMT is depicting IFR but is surrounded by stations depicting VFR and low IFR conditions. KEMT is also more geographically distant from its nearest neighbors. Because weather conditions between KEMT and its nearest neighbors differ, weather conditions surrounding KEMT likely have more variation, and those varied weather conditions are more likely to be incompletely represented by the METAR at KEMT.

By contrast, KWHP has a low weather condition representation score. Again, this value is illustrated in Figure 13, as KWHP and its nearest neighbors are each depicting VFR conditions: The weather conditions surrounding KWHP are relatively consistent, and the METAR observation at KWHP represents the actual weather conditions in the vicinity with reasonable completeness. It should be noted that there are nearby weather stations located south of the region depicted in Figure 13. If these weather stations were included in the KNN analysis, KAJO would have had closer nearest neighbors, and would have had a lower incomplete weather condition representation score.

This issue was specific the boundaries of this analysis, and the problem would not persist if the analysis were performed on a larger scale.

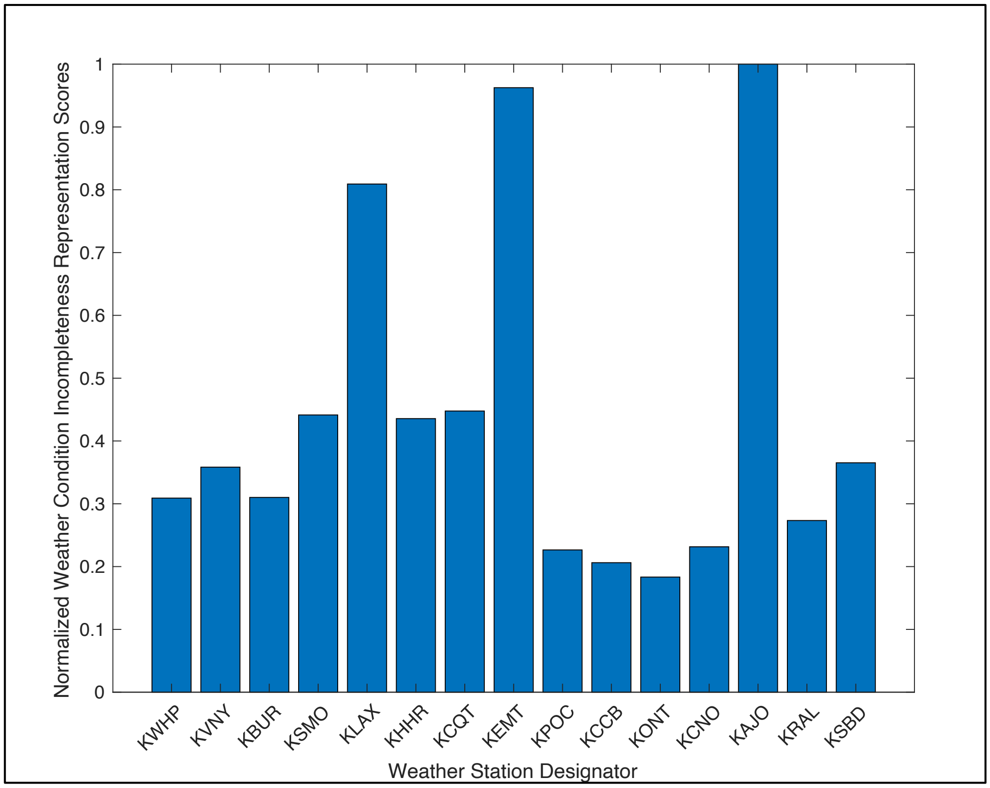

Figure 16. Normalized weather condition incompleteness representation scores

The KNN analysis numerically identified weather stations whose METAR observations were less likely to completely represent weather conditions in the vicinity. This was done using two input parameters: visual depiction status and relative distance. This two-dimensional KNN analysis was relatively simplistic. However, should machine learning (ML) be used to expedite the analysis process, the number of input parameters that could be included in calculations, as well as the number of stations and KNN comparisons could be expanded for any given time period. Consider how the KNN-distance would be calculated if temperature were also considered. A third axis would be added to the scatter plot to represent each weather station's temperature. Now, the KNN-distance would be calculated using three parameters: visual depiction status, relative distance, and temperature. Should other observed weather parameters such as wind, precipitation, visibility, cloud coverage, cloud types, icing, fog, humidity, and pressure be used as inputs, additional axes would be added for each input. By considering additional components of an observation station's METAR data, the KNN-distance calculation could evaluate weather condition variation between stations using a wider variety of parameters. This would allow for a more accurate evaluation of weather condition variation between the station of evaluation and its neighbors. Therefore, the KNN-score would more accurately reflect how a METAR observation represents weather conditions in the vicinity of the station.

Considering time-dependent inputs in the KNN analysis would better reflect how weather condition representation on weather displays can become more incomplete over time. METAR stations report conditions hourly, and stations report observations at the same minute of the hour. This means that all weather stations would have the same age-of-data value, so a traditional KNN approach would not consider this parameter in assessing weather information representation. However, an age-of-data coefficient could be used as a situational factor to adjust the final KNN-distance answer (say, if additional METARs from other sensors are included, or a weather station's METAR reporting is compromised). Data that is older would have a higher age-of-data coefficient, resulting in a larger KNN-distance and indicating that weather conditions between stations are more likely to be incompletely represented. Results from the PEGASAS weather data correlation study showed that certain months have greater weather condition variations within the same geographic area than others. A seasonal parameter could be used to reflect these differences. In a similar way, a time-of-day parameter could be included if average weather condition variability were higher during specific periods of the day (daytime, nighttime, dusk, dawn, etc.).

The ML algorithm would be trained using a supervised approach, meaning that the algorithm would be presented with labeled datasets, which allows the model to learn and become more accurate over time (Brown, 2021). These labeled datasets would be presented as a map containing weather stations and their respective METAR data. The data can be visualized as a multivariate scatter plot, similar to what is shown in Figure 15. Areas where weather condition variation is high between stations would be manually labeled, and the ML algorithm would begin identifying patterns that can predict these areas in the labeled datasets. As the algorithm is trained, new relationships may be identified. Just as the relative distance was given an empirically derived distance-coefficient (γ) in the two-dimensional KNN approach, each parameter added to the multivariate KNN analysis would also be given its own coefficient. The ML algorithm could manipulate these coefficients as it identifies that certain parameters are more indicative of incomplete weather condition representation than others. Some parameters may not be used at all, due to relative insensitivity of those parameters in determining variations in weather conditions due to terrain, climate zone, or other effects. After being sufficiently trained, new datasets could be analyzed by the algorithm to test the fidelity of the model and show that the algorithm can consistently and accurately identify areas where weather conditions between stations are highly variable and are therefore likely to be incompletely represented at a particular time (and thus of real-time value to ES pilots). As PIREPs, AMDAR data, and data from weather observations drones are collected, these data could also be used as input parameters.

4.2 Identifying and Depicting Areas with a High Risk of MVFR to IMC Transition

Further analysis is needed before areas with an increased risk of an MVFR to IMC transition can be identified. It is not sufficient to simply note that a METAR observation may incompletely represent weather conditions in the vicinity. A pilot may wonder, how close to or how far from the weather station are conditions completely represented? The answer to this question would be specific to the time, location, local geography, and meteorological dynamics of each weather station. Thus, this research does not seek to answer this question specifically. Instead, this research identifies regions where weather conditions may be incompletely represented by using weather stations as the vertices of polygonal areas. By doing so, each area could be given a regional condition representation incompleteness score based on the KNN-distance calculations. This process is demonstrated in Figure 17, using triangular sections. The process to calculate each section's score is as follows: Each side of the triangle would be given a station-to-station weather condition incompleteness representation score, equivalent to the KNN-distance between the two stations. By calculating the mean score of all the sides of the triangle, an weather condition incompleteness representation score can be assigned to the entire area. A higher mean score indicates that weather conditions in the area are more likely to be incompletely represented by the available METAR observations. Notably, this also indicates that a pilot would be less accurately certain about weather conditions in the area when assessing safety for flight.

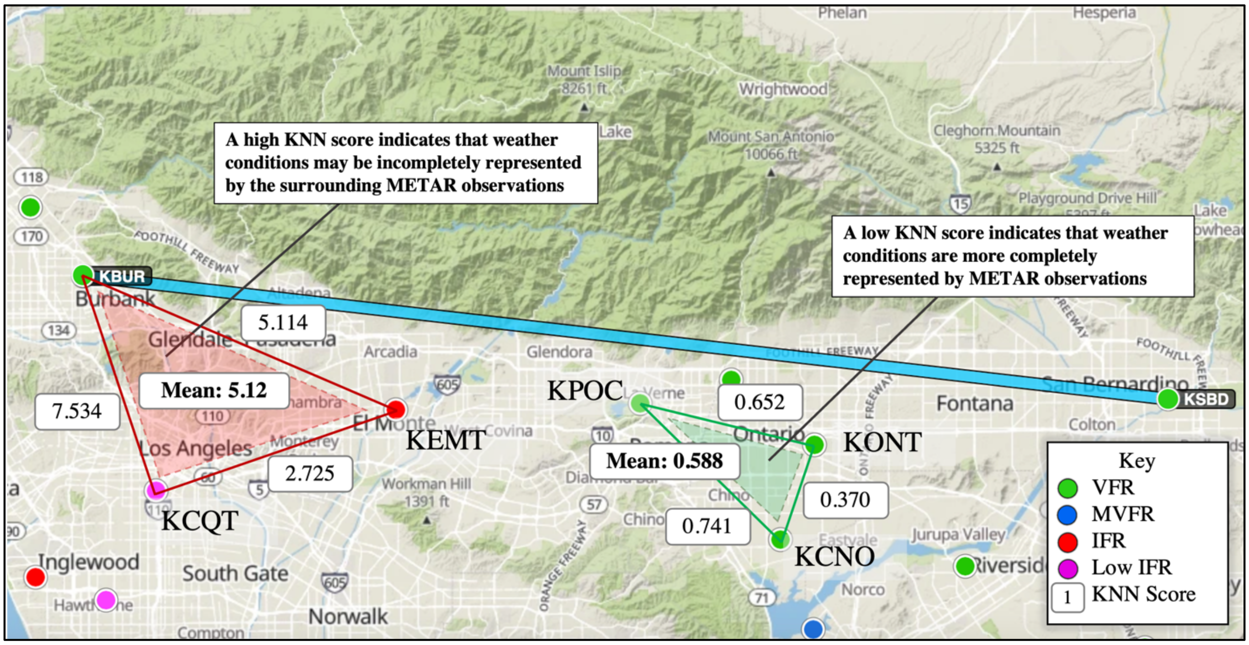

Figure 17. Identifying areas where weather conditions are incompletely represented using KNN scores. Visual depiction map generated using ForeFlight

Larger differences in observed weather conditions, greater terrain / climate zone variability, and greater geographic distance between stations increases station-to-station scores. For example, in Figure 17, the score between KCQT and KBUR is the highest (7.534) because these two stations have the highest possible difference in weather conditions (one is VFR and the other is low IFR), and because they are also moderately geographically spaced apart. Alternatively, the score between KONT and KCNO is the lowest (0.370), because their reported weather conditions are the same and they are geographically close to one another.

A flight through the red-shaded area in Figure 17 would be more likely to encounter hazardous weather that is not directly depicted by the METAR observations. Oppositely, a flight through the green-shaded area in Figure 17 is likely to encounter weather conditions similar to what is depicted by the surrounding METAR stations. This is a critical difference; A pilot could underestimate weather-related risk within the red-shaded area if they were too heavily focused on the VFR METAR observation at KBUR. However, weather-related risk can be correctly assessed using any of the METARs observed at the weather stations forming the green-shaded triangle.

The final step in this analysis is to identify areas where incompletely represented weather conditions could cause an unintended transition into IMC to occur. This can be done by evaluating how weather conditions within a region change from one vertex to another. If the METAR observation at one vertex of a triangle is reporting MVFR conditions, and another vertex is reporting IFR, it is reasonable to assume that somewhere between the two, a point exists where weather conditions transition from MVFR to IMC. This is known as crossing the *MVFR to IMC boundary*. It can also be assumed that this boundary is crossed if one station is reporting VFR, and another is reporting low IFR.

There are two criteria used to identify areas where there is a high risk of MVFR to IMC transition: (1) Weather conditions within an area are at risk of being incompletely represented by available METAR observations, and (2) weather conditions between two of the vertices of the area logically indicate crossing the MVFR to IMC boundary. By identifying that the MVFR to IMC boundary is crossed in an area where weather conditions may be incompletely represented, one can identify where IMC may exist near a weather station, but may not be represented by that weather station's METAR observation. This is critical: because those IMC are not represented by the nearby METAR, a pilot making a decision to fly using that METAR would have a high risk of unintentionally transitioning into IMC.

Figure 18 demonstrates the process to evaluate if areas contain a high risk of an MVFR to IMC transition. In Figure 18, the red-shaded triangle has two sides that cross the MVFR to IMC boundary. The upper right side of the red-shaded triangle transitions from VFR to IFR conditions, while the lower left side transitions from VFR to low IFR conditions. In contrast, the yellow-shaded triangle does not cross the MVFR to IMC boundary, and the green-shaded triangle does not cross the MVFR to IMC boundary, nor are the weather conditions in the area likely to be incompletely represented by the available METAR observations.

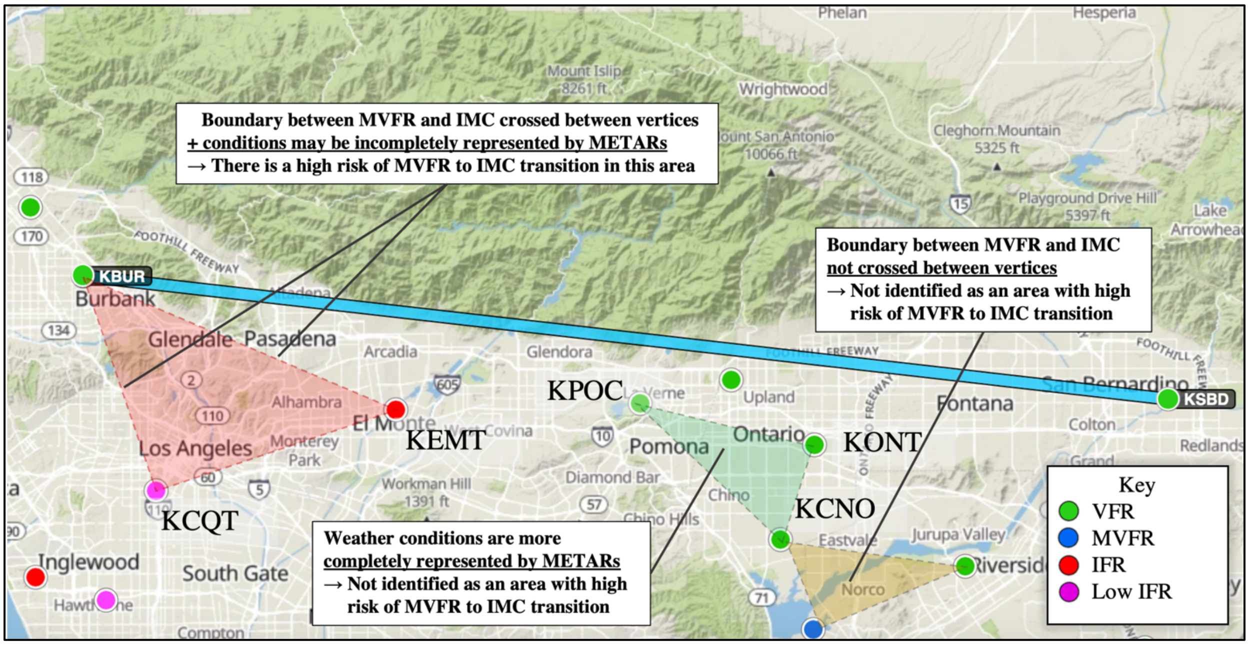

Figure 18. Depicting areas where there is a high risk of transitioning into IMC. Visual depiction map created using ForeFlight

There are three primary reasons why the KNN analysis was chosen as the method to evaluate where high-risk MVFR to IMC transition areas exist. First, as shown in Figures 16 and 17, the KNN analysis provides a method to quantitatively evaluate weather condition variation within regions surrounded by several weather stations, which in turn allows weather condition representation to be numerically analyzed. Second, the distance equation can be modified to accommodate as many additional parameters as needed. Equation 1 uses a Euclidean distance to calculate KNN-distance. If additional parameters were included, the distance could be calculated in higher dimensions. Finally, each parameter can be scaled within KNN-distance calculations according to how greatly it is associated with weather condition variation (and incomplete representation on a weather display). This would be done by using a multiplicative coefficient for each parameter in the KNN-distance equation. Equation 1 demonstrates how the multiplicative distance-coefficient (γ) is used to scale the geographic distance parameter in the KNN-distance calculation.

Once areas are identified where there is a high risk of transitioning from MVFR and into IMC, they must be depicted on weather displays in a manner that does not restrict a pilot's ability to interpret other information. ES pilots have a higher task-load than other GA pilots and have reduced mental capacity available for interpretation and decision making regarding weather data presentation. It is therefore critical that the presentation of this information is easily disseminated and is not cognitively intensive. One study identified several ergonomic principles that graphic weather data presentations can use to make comprehension and interpretation easier. These principles include making critical information the most apparent, representing data visually, using color-coding, reducing visual noise, using redundancy to reinforce critical messages, and keeping displays consistent (O'Hare & Stenhouse, 2008). Table 3 lists each of these ergonomic principles and identifies how they can be used to depict these areas on a pilot weather display.

Table 3. Ergonomic principles to consider when depicting areas where there is a high risk of transitioning into IMC on pilot weather displays, adapted from O'Hare, 2008

Ergonomic Principle	Use in Depicting Areas Where There is a High Risk of Transitioning into IMC
Make critical information the most apparent	• Areas of with a high risk of MVFR to IMC transition would be depicted using bright red shading on weather displays. • A notification box would also indicate these areas. • Text alerts could flash to draw the attention of the pilot.
Represent data visually, use color-coding, and reduce visual noise	• The color of the shading could correspond to the severity of the risk. Bright reds would indicate areas with higher risk, while yellows could indicate areas with mild risk. • Unnecessary data would be hidden so that the display is not crowded. • Pilots would have the ability to hide shaded areas to declutter the map.
Use redundancy to reinforce critical messages	• Areas with a high risk of MVFR to IMC transition would be shaded in bright red on the map. • Text warning messages would also be displayed near high-risk areas to add redundancy.
Keep displays consistent	• The text color of alerts would keep consistent with other aviation presentation systems. Critical information would be displayed in red text, non-critical cautionary messages would be displayed in yellow text, and other non-critical information would be displayed in black text. • The "declutter" feature would function like other aviation weather displays: pilots could declutter a display in one motion (a key stroke, or a turn of a menu dial). This is considered a safety feature, so that unnecessary information can be hidden in emergency situations.

4.3 **Verification Methods for the KNN Analysis**

The KNN analysis should be examined to verify that the model can predict with reasonable accuracy areas where IMC may exist. Generally speaking, if an area is identified as having a high risk of an MVFR to IMC transition, one would expect that IMC would be frequently observed by METAR observations in that area (a METAR in that area would be reporting IFR or low IFR conditions). Similarly, if another region is identified as not having a high risk of an MVFR to IMC transition, one would expect not to see IMC observed in that area (VFR or MVFR conditions would be reported).

The KNN analysis identifies that there is a risk of an IMC transition across a region by evaluating where unrepresented IMC may exist. It does not suggest that *all* areas of that region will contain IMC. Therefore, it is possible that a weather station could be reporting MVFR conditions yet be located in an area which is identified as a high-risk IMC transition area. However, by conducting a statistically significant number of verification tests, one could identify if high-risk IMC transition areas frequently contain IMC observations within the region.

Figure 19 demonstrates the method to conduct such verification tests. In this method, a KNN analysis was performed over two regions. Within each region, one METAR observation datapoint was excluded from the dataset. The first region (shown by a red triangle in Figure 19) included KBUR, KEMT, and KHHR. The first region excluded the METAR observation at KCQT. The second region (shown by a green triangle in Figure 19) included KPOC, KCNO, and KSBD, and excluded the METAR observation at KONT. In Figure 19, KCQT (the excluded datapoint in region 1) is reporting low IFR conditions and is located within a region identified as having unrepresented IMC. The KCQT METAR was not included in the regional KNN calculation, but the low-IFR observation supports the claim that unrepresented IMC exists in this region. A similar but opposite case is shown in the second region. In Figure 19, KONT (the excluded datapoint in region 2) is reporting VFR conditions and is located in a region identified as not having unrepresented IMC. The VFR METAR observation at KONT supports the claim that unrepresented IMC does not exist in this region.

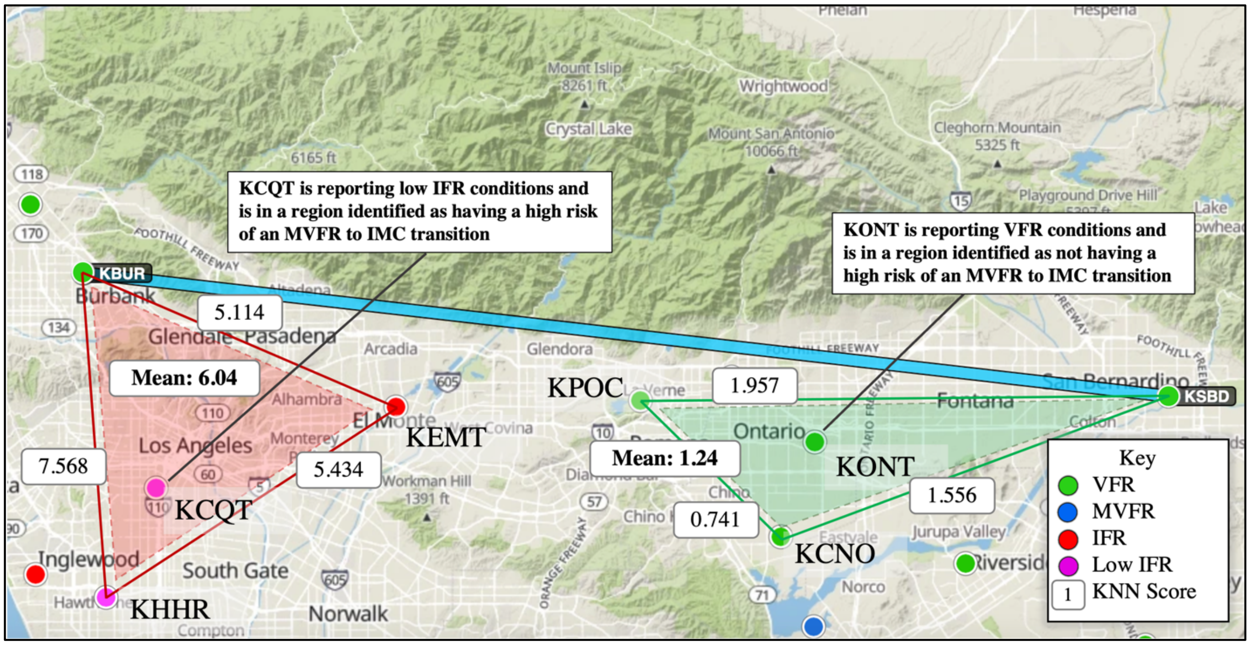

Figure 19. KCQT and KONT are excluded in KNN analysis calculations during verification testing. Visual depiction map created using ForeFlight

There are other weather observation data that could be used in verification analyses. FAA-certified observation data such as PIREPs or AMDAR reports could be used in place of the excluded METAR observation datapoints. Also, weather data gathered through drones or other weather observation datasets (such as MesoNet reports) could be used. Both the agriculture industry and energy providers have weather observation networks to monitor local weather conditions. It is not recommended by the FAA to use non-certified weather observations to make tactical piloting decisions, as these observations are not as strictly standardized as those available on the AWC. However, these observations could still serve as a useful tool during the KNN model verification process.

4.4 Introducing Additional Weather Observations to the Dataset to Improve Weather Condition Representation

As demonstrated in the KNN analysis, an increased geographical distance or terrain variability between weather stations increases the chances that weather conditions are more variable between observed conditions at those weather stations. This increases the chances that a METAR observation incompletely represents conditions in the surrounding area. By reducing the geographic distance between weather observations, risk of variability regarding weather conditions can be more completely represented, and uncertainty about weather conditions can be reduced. When provided with additional weather observations, as well as a display that shows regions where there is a high risk of transitioning into IMC, an ES pilot performing LAO in marginal weather would have an improved ability to assess weather-related risk.

Three emerging technologies are noted here as mechanisms to provide additional weather observations to ES pilots: hands-minimized PIREP submission software, AMDAR reporting technology, and weather observation drones. Each of these technologies could be enhanced by the promised improvements of a 5G network. However, there are perceived challenges associated with the rollout of 5G networks and their interaction with aircraft systems. These challenges must first be discussed so that realistic applications of a 5G network can be proposed.

In 2021, the Federal Communications Commission granted mobile wireless industries the authorization to utilize the radio spectrum ranging from 3.7 to 3.98 Gigahertz (Rogers, 2022), known as the *C-Band* (APLA, 2022). By using the C-Band to provide wireless services, companies can provide customers with faster wireless internet upload and download speeds, at higher resolutions, and with better coverage across more areas of the United States. The mobile wireless service network utilizing the C-Band is more commonly referred to as a 5th Generation (5G) network.

Compared to radio spectrum ranges used in previous generations of cellular networks, the frequency spectrum of 5G networks is much closer to the frequencies used in aircraft radar altimeters (NBAA, 2022). The FAA and others in the aviation industry are concerned that C-Band signals used in 5G networks could interfere with radar altimeters used in commercial aircraft, causing erroneous altitude readings (APLA, 2022). This is problematic, as data from radar altimeters are integrated into the landing capabilities of commercial aircraft (APLA, 2022). The overwhelming concern among FAA officials is that 5G networks will cause inaccurate radar altimeter readings in a commercial aircraft, interfere with landing equipment or altitude-based landing systems operations, and cause an aviation accident.

The FAA has proactively taken several steps to mitigate signal interference issues caused by 5G networks. First, the full rollout of 5G networks using the C-Band has been delayed until it can be shown that C-Band signals will not interfere with aviation systems (APLA, 2022). Also, 5G transmitters within 2 nm of an airport runway will not be turned on for a period of time (APLA, 2022). Furthermore, 5G transmitters near over 50 airports will be operating at a reduced power until July of 2022 (APLA, 2022).

Fortunately, there is some evidence supporting that 5G networks and aviation systems can exist together without complication. In a statement, the FAA reported that two radar altimeters common to a variety of Boeing planes have been approved for use in areas with 5G network transmission (Rogers, 2022). In addition, GA aircraft do not have the same complex landing systems that large commercial aviation aircraft have. Thus, GA aircraft typically do not require radar altimeters to initiate or inform landing systems and landing capabilities in GA aircraft will likely not be inhibited by 5G signal interference. Furthermore, ES operations typically occur further than 2 nm from airports, beyond the area where 5G transmitters will not be turned on.

Financial investments for 5G network development and infrastructure have been a significant emphasis for the mobile wireless industry. There is a substantial amount of pressure to push the FAA to find aviation solutions so that 5G networks can be rolled out in their entirety. Because of this, it is reasonable to assume that the FAA will eventually find solutions, countermeasures, or mitigations to persisting C-Band signal interference issues. Even if 5G networks were to rollout with some of the existing restrictions still imposed, such as 2 nm no-transmission zones near airports, there would be less of an effect on remote ES operations. This research assumes that 5G networks will eventually rollout and be usable to support ES operations. Due to the criticality of radar altimeter signal interference issues, this research does not recommend any 5G applications that directly require 5G network transmission within 2 nm of an airport.

The improved capabilities of a 5G network enable certain weather observation reporting technologies to be used to an extent beyond that which was previously possible. 5G networks offer higher bandwidth and faster data transmission rates. This means that more information can be transmitted to, from, and between aircraft and ground-stations. This information can include PIREPs and AMDAR reports. The hands-minimized PIREP submission software, developed by the PEGASAS team, demonstrated that pilot reporting via radio can be autonomously translated into PIREPs using ML techniques. However, analyzing all pilot radio chatter, converting relevant weather reporting data into PIREPs, and uploading PIREP data to the weather observation dataset would require significant data transmission. The anticipated capabilities of a 5G network would allow for a larger amount of communication data to be analyzed, turned into PIREPs, and uploaded through network transmission. Similarly, the frequency at which AMDAR data is reported could be increased with improved network bandwidth. Currently, AMDAR data is reported at a frequency of every 6 seconds in the first 90 seconds after takeoff, every 20 to 60 seconds during decent, and every 3 to 7 minutes during cruising ("Aircraft Meteorological Data Relay", n.d.). It is proposed that a 5G network would be able to support AMDAR reports at consistent intervals of 6 seconds throughout the flight.

Introducing both PIREPs and AMDAR data into a weather observation dataset allows for a wider variety of meteorological phenomenon to be represented. AMDAR data is gathered via atmospheric sensors mounted on an aircraft. Weather data such as temperature, wind, and pressure can be reported with relatively high accuracy. Certain weather phenomena can also be more specifically reported through PIREPS, because they require additional pilot interpretation to be identified. These phenomena can include volcanic ash, wave turbulence, or icing ("Aircraft Meteorological Data Relay", n.d.).

PIREPs and AMDAR reports both require aircraft to be flying when observations are taken. Unfortunately, this means that these types of observations provide little benefit during prefight weather assessment. However, a drone outfitted with weather observation capabilities could be deployed during preflight assessment to gather additional weather observations. There is significantly less financial, operational, and human risk associated with flying drones in marginal weather. Unlike other aircraft, no people are harmed if a drone crashes during a preflight assessment. Drones can also be flown at very low altitudes, and in areas where low-altitude flight is otherwise too hazardous for crewed aircraft. If weather observations are needed with reduced geographic separation, or within a region of high terrain variability, a swarm of drones could be deployed to gather an array of low-altitude weather observations. Controlling a drone swarm and transmitting weather observations would require substantial network bandwidth. A 5G network has the capability to handle such transmission rates (Sunil et al., 2020), allowing drone swarms to be used to report weather observations.

5. RECOMMENDATIONS AND ANALYSIS

Depicting areas on a weather display where a pilot would have a high risk of an MVFR to IMC transition would improve an ES pilot's sensitivity to detect weather-related risk. Providing additional weather observations through PIREPs, AMDAR reports, and a swarm of weather observation drones would improve weather condition representation between existing weather stations, decrease uncertainty about potentially dangerous variability in weather conditions, and increase the "unflyable weather" signal strength. The combination of these technologies would help ES pilots perform more accurate weather assessment, allowing them to execute ES operations more confidently in marginal weather.

5.1 Primary Technology Application: ES Low-Altitude Operations

The primary application of the proposed technologies includes any ES mission flying LAO, in marginal weather conditions, near variable terrain, and with access to a 5G network. As mentioned, this does not include 5G network use within 2 nm of an airport, due to concerns with C-Band signal interference issues. To examine how using these technologies would benefit ES pilot decision-making, a demonstrative SAR operation near Bob Hope Airport (KBUR) in California is proposed, and the advantages of using a weather display that depicts areas where there is an increased risk of MVFR to IMC transition are detailed. Although this SAR operation is fictitious, it is plausible in its nature. Figure 20 shows an event and decision-flow diagram of the SAR operation and identifies how decision-making can be improved in the scenario by using these technologies.

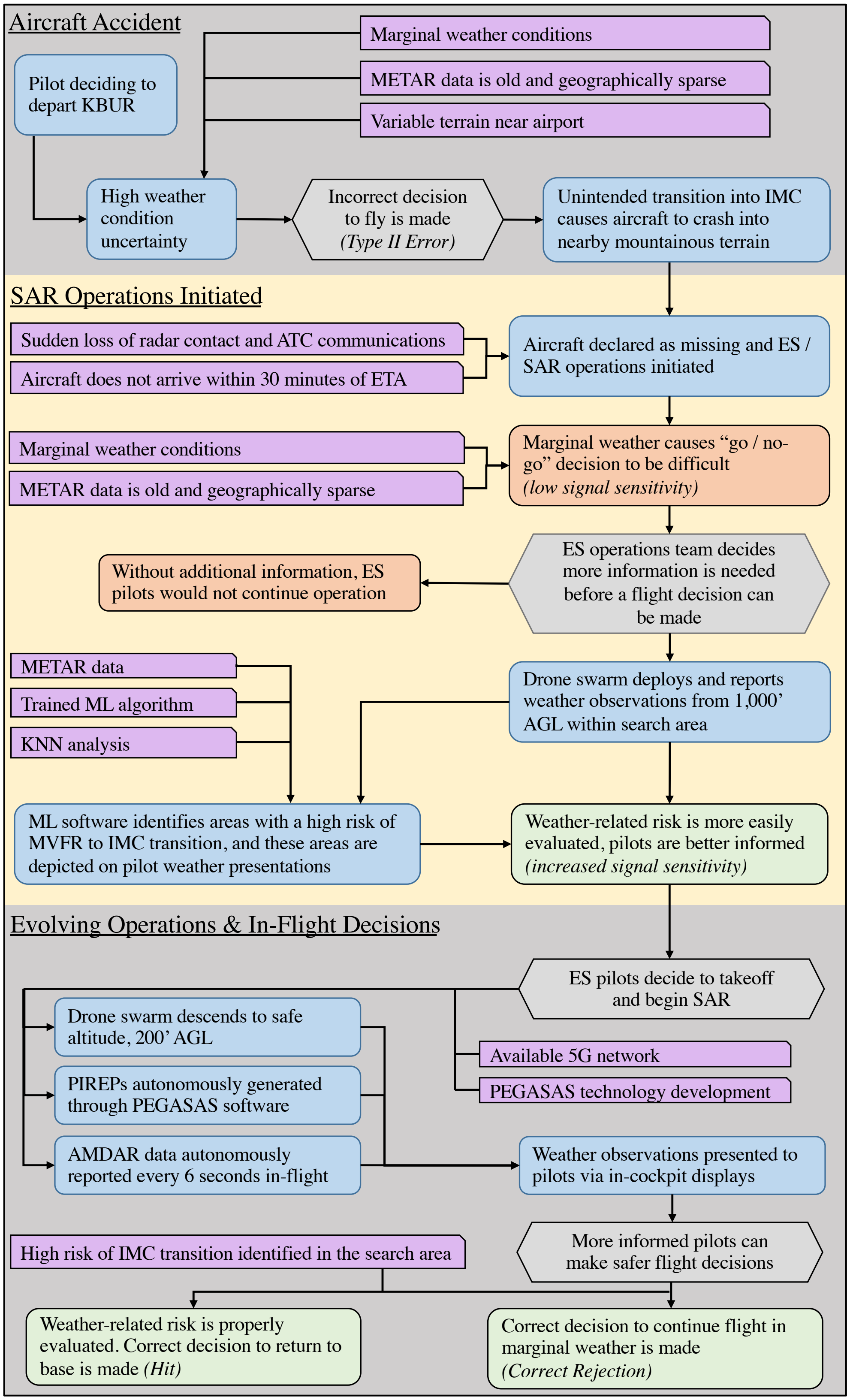

Figure 20. Event and decision-flow diagram for an example SAR operation

Consider a VFR pilot departing KBUR with the intent of flying to San Bernardino Airport (KSBD). As shown by the visual depiction map in Figure 21, KBUR and KSBD are reporting VFR conditions at the time of departure. Based on these weather observations, the pilot determines that weather conditions are safe for flight. However, weather conditions between the weather observation stations are incompletely represented by the METAR observations at KBUR and KSBD, and IMC exists between KBUR and KSBD. Shortly after taking off, the VFR pilot inadvertently transitions into IMC. Because the pilot does not have IFR training, they have trouble keeping the correct heading without a visual reference available. The pilot unintentionally veers northward, toward the peak of Mount Bliss (3,678' mean sea-level). Before the pilot can realize their mistake, they lose control and collide into the terrain. After the aircraft fails to arrive at their destination within 30 minutes of their ETA, a SAR is initiated to find the missing pilot and crew. Figure 21 displays the flight path on a visual depiction map, along with the area where there was an increased risk of transitioning from MVFR into IMC.

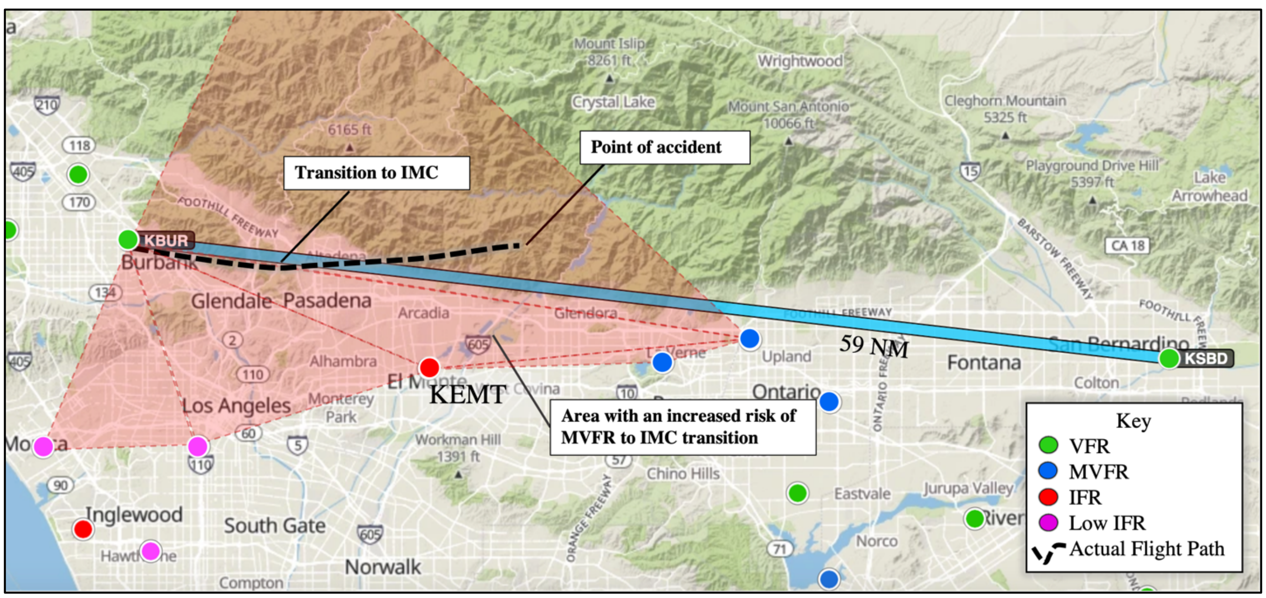

Figure 21. Demonstrative flight profile from KBUR to KSBD, including areas with an increased risk of MVFR to IMC transition. Visual depiction map created using ForeFlight

Unfortunately for the downed pilot, the aircraft did not contain an ELT, but ES operators determine that the accident most likely occurred somewhere in the mountains north of KEMT. By the time the search is started, METAR observations at KEMT are reporting marginal weather. Mountains in the search area present ES pilots with a high risk of accidental controlled flight into terrain. ES pilots deciding to takeoff must weigh the risk of flying in marginal weather near hazardous terrain, with the reward of potentially saving the lives of the pilot and crew of the downed aircraft. The hazardous terrain and low-altitude search profiles leaves little room for corrective action in the event of aircraft mechanical failure or pilot error. Temperatures outside are moderate, but incoming precipitation would limit the survivability time of the victims in the accident. Thus, the ES pilots have extremely high pressure to fly, and there is a strong conservative bias in the pilots' decision making.

Because SAR is a highly time-sensitive operation, ES pilots must make a decision to fly now or risk compromising the mission. There are no weather observation stations in the search area, and recent METAR data is nearing being an hour old. While the few weather data that the ES pilots have indicate that the weather is marginal and flyable, any worsening of conditions would call for the mission to be grounded until conditions improve.

Due to the lack of weather observation stations in the search area, uncertainty about actual weather conditions within the area of operations is high, and it is difficult for ES pilots to assess weather-related risk and make a decision to fly or not. More than just the lives of the accident victims are at risk. Should one of the ES aircraft crash during the operation, the marginal weather and dangerous terrain would limit a response to recover the downed ES pilots, and the SAR response for the original accident victims would be diminished. However, not flying at all means that there is zero chance that the accident victims will be rescued. Due to the high variability and large distances between METAR observations surrounding the search area, weather conditions could be worse than what is presented, or they could be better. Other weather reports such as radar, the HEMS tool, and TAFs indicate that conditions are marginal, and don't provide sufficient evidence to definitively prove that weather conditions are either safe or too dangerous for flight.

To improve their ability to assess weather-related risk, the ES pilots deploy five weather observation drones to gather weather observations within the search area. Utilizing the available 5G network, the drones begin broadcasting their weather observations immediately. The drone and METAR data are depicted on a weather presentation, similar to what is shown in Figure 22. As noted, by the time the search has started, conditions at KEMT have changed from IFR to MVFR. A KNN analysis is performed on the data and a low KNN score indicates that weather conditions in the search area are being represented by the observations with relative completeness. The previously uncertain weather conditions within the search area are now known to be marginal with reasonably high confidence, and ES pilots can more precisely assess weather-related risk.

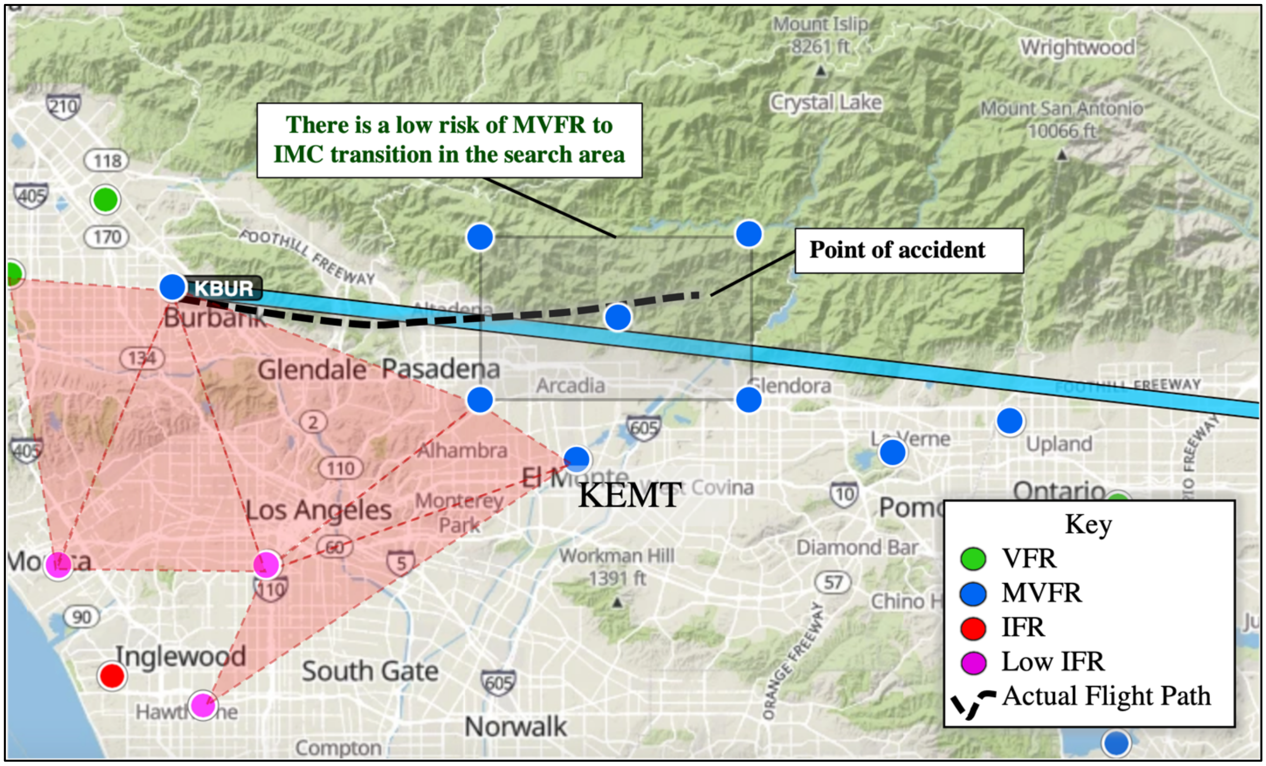

Figure 22. Drone-based weather observations improve weather condition representation accuracy and pilot risk assessment. Visual depiction map created using ForeFlight

By gathering additional weather observations through the weather drones, the ES pilots are confident that weather conditions between observations in the search area are now more completely represented on the weather display. The pilots decide that the risks of low-altitude flight are acceptable here and the correct "go" decision to takeoff is made. As the ES aircraft enter the area of operations, the weather observation drones descend to an altitude of 200' AGL to avoid a mid-air collision with other aircraft. While en-route and while performing searches, AMDAR observations are reported every 6 seconds from the aircraft. As the ES pilots communicate with one another, weather-related information is converted to standard PIREP format and uploaded to the weather observation database. AMDAR data, PIREPs, METAR data, and data from weather observations drones would be presented to pilots along with other commonly available AWC reports.

Assume that the aircraft wreckage is found. However, weather conditions have started to decline from MVFR to IFR, and the weather conditions between weather observations are now represented less completely. Areas where there is a high risk of an MVFR to IMC transition are identified through the KNN analysis and are being depicted through red shading on the pilot weather displays, similar to what is shown in Figure 23. After seeing this, the pilots begin performing more conservative risk assessments in the higher risk areas. Where a pilot would confidently fly in an area where marginal weather was reported before, they may now avoid such areas because weather conditions may be worse than they appear on the weather displays: "instrument conditions may be present but not depicted". Pilots assess that weather-related risk is high and choose to depart the search area and return to KEMT. Flights en-route to KEMT are directed to remain east of the higher risk area. This proves to be a correct decision, as hazardous weather is entering the search area from the west.

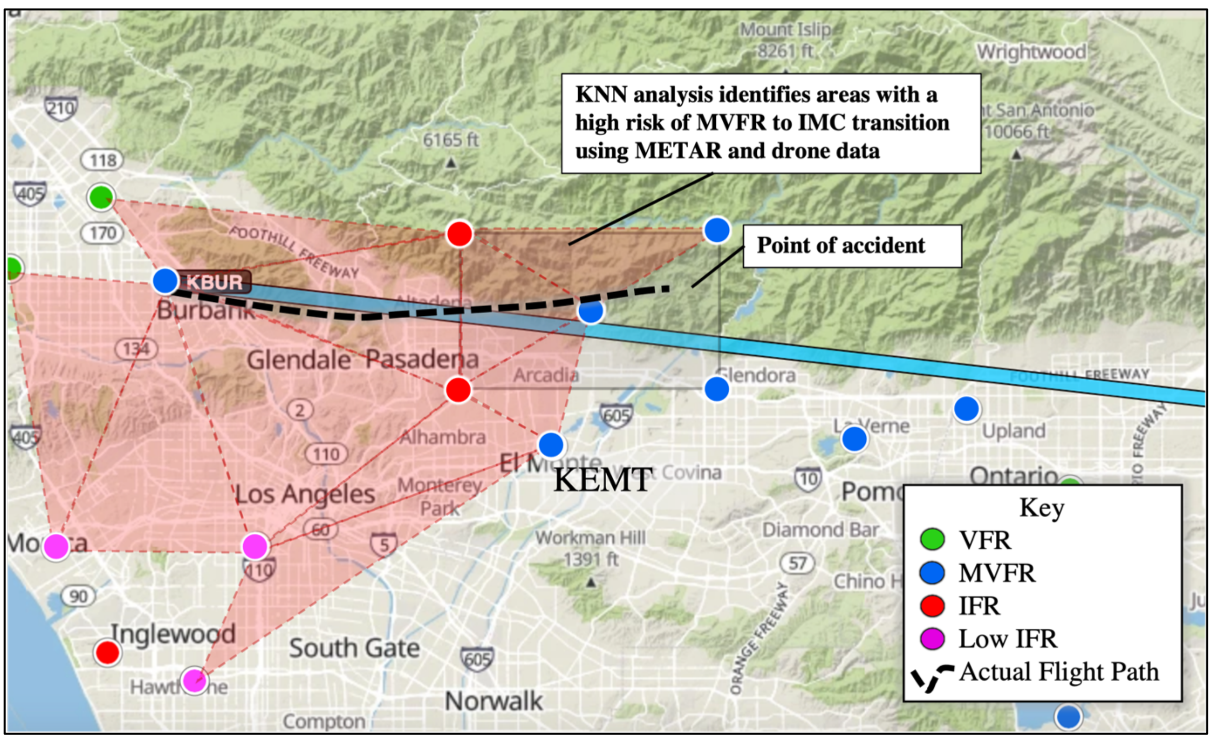

Figure 23. Areas with an increased risk of transition into IMC are identified near the search area using METAR and drone data. Visual depiction map created using ForeFlight

Finally, the ES pilots make a safe landing at KEMT. By using weather observation drones during the preflight weather assessment, weather conditions were more completely represented in the search area and ES pilots were able to make the correct decision to fly in marginal weather. During the mission, PIREPs and AMDAR data helped the pilots to assess risk during dynamic weather conditions. By depicting that there was an increased risk of a transition from MVFR into IMC on the weather displays, pilots were alerted to severe weather-related risks that were otherwise not obvious. Overall, depicting these high-risk IMC transition areas, but also identifying those areas where the risk of an IMC transition was lower, allowed the mission to be successfully completed in weather conditions that the pilots would not have otherwise flown in.

If the ES pilots performing the preflight weather assessment were not aware that incompletely represented weather conditions can contain severe or hidden risks, an incorrect flight decision could have been made. Consider how the situation would have changed if the initial weather conditions were similar to those shown in Figure 23: the western border of the search area has instrument conditions and there is an increased risk that flight near that area would result in an unintended transition into IMC. If the ES pilots had not deployed the drones to gather additional weather observation data, the pilots may have flown directly into dangerous weather conditions. Deploying weather observation drones during the preflight weather assessment allows weather conditions to be more completely represented on weather displays, which allows more informed flight decisions to be made.

5.2 Application Towards the Broader GA Community

It is apparent that the application of these technologies is of most benefit to ES pilots flying in marginal weather. However, this does not preclude that this technology has applications in the greater GA community. Although GA pilots do not have the same pressures to fly in marginal weather, those choosing to do so would benefit if they were alerted to areas where a transition into IMC is likely to occur. While ES aircraft are prime candidates to be outfitted with AMDAR reporting technology, AMDAR reporting is by no means restricted to ES aircraft, and non-ES aircraft used in commercial applications already have such technology onboard. It is feasible that GA aircraft could also use AMDAR reporting technology during low-altitude flight. Hands-minimized PIREP submission software would also be a helpful technology to GA pilots, even though they do not experience as high of a task-load as ES pilots do.

It is unlikely that a GA pilot would need weather data at the resolution provided by an array of weather observation drones. Furthermore, the cost and logistics of operating a drone swarm frequently would deter its use when not absolutely necessary. However, as demonstrated in Figure 21, a KNN analysis can still be performed using only METAR data. PIREPs and AMDAR data could be included in this analysis as they are made available. A GA pilot using these technologies as a decision-support tool, in combination with other AWC reports, would be more likely to avoid an unintended transition into IMC.

As a local technology feasibility exercise, the author considered how this technology could be used by the GA community at Purdue University Airport, which has one of the busier Class D airspaces in the country. Here, dozens of pilots and instructors are performing takeoffs, landings, and flight maneuvers in the vicinity of the airport. Flight maneuvers, takeoffs, and landings are considered critical phases of flight, because errors are more likely to have higher consequences. Pilots alerted to areas where an MVFR to IMC transition is likely could avoid weather-related decision errors during critical phases flight. For example, a pilot alerted to high-risk IMC transition areas could better identify hazardous weather when performing power-off stalls, making it less likely that unanticipated hazardous weather conditions cause the stall to develop into an uncontrolled spin. Similarly, a student-pilot could more easily see that preflight conditions are unsuitable for flight and make a correct "no-go" preflight decision. Moreover, a student on their first solo cross-country could adjust their route to avoid areas where they are more likely to transition into IMC.

5.3 Technology Requirements

Controlling a drone swarm over a network requires a strong emphasis on cybersecurity. While it is important to protect against malicious intent, it is also important that accidental network interference is avoided. Drones would need to have the "intelligence" to descend to and hover at a safe altitude in the case of a loss of network coverage; the risk of a collision with a drone due to unintended drone behavior must be minimized. The drones must have sufficient battery life to fly to the area of operations, report weather observations, and fly back. The size of a drone swarm could be adjusted to accommodate location remoteness, search area size, and the area's potential for rapidly changing weather conditions. A larger search area with more rapidly changing conditions would prompt a larger drone swarm to be used.

AMDAR data should have relatively high accuracy to avoid introducing an additional layer of uncertainty into the dataset. Like a METAR, an AMDAR report could contain wind information, temperature, dewpoint, and atmospheric pressure. More sophisticated AMDAR equipment could also report visibility and precipitation measurements. Although the reporting frequency was suggested to be every 6 seconds, being able to manipulate that frequency would provide the capability to accommodate varying levels of network availability.

Speech recognition errors in the hands-minimized PIREP technology must also be minimized. It is also important to consider that PIREP data is generated via pilot interpretation and is subject to the pilot’s discretion. For example, one pilot may report moderate turbulence, but another may report the same conditions to be heavily turbulent. This range of possible actual conditions must be considered in weather analysis and weather data presentation.

The ML algorithm must have a sufficiently large training dataset to accurately calibrate the KNN model. Training datasets should target those areas where there has historically been a higher concentration of accidents due to incomplete weather condition representation. These areas have highly variable terrain and quickly changing local weather conditions. Examples of these areas include the LA basin, the Grand Canyon, and coastal regions near the Great Lakes during the winter season. Similarly, regions with a geographically sparse array of METAR stations and regions with a geographically dense array of METAR stations should be included. The age of the METAR data in training datasets should range from recently observed to an hour old. Datasets should be taken from various seasons and from different times of the day.

6. DISCUSSION

6.1 Technology Application in the Missing Learjet Accident

Pilots in the SAR response to find the two missing Learjet pilots near KLEB would have been able to better assess weather-related risk if they were alerted to areas where there was a high risk of an MVFR to IMC transition, or if they were provided with additional weather observations in their area of operations. Not unlike the example SAR operation near KBUR, in many ways, the KLEB SAR was a worst-case scenario: weather conditions were marginal, terrain surrounding the airport was variable and hazardous, and only two weather stations existed in the search area. To fly meant that ES pilots had an opportunity to rescue the pilots, but such flights came with significant risk. Not to fly, however, meant that the accident victims had no chance to be saved at all. There was high pressure and a high reward for the ES pilots to fly the mission, but the operation was time-sensitive, high-risk, and a lack of weather observation stations made accurate risk assessment difficult.

Consider how weather assessment in the search response could have benefitted if additional weather datapoints were available. Weather observation drones could have been spaced in an array within the search area. An example weather data presentation near KLEB using fabricated weather observation drone data is shown in Figure 24. Areas where there is a high risk of a transitioning from MVFR into IMC are depicted by red shading. Using a presentation such as this, an ES pilot's ability to assess risk and make correct flight decisions would be improved. The added weather observations would improve the strength of the "unflyable weather" signal assessment and improve a pilot's sensitivity to identify that unflyable weather. Providing a cautionary message to pilots that an area has a higher risk of an MVFR to IMC transition, in addition to depicting the information through shading, would adhere to the redundancy principle identified by O'Hare & Stenhouse (O'Hare & Stenhouse, 2008).

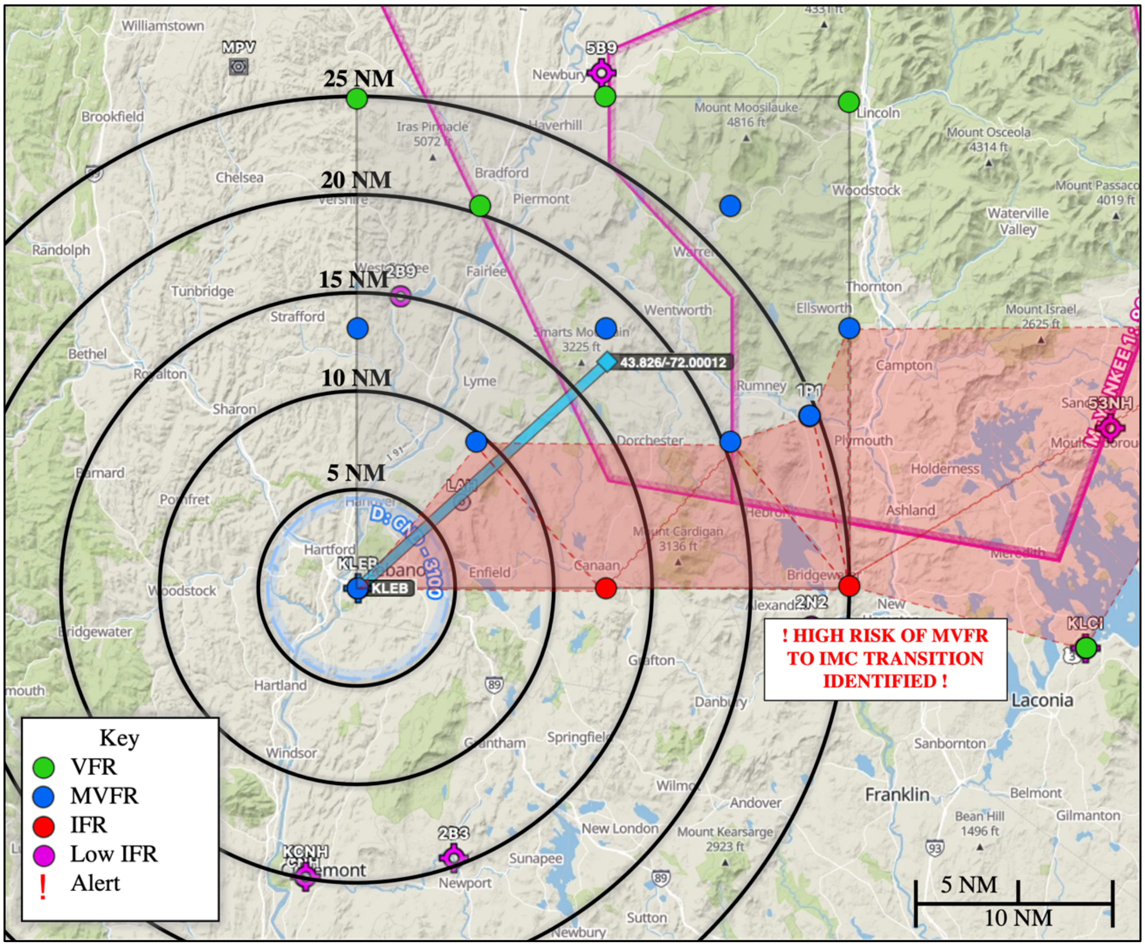

Figure 24. Learjet accident location relative to Lebanon Municipal Airport (KLEB), shown on an example weather display with drone data and a depiction where the risk of an MVFR to IMC transition is high. Visual depiction map created using ForeFlight

In the Learjet response, aircraft were flying various search patterns at 500’, 1,000’, and 2,000’ AGL (Rossier, 1998). Once these aircraft had entered the search area, the swarm of weather observation drones could descend to 200’ AGL. If ES aircraft were equipped with AMDAR reporting equipment, then weather data observations would be generated at 200’, 500’, 1,000’, and 2,000’ AGL within the area of operations. Providing pilots with this amount of weather observations would help weather conditions to be more completely represented on weather displays in both the surface plane and in the vertical column. In areas with mountains, a change in altitude from the surface to 2,000’ is not trivial when assessing variations in weather conditions. Mountain waves can cause wind directions to oscillate between blowing towards and away from the mountain, and on a very small geographic scale. Mountain waves also cause severe low-altitude turbulence, updrafts, and downdrafts. Each of these conditions are somewhat unpredictable in how close to the ground and how far from the mountain they will occur. Including additional weather observations across the spatial and vertical plane would give pilots additional insight into these weather phenomena and help them avoid areas of dangerous weather conditions.

6.2 Locations and Circumstances for Greatest Benefit

The proposed technology applications are of greatest use in situations where the signal sensitivity regarding unflyable weather is low. In terms of atmospheric conditions, this primarily refers to marginal weather, and a pilot's signal detection / discrimination capability is particularly reduced in areas where weather stations are few and far between. However, as noted when discussing the KNN analysis methodology, weather conditions can cross the MVFR to IMC boundary without MVFR conditions being reported in METAR observations. A pilot flying between two stations depicting VFR and IFR would also be at risk of unintentionally transitioning into IMC. This pilot would have made an incorrect "go" decision (Type II Error). The same is true if the weather stations were reporting VFR and low IFR; MVFR is not depicted, but the risk of transitioning through MVFR and into IMC is still present.

Using the proposed technologies where a 5G network is available enables weather observation reporting equipment to be used to its fullest potential. Without an available 5G network, AMDAR data could not be reported at the desired frequency, the amount of pilot radio chatter analyzed for PIREP conversion would be reduced, and drone swarm control would be limited. However, areas lacking 5G network coverage could still benefit from partial implementation of the proposed technologies, albeit at a reduced operational capacity. AMDAR reports could be generated at the current standard rate of every 3 to 7 minutes during flight, hands-minimized PIREP submission software could be used to help air traffic controllers submit PIREPs in a more traditional manner, and single weather observation drones could be flown, instead of a swarm.

6.3 Benefits to ES Pilots and the Broader GA Community

Alerting pilots that they are at risk of flying from MVFR and into IMC would be an effective method to improve pilot situational awareness and risk assessment, and would reduce aviation accidents caused by an unintended transition into IMC; These types of accidents are the most frequent cause of aviation fatalities. Providing additional weather observations using PIREPs, AMDAR data, and drone swarms would allow the risk of dangerously variable weather conditions between stations to be more completely represented and would give pilots additional insight into weather conditions about which they would have been previously uncertain. Particularly during LAO in marginal weather and near rapidly varying terrain, this would improve a pilot's ability to make informed flight decisions and would reduce the chances of spatial disorientation and controlled flight into terrain.

Using weather observation drones provides flexibility in the geographic location and altitude where observations can be taken, and the density of the swarm can be changed to accommodate varying ES operational area sizes. Similar to how a finite-element analysis performs more detailed and higher resolution calculations in areas where stress is highest, drones can be strategically placed in areas where dangerous and risky weather conditions are more likely to be incompletely represented by weather observation station reports. This allows for a more detailed analysis to be performed on an as-needed basis. For example, drones placed on the backside of a mountain ridge could observe conditions in an area where mountain waves cause frequent and significant changes in weather conditions. The autonomous or semi-autonomous nature of drones also means that human lives are not at risk by taking weather observations at low altitudes, over dangerous terrain, or in potentially hazardous weather. Drones are becoming more cost-effective, which reduces the financial risk associated with the loss of an observation drone.

It is commonly taught in private pilot instruction to *aviate, navigate,* and then *communicate.* The order of these operations is critical, as a pilot must maintain safety and control over an aircraft before any other task can be performed. This also indicates that communication can only occur once safe flight and navigation have been established. PIREP submission is a form of communication and submitting PIREPs already has a lesser priority than other required communication tasks, such as pilot-to-ATC instruction (in a controlled airspace) or pilot-to-pilot traffic pattern calls (in an uncontrolled airspace). It is reasonable to assume that, once all aviation, navigation, and required communication tasks have been completed, that a pilot has little remaining time or attention to give towards submitting PIREPs. Using hands-minimized technology to submit PIREPs is much less time-consuming and cognitively intensive than the traditional method of doing so. The ES pilot, whose cognitive budget is already strained by other ES-related tasks, would benefit most from using this hands-minimized technology, and using the technology would allow ES pilots to submit more PIREPs while maintaining focus on completing mission objectives.

The KNN analysis demonstrated that areas between weather stations where variability in weather conditions is more likely to be incompletely represented by METAR observations can be numerically evaluated. Improved awareness of such variability and increased risk of transitioning from MVFR into IMC can be of significant value to ES pilots. Should a ML algorithm be trained using a KNN approach, areas of weather condition variability and observation incompleteness could be more accurately evaluated using a wider variety of input parameters. Depicting high-risk IMC transition areas would assist pilots in evaluating risk in weather assessment. A pilot who is alerted to the potential risks present among incompletely represented weather conditions could make safer and more informed flight decisions.

The KNN analysis evaluated weather conditions using a METAR dataset captured at a single point in time. This contrasts with the PEGASAS analysis, which examined average monthly trends in the data. Both methods provide useful insight. However, the KNN methodology allows a current weather display's data to be evaluated for areas where there is a higher risk of an MVFR to IMC transition. This means that a pilot assessing weather conditions could see if their flight path has a higher risk of crossing into an area with unrepresented IMC "right now".

The risks associated with incompleteness in weather variability representation and pilot uncertainty about weather conditions between weather stations are often invisible to pilots. Alerting pilots to these risks would help weather condition representation inaccuracies be a more informative factor in decision-making. As demonstrated by the flow chart in Figure 12, a decision bias that does not consider that weather conditions may be incompletely represented can ultimately lead to an incorrect flight decision being made. Alternatively, a decision bias formed by a pilot who is accustomed to performing weather assessment using a model that depicts high-risk IMC transition areas would be more likely to consider the effects of incompletely represented weather conditions between weather stations.

Overall, the proposed technology applications would help ES pilots avoid an unintended transition into IMC and better consider the effects of incompletely represented weather conditions in the areas between weather observation stations. This would improve a pilot's weather-related risk sensitivity. In LAO, during marginal weather and near highly variable terrain, where the penalty for incorrect flight decision is highest, alerting pilots that there is a risk of transitioning from MVFR into IMC would help ES pilots fly less often in weather conditions that are unsuitable for flight, and more confidently fly in marginal weather when appropriate. This would result in fewer weather-related aviation accidents occurring, and flying more frequently in appropriate marginal weather conditions would increase the chances for ES mission success.

6.4 Future Work & Limitations

Several research activities conducted within the PEGASAS center of excellence program have the potential for future impacts. The hands-minimized PIREP submission software prototypes developed by PEGASAS team members are still in a preliminary, non-deployable state. Very specifically, PEGASAS is not meant to create or distribute market-ready products. Therefore, any algorithms for analysis of pilot speech for PIREP phrases must be trained and commercially verified using a database containing a wide population of people, reporting a range of PIREPs, and with different accents and local phraseology included.

Drone swarm technology has significantly advanced in recent years. However, before drone swarms can safely and reliably be used in aviation to this magnitude, additional work must be completed. Such work includes improving swarm control and navigation technology, introducing reliable failsafe modes and collision avoidance maneuvers, and verifying that drone swarm operation and control does not interfere with other aviation operations. The ability to control the drone swarm using a 5G network, and over the range and area required for an ES operation, must also be verified.

The input parameters used in the KNN approach consisted of those available from METAR data and drone observations. PIREPs and AMDAR reports were proposed as other sources of usable inputs. However, if feasible, future analyses could also consider other weather reports such as radar, TAFs, SIGMETs, and AIRMETs. Considering parameters available from other weather information products could help identify the rapidity at which conditions in an area are changing, and therefore report on risks that weather conditions are incompletely represented by METAR observations.

This study made several assumptions that must be discussed to examine the limitations of the research. Many of the proposed technologies were based off initial, low-fidelity or fundamental technology demonstrations. As noted above, many of these demonstrations require additional development or verification to be completed before being applicable to an ES or GA setting. The methodologies to control, coordinate, or utilize a drone swarm is the topic of multiple theses or dissertations. The field is deep and complex, and this study assumed that drone swarm control and navigation would not be a limiting factor in the technology application. It was also assumed that drones could accurately and reliably take weather observations and function at the durations and distances seen in ES operations. It was also assumed that hands-minimized PIREP submission technology would be sufficiently developed by the time other relevant technologies are ready for use. Though several types of ML algorithms exist which could be applied to a KNN weather condition representation analysis, this thesis does not propose to assess strengths and weaknesses of specific algorithms or parameter assessment functions. No specific type of algorithm was identified, but instead general weather-related assessment using ML was shown to be feasible and it was assumed that an appropriate method would be chosen at the time that each of the other technologies are of a suitable technological readiness.

7. CONCLUSION

Weather conditions, and especially their variability, in the areas between weather observation stations can be incompletely represented by METAR observations. It is critical that ES pilots can assess how incomplete representation of weather conditions can influence weather-related risk. This is particularly true for ES pilots performing LAO in marginal weather conditions and near highly variable terrain, where the consequences for an incorrect flight decision are severe. The current ASOS / AWOS weather observation reporting system does not indicate how incompletely represented or uncertain weather conditions can affect risk. By analyzing available METAR weather observation data using a KNN analysis, areas where there is a high risk of transitioning from MVFR into IMC can be identified. Depicting these areas on aviation weather displays may help pilots better assess weather-related risks and would improve safety in pilot decision-making. To improve the representation of weather condition variability on weather displays, technological capabilities enhanced by 5G networks such as AMDAR reports, PIREPs, and swarm of weather observation drones could be used to collect additional weather observation data. When used in combination with other standard AWC resources, the additional weather observation data and weather displays can be combined to depict areas where there is a high risk of MVFR to IMC transition. Information about these increased weather-related risks would be a useful tool to support pilot decision making in marginal weather conditions. This would help ES pilots avoid errors in weather assessment and decision making, would increase the chances of ES operation mission success, and would decrease the likelihood of a weather-related aviation accident.

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