Improving aeromagnetic surveying capabilities of uninhabited aircraft systems

by

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Abstract

Uninhabited aircraft systems (UAS) have grown in popularity for aeromagnetic surveying. While the technology has been demonstrated to be viable, studies have not addressed three areas. First, comparisons with traditional platforms over geologically interesting regions are limited. Second, demonstrations of advanced processing with UAS data are rare. And lastly, methods for magnetic compensation of UAS data is outstanding. This thesis addresses these three areas and provide approaches to evaluate UAS performance and improve data quality.

A hexacopter UAS was used to fly an aeromagnetic survey over a property with prospective gold targets. The UAS data was found to be repeatable and consistent. Qualitative and quantitative comparison with data from traditional magnetic surveys revealed that the UAS data could delineate geological structures better than the helicopter data and more efficient to collect than ground data. Unconstrained and constrained magnetic inversion demonstrated that the quality of the data collected by the UAS was sufficient to model the structural framework of banded iron formations within the survey area. It highlighted that the potential gold ore zones are not directly associated with them, but rather with steeply dipping faults that transect the area. The exercise showed that, at the early stage of exploration, performing unconstrained inversion yielded a realistic and detailed model of the subsurface, opening the possibility of implementing magnetic inversion as a continuous process during targeted high-resolution surveying for mineral exploration.
Magnetic compensation of noise from aircraft attitude variations is typically modelled by performing a least-squares fit to a 16-term model by bandpass filtering data from a high-altitude (3,000 m) figure-of-merit flight. Government and hardware limitations generally prevent UAS to fly at such altitudes (over 122 m AGL), so an alternative solution was developed that uses recurrent neural networks on survey data, without the need of an FOM. The algorithm was tested on data from a traditional fixed-wing airplane survey and data from UAS flying at 120 m and 50 m above ground level. Comparisons with established compensation methods showed that the proposed algorithm could become a practical alternative.
Acknowledgements

This thesis would not have been accomplished without the contributions and support of many people.

First, I would like to thank both of my supervisors, Dr. Claire Samson, and Dr. Jeremy Laliberté for their guidance, expertise, and support through my graduate studies. I would also like to thank Dr. Loughlin Tuck for the breadth of knowledge in UAS and machine learning and making time to have regular discussions on my research and providing invaluable guidance in helping me complete my graduate studies. I would also like to thank Mr. David Birkett, Mr. Alan Wood, and the rest of the Stratus Aeronautics Inc. team for organizing and performing the UAS survey work in Nelligan, QC and for providing valuable insight into their UAS. Thank you to Mr. Mark Goldie (IAMGOLD Corporation) for making supporting this project by allowing for the aeromagnetic survey over the Nelligan, QC property as well as taking time to bring me to your Quebec exploration office to discuss details of the property. A big thank you to Mr. Steve Balch for encouraging me to push beyond my perceived limits, mentoring me in all things related to airborne geophysics, and providing me opportunities to gain working experiences in the industry; your guidance and support has been invaluable. And thank you to the Department of Earth Sciences and Carleton University for the support they have provided during my studies.

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Preface

This document is an integrated thesis consisting of three articles published or submitted to peer-reviewed scientific journals on the topic of aeromagnetic surveying with uninhabited aircraft systems:


Section, table, and figure numbers have been standardized and updated to be consistent with the thesis, and a list of references has been compiled at the end. Within academia and industry, the terms 'manned' and 'unmanned' are being replaced with the non-gendered terms 'inhabited' and 'uninhabited'; as such these changes have been made Chapter 3 and 4.
At the beginning of each Chapter, 3, 4, and 5, detailed description of each authors roles are provided. In summary, M. Cunningham was the primary research on each of the three articles where he contributed to all aspects from aeromagnetic surveying, data processing, and manuscript writing. C. Samson assisted in planning research objectives. Both C. Samson and J. Laliberté provided extensive resources to the research and comments on the manuscripts. M. Goldie (IAMGOLD Corporation) provided access to and knowledge on the survey area. A. Wood and D. Birkett (Stratus Aeronautics) planned and collected the Nelligan UAS survey data. L. Tuck provided extensive guidance, knowledge, and comments on article 3.

The thesis co-supervisors, Dr. Claire Samson, and Dr. Jeremy Laliberté, acknowledge the above information is accurate.
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<table>
<thead>
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<th>Acronym</th>
<th>Description</th>
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<tbody>
<tr>
<td>3-D</td>
<td>Three Dimensional</td>
</tr>
<tr>
<td>AGL</td>
<td>Above Ground Level</td>
</tr>
<tr>
<td>ANN</td>
<td>Artificial Neural Network</td>
</tr>
<tr>
<td>ASL</td>
<td>Above Sea Level</td>
</tr>
<tr>
<td>BIF</td>
<td>Banded Iron Formation</td>
</tr>
<tr>
<td>BP filter</td>
<td>Bandpass filter</td>
</tr>
<tr>
<td>DAE</td>
<td>Deep Autoencoder</td>
</tr>
<tr>
<td>DuPMaD</td>
<td>Dual Permanent Magnetic Dipole</td>
</tr>
<tr>
<td>EAST</td>
<td>Environmental Research Aircraft and Sensory Technology</td>
</tr>
<tr>
<td>FOM</td>
<td>Figure-of-merit</td>
</tr>
<tr>
<td>GPS</td>
<td>Global Positioning System</td>
</tr>
<tr>
<td>GRNN</td>
<td>Generalized Regression Neural Network</td>
</tr>
<tr>
<td>IF</td>
<td>Iron Formation</td>
</tr>
<tr>
<td>IGRF</td>
<td>International Geomagnetic Reference Field</td>
</tr>
<tr>
<td>IMU</td>
<td>Inertial Measurement Unit</td>
</tr>
<tr>
<td>IR</td>
<td>Improvement Ratio</td>
</tr>
<tr>
<td>JARUS</td>
<td>Joint Authorities for Rulemaking on Unmanned Systems</td>
</tr>
<tr>
<td>KIGAM</td>
<td>Korea Institute of Geoscience and Mineral Resources</td>
</tr>
<tr>
<td>LiPo</td>
<td>Lithium Polymer</td>
</tr>
<tr>
<td>LS</td>
<td>Least Squares</td>
</tr>
<tr>
<td>LSTM</td>
<td>Long Short-Term Memory</td>
</tr>
<tr>
<td>MAC</td>
<td>Magnetic Attitude Correction</td>
</tr>
<tr>
<td>MSE</td>
<td>Mean Squared Error</td>
</tr>
<tr>
<td>NSERC</td>
<td>Natural Sciences and Engineering Research Council</td>
</tr>
<tr>
<td>nT</td>
<td>nano Tesla</td>
</tr>
<tr>
<td>PMaD</td>
<td>Permanent Magnetic Dipole</td>
</tr>
<tr>
<td>PSNR</td>
<td>Peak Signal to Noise Ratio</td>
</tr>
<tr>
<td>RMI</td>
<td>Residual Magnetic Intensity</td>
</tr>
<tr>
<td>RNN</td>
<td>Recurrent Neural Network</td>
</tr>
<tr>
<td>SFOC</td>
<td>Special Flight Operations Certificate</td>
</tr>
<tr>
<td>SQUID</td>
<td>Superconducting Quantum Interference Device</td>
</tr>
<tr>
<td>SSIM</td>
<td>Structural Similarity Index</td>
</tr>
<tr>
<td>TL</td>
<td>Tolles-Lawson</td>
</tr>
<tr>
<td>TMI</td>
<td>Total Magnetic Intensity</td>
</tr>
<tr>
<td>UAS</td>
<td>Uninhabited Aircraft System (formerly Unmanned Aircraft System)</td>
</tr>
<tr>
<td>UC</td>
<td>Upward Continued</td>
</tr>
<tr>
<td>UXO</td>
<td>Unexploded Ordnance</td>
</tr>
<tr>
<td>VTOL</td>
<td>Vertical Take-Off and Landing</td>
</tr>
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1. Introduction

1.1 Aeromagnetic surveying and uninhabited aircraft systems

The research described in this thesis was performed to address current topics of interest that have come from combining the use of uninhabited aircraft systems (UAS) and aeromagnetic surveying: (1) demonstrating qualitatively and quantitatively that UAS compare favorably with traditional survey methods; (2) performing advanced processing and interpretation of aeromagnetic data collected by an UAS, in particular 3D inversion; and (3) providing a solution to attitude compensation that does not require UAS platforms to perform a high-altitude figure-of-merit (FOM) flight. By addressing these three topics, the use of UAS for aeromagnetic surveying should gain further acceptance in the mineral exploration industry and geophysics’ sector.

There has been a large increase in the use of UAS in geophysics, particularly for aeromagnetic surveying for mineral exploration. With undeveloped and/or unidentified high-grade large-scale mineral deposits being less frequently discovered (Mudd, 2007; West, 2011), there is a need during the early stages of a mineral exploration campaign for cost-effective methods to collect targeted high-resolution datasets. UAS provide an opportunity to bridge the gap between high-resolution ground surveys and high-efficiency traditional airborne survey. They can survey regions much faster (high efficiency) than ground methods, but also collect densely spaced data that closely follows topography (high-resolution) (Zheng et al., 2021a).
UAS are expected to provide several benefits to aeromagnetic, and other geophysical survey methods, in comparison to traditional ground and airborne methods. A major benefit of UAS surveying is the added level of safety of the operators as they are not traversing on the ground through large areas or flying with the risk of aircraft failure or pilot error. UAS are also more environmentally friendly; ground surveying will typically require cut lines, where large amounts of forest are removed to allow for optimal surveying, and airborne surveys have significant fuel needs. UAS can traverse terrain much faster than a ground survey team, and with an experienced UAS crew can compete with production levels of helicopter surveys. A summary of some of the advantages and disadvantages of traditional airborne, ground, and UAS platforms are listed in Table 1-1.

Table 1-1: Advantages and disadvantages between the different aeromagnetic survey platforms.

<table>
<thead>
<tr>
<th>Platform</th>
<th>Advantages</th>
<th>Disadvantages</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed-wing (inhabited)</td>
<td>• High daily production</td>
<td>• Hazardous to operators</td>
</tr>
<tr>
<td></td>
<td>• Low sample density</td>
<td>• Low sample density</td>
</tr>
<tr>
<td></td>
<td>• High survey altitude</td>
<td>• High survey altitude</td>
</tr>
<tr>
<td></td>
<td>• Limited by access to airports</td>
<td>• Limited by access to airports</td>
</tr>
<tr>
<td>Helicopter (inhabited)</td>
<td>• High daily production</td>
<td>• Hazardous to operators</td>
</tr>
<tr>
<td></td>
<td>• Good sample density</td>
<td>• Limited by access to fuel</td>
</tr>
<tr>
<td>UAS</td>
<td>• Safe to operators</td>
<td>• Moderate daily production</td>
</tr>
<tr>
<td></td>
<td>• Environmentally friendly</td>
<td>• Limited flight endurance</td>
</tr>
<tr>
<td></td>
<td>• Moderate sample density</td>
<td></td>
</tr>
<tr>
<td>Ground</td>
<td>• High sample density</td>
<td>• Hazardous to operators</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Low daily production</td>
</tr>
</tbody>
</table>
Presently, there are several publications demonstrating that UAS are a viable option for aeromagnetic surveying. These publications primarily describe different UAS and show some aeromagnetic survey data collected by them; however, these surveys are relatively small, not over geologically interesting features (i.e., minimal structural and magnetic variation), and there are few publications directly comparing datasets with traditional surveys. Compounding this, the comparisons that have been made with traditional airborne (i.e., fixed-wing aircraft or helicopter) and ground surveys have primarily been performed over areas of approximately 1 km² or less (de Smet et al., 2021; le Maire et al., 2020; Schmidt et al., 2020; Shahsavani, 2021; Walter et al., 2020), with little geologically interesting features. Furthermore, there have only been a few advanced applications published, such as magnetic inversion, with UAS collected aeromagnetic datasets (D. Jiang et al., 2020; Koyama et al., 2021; Porras et al., 2021); thus, it is still unclear where the use of UAS for aeromagnetic surveys stands in comparison to traditional methods in terms of the quality of the final survey deliverables.

Aeromagnetic data collected by UAS still has room for improvement (Tuck, 2019; Tuck et al., 2018, 2019). Magnetic interference is well understood with traditional airborne platforms and its effects are effectively reduced through attitude compensation techniques (the reduction in magnetic noise due to the aircrafts motion during flight) (Bickel, 1979; FitzGerald & Perrin, 2015; Leliak, 1961; Tolles & Lawson, 1950) but little research has focussed on addressing this topic for UAS. Due to regulatory constraints (Hao et al., 2022; Stöcker et al., 2017) and aircraft limitations, performing UAS attitude compensation with approaches used for
traditional surveying platforms is not possible. Without specific permission to do so, UAS are unable to fly at altitudes above 122 m above ground level (Transport Canada, 2020) and their ability to fly at nominal FOM altitudes 3,000 m is also physically limited by the UAS hardware, radio communication ranges, line-of-sight requirements, and ability of programming FOM manoeuvres, preventing the completion of the high-altitude FOM flight that is needed. Efforts have been made to identify magnetic interference sources on UAS (Cherkasov & Kapshtan, 2018; Forrester, 2011; Forrester et al., 2014; Hansen, 2018; Huq et al., 2015; Sterligov & Cherkasov, 2016; Tuck, 2019; Tuck et al., 2018, 2021; Wells, 2008) but only a few studies have attempted to perform attitude compensation (Tuck et al., 2019; P. Yu et al., 2021, 2022), and they still require the high-altitude FOM flight. To effectively remove magnetic interference effects from changes in UAS attitude, an alternative, practical approach is necessary.

1.1.1 History of magnetic surveying

Magnetism is a physical attribute of a material that refers to ability to induce attractive or repulsive phenomenon in other objects. Material can inherently possess magnetism (permanent magnetism), or it can be induced through an external magnetic field (remanent magnetism and induced magnetism) (Dentith & Mudge, 2014). Magnetism observed from a material depends on its chemistry, temperature, pressure, and the applied external magnetic field. Earth exhibits a magnetic field due to the fluid motion of its outer metallic core; within the outer
core, electrically conductive fluid continually rotates and convects due to chemical differentiation and radioactive heating (Ranalli, 1995) allowing for the conversion of kinetic energy into electrical and magnetic energy. Fluid motions within the outer core then induce further electric currents, generating their own magnetic fields in a self-sustaining process due to internal feedback. The average strength of the Earth’s magnetic field is about 50,000 nT (Dentith & Mudge, 2014) but can range from about 20,000 nT to 65,000 nT mainly due to variation in latitude (Alken et al., 2021).

Approximately 80% to 90% of the observed magnetic field at Earth’s surface is due to the outer core (Nabighian et al., 2005), however, at depths of 20 to 30 km or less, the Earth’s magnetic field interacts with material, predominantly iron-bearing rocks, where temperatures are below its Curie temperature, allowing for the material to be magnetically susceptible (i.e., below 580°C for the mineral: magnetite \( \text{Fe}_3\text{O}_4 \)) and contribute its own magnetic field (Nabighian et al., 2005).

Humans have exploited Earth’s magnetic field for centuries (Nabighian et al., 2005). Since the 6th century BCE, the ancient Greeks had magnets and observed their effects but they were not readily employed until between 1100 AD and 1300 AD by the Chinese, western Europeans, Arabs, and Scandinavians (ordered from first to most recent) as lodestones, a piece of magnetite, for navigation. In the late 1500s, during the Scientific Revolution, the magnetic field of the Earth was scientifically investigated, eventually leading to the development of compass needles as surficial prospecting tools in the 1800s; a compass needle deflects vertically near a magnetically susceptible structure. It was not until the World War
that more advanced and sensitive instrumentation was developed for submarine
detection; specifically, the fluxgate magnetometer with a 1 nanotesla (nT) sensitivity (Hood, 2007).

Since World War 2, magnetic surveying has been used for geological mapping, oil exploration, and mineral exploration. In the late 1940s, magnetic measurements were used to confirm the theory of plate tectonics, seafloor spreading, and the dynamo theory in the generation of the Earth's outer core magnetic field (Nabighian et al., 2005). Using a fluxgate magnetometer, the Geological Survey of Canada performed its first aeromagnetic survey west of Ottawa, near Arnprior, Ontario in 1947 (Hood, 2007). In the 1960s, aeromagnetic data was used to reveal geology underneath glacial till and lake covered regions of the Canadian Precambrian Shield. In the fall of 1960 a federal, provincial, and industry supported project was started with the aim being to magnetically map all of Canada. By 1981 a nearly complete magnetic map of Canada was produced; significantly ahead of other nations national magnetic survey programs (Hood, 2007; Teskey et al., 1993).

Between the 1950s and 1980s, further advances in magnetometer technology were made. Proton precession and optical absorption technologies were developed in the 1950s and began to be regularly employed in the 1960s. The Superconducting Quantum Interference Device (SQUID) magnetometers were first developed in the 1960s and are now finding uses in various applications (Jaklevic et al., 1964; Tumanski, 2011). By the 1970s, sampling rates were down to 0.3 s at sensitivities of 1 nT. In the 1980s, the Overhauser proton precession
magnetometer, which is still used today, was developed with a 1 s sampling rate but a 0.01 nT sensitivity. With the arrival of these new sensors, sensitivities were low enough that magnetic noise from the sensor carrying platforms (i.e., aircraft) could contribute to the magnetic signal, so adaptive real-time compensation was developed to remove in situ or current-induced signals (Hood, 2007; Nabighian et al., 2005).

Presently, ground and airborne (fixed-wing aircraft, helicopter, or satellite) magnetic surveying uses magnetometer technology developed since the 1950s, albeit with improved sampling rates and sensitivity noise levels. The choice in magnetometer, whether fluxgate, proton precession, Overhauser, cesium (rubidium, or potassium) vapour, or SQUID, typically depends on specific needs and preferences. In general, magnetic surveying is a powerful tool for: (1) making detailed maps of regional geology; (2) detecting mineral deposits, specifically iron oxides, copper and gold, skarns, massive sulphides, heavy mineral sands, carbonatites, kimberlites, porphyritic intrusions, and hydrothermal alterations; (3) acquiring magnetic susceptibility measurements in borehole data; (4) biological and medical uses; and (5) detecting cultural structures and vehicles (archaeological or present-day) (Tumanski, 2011).

1.1.2 Overview of UAS

Surprisingly, uninhabited aircraft have been in use since the mid 1800s. During the Battle of Novara (23 March 1849), Austrians ineffectively used uninhabited hot-
air balloons to bombard Venice, and a similar approach was used during the American Civil War (Watts et al., 2012). During the Spanish-American War (1898) remotely triggered cameras mounted to kites were used for reconnaissance missions. In 1916, the first aircraft with automatic steering and attitude control was developed by Lawrence and Sperry, called the “aviation torpedo”, and flew over 48 km (Gupta et al., 2013). More significant developments, for military use, started in the late 1950s during the Vietnam War and Cold War, continuing into the 1970s, with significant use for surveillance and some combat. The SD-1, also known as the MQM-67 Falconer, carried a camera and flew for 30 minutes, and returned to base, and landed with a parachute (Dalamagkidis et al., 2012). The United States Air Force supported development of the Ryan Model 147 UAS, which had 3,500 missions launched, and one aircraft given ace status for its use on North Vietnamese MIGs. The US Navy acquired the QH-50 DASH, a helicopter UAS, used to launch torpedoes and for surveillance. Following the 1991 Gulf War, the United States quickly developed more advanced UAS for military use, such as the General Atomics MQ-1 Predator drone family, as well as for civil use, particularly by NASA and its Environmental Research Aircraft and Sensory Technology (ERAST) project (Dalamagkidis et al., 2012). Private companies also began developing their own UAS for their industry specific needs (Watts et al., 2012).

Presently, UAS platforms are employed for a wide range of applications, including but not limited to, surveillance; patrolling; photography (i.e., optical, hyperspectral, etc.); videography; remote sensing (i.e., magnetic and radiometric surveying, aeronomy, etc.); delivery of goods (i.e., healthcare, and Amazon
orders); agricultural uses (i.e., spraying, and seeding); safety inspections; infrastructure monitoring; and entertainment (Aleshin et al., 2020; Watts et al., 2012; Zheng et al., 2021a). There are three primary UAS platforms. First, the fixed-wing UAS, which tend to be used more for military purposes, due to their take-off and landing requirements as well as their high level of endurance (1 hour to over 30 hours of flight time) (Zheng et al., 2021a). Second, the rotary-wing UAS (single- or multi-rotor) tend to be used more frequently by the public and for civilian applications. They have functionality that is difficult to achieve with fixed-wing UAS, such as vertical take-off and landing (VTOL) and the ability to loiter or hover over a single location. Lastly, airships, such as blimps or hot-air balloons, which are capable of handling higher payloads and have longer flight endurance than rotary-wing UAS (Kim, Lee, et al., 2021). For most geophysical purposes, research has generally focussed on the use of fixed-wing and rotary-wing UAS with some efforts on using airships and hybrid (i.e., fixed-wing VTOL) UAS.

UAS consist of three subsystems: aircraft, ground station, and communications. Technological improvements in equipment for all three have contributed to a rapid increase in the use of UAS. Typically, the aircraft subsystem includes an autopilot, global positioning system (GPS), altimeter, LiDAR, inertial measurement unit (IMU), accelerometers, gyroscopes, and radio control (Pajares, 2015). The ground station subsystem includes take-off and landing space, recovery systems, and communication capabilities for remote control of the UAS or adjusting the pre-planned flight. The communication subsystem allows for remote communication between the UAS and the ground station, enabling the ability to perform remote
control of the UAS, update the flight path during flight, and transfer of survey data. Presently, most UAS are only capable of automated and semi-autonomous flight. They can follow a pre-planned flight path or perform simple tasks without intervention. However, full autonomous flight has still not been demonstrated outside of highly controlled trials since object identification, collision avoidance and airspace traffic integration systems are not yet completely realised. Full autonomy involves the freedom of the aircraft from external control or influence; it is fully independent of an operator. The stages of flight control for automated and autonomous flight are detailed in Table 1-2 where a fully autonomous aircraft must be able to manage the interplay of the safety defining risks in air and on the ground (Figure 1-1). Furthermore, in many countries, including North America (Canada, Mexico, and USA), South America, Europe, Oceania and Australia, and parts of Asia (i.e., China, Japan, India) and Africa (i.e., South Africa, Madagascar, and Nigeria), the use of UAS remain regulated separately from other aircraft systems by strict regulations to minimize the risks to other airspace users and to people and property on the ground (Stöcker et al., 2017). Many countries are beginning to adopt a common set of technical, safety, and operational requirements for UAS outlined by the Joint Authorities for Rulemaking on Unmanned Systems (JARUS) (Hao et al., 2022).
Table 1-2: Description of aircraft automation levels. Source: E. Anderson et al., 2018

<table>
<thead>
<tr>
<th>Level</th>
<th>Name</th>
<th>Description</th>
</tr>
</thead>
</table>
| 0     | No Automation                 | • Operator performs all aspects of a task; aircraft control is 100% manual  
• Warning & Intervention systems may be present                                                                                           |
| 1     | Task Assistance                | • Operator delegates execution of a specific action/limited responsibility of a task to a specific system  
• Operator performs all remaining aspects of the task  
• Operator monitors performance of the system                                                                                           |
| 2     | Partial Automation            | • Operator delegates execution of multiple aspects of a task to one or more systems  
• Operator performs all remaining aspects of the task  
• Operator monitors performance of the systems                                                                                           |
| 3     | Highly Automated (Semi-autonomous) | • Operator delegates flight phase specific execution of most aspects of a task to an automated system  
• Operator performs a limited set of actions in support of the task  
• Operator monitors automation and will respond if intervention is requested / required                                                 |
| 4     | Fully Automated               | • Operator delegates execution of all aspects of a task in any flight phase to an automated system  
• Automation can manage most aspects of the task under most conditions  
• Automation is capable of safe/reasonable responses if Operator does not respond to request for intervention  
• Operator monitors automated system and has full authority over the task                                                               |
| 5     | Autonomous                    | • Execution of all aspects of a task in all flight phases by an automated system  
• Automation can manage all aspects of the task under the conditions that can be managed by an operator                                      |
1.1.3 Aeromagnetic surveying with UAS

With the onset of commercial development of practical and reliable UAS, there has been interest in their use for aeromagnetic surveying. Many regions of geological interest are in remote, potentially hazardous, locales (such as dense forest or jungle; rough, steep, or mountainous terrain; cliffs; or volcanoes). Aeromagnetic surveying with UAS has taken place since the mid-2000s, but since 2015 technological advances have seen their use drastically increase for both research and commercial applications.

The early to mid-2000s saw some of the first publicly available publications on aeromagnetic surveying with UAS. Perry et al. (2002) discussed the possibility of...
using a fixed-wing glider UAS for unexploded ordnance detection (UXO) with aeromagnetic magnetic sensors. In 2005, the GeoRanger, a fixed-wing UAS intended for surveying was demonstrated (D. Anderson & Pita, 2005). In 2008, the Ant-Plane, also a fixed-wing UAS was deployed in Antarctica for scientific research (Funaki & Hirasawa, 2008). Since these initial demonstrations the development of aeromagnetic surveying with UAS has been focussed on developing different platforms and detailing their results over small areas, identifying optimal sensor integration setups, and magnetically characterising and minimizing on-board components (Aleshin et al., 2020; Zheng et al., 2021a).

1.2 Literature review on UAS-based aeromagnetic surveying

Currently there are four key publications reviewing and summarizing the available literature on different UAS used for aeromagnetic surveying, including descriptions of their capabilities and magnetic noise characteristics. Watts et al. (2012) and Gupta et al. (2013) provide early summaries of UAS applications for both small (<30 kg) and light, and large and heavy (≥30 kg) platforms. Aleshin et al. (2020) provides a review with more emphasis on UAS selection for geological and geophysical case studies, having a specific focus on light UAS platforms and their individual capabilities. Zheng et al. (2021a) provide the most recent review on UAS platform selection for geoscience applications and is focussed specifically on their use for magnetic surveying. They also mention research directions to further advance the use of UAS for aeromagnetic surveying.
The following subsections provide a literature review on: (1) the different UAS used for aeromagnetic surveys (Section 1.2.1); (2) case studies related to aeromagnetic data collected with UAS (Section 1.2.2); (3) magnetic noise characterisation, noise reduction, and compensation methods with a focus on UAS (Section 1.2.3); and (4) alternative geophysical and geological applications of UAS (Section 1.2.4).

1.2.1 UAS for aeromagnetic surveying

In general, UAS are classified as heavy or light, which is primarily differentiated by the platforms weight (Aleshin et al., 2020; Gupta et al., 2013; Watts et al., 2012). Heavy UAS tend to resemble traditional inhabited fixed-wing aircraft and can be further categorized based on their flight altitude, endurance, and weight (see Table 1-3 for specifications and Figure 1-2 (A - through D) for examples). These UAS subcategories are: LALE - low altitude, long endurance (15 - 25 kg), or TUAV – tactical UAV (150 – 600 kg); MALE – medium altitude, long endurance (> 600 kg); and HALE – high altitude, long endurance (> 600 kg) (Dalamagkidis et al., 2008; Gupta et al., 2013; Watts et al., 2012). These larger UAS platforms tend to be used for military applications such as patrolling, surveillance, and combat. Because of their size, flight requirements (i.e., take-off and landing site), and inability to fly close to the ground, they are not practical for aeromagnetic surveying for mineral exploration, archaeology, or UXO detection (Aleshin et al., 2020). Light UAS tend to be under 30 kg in weight. Due to their versatility, light UAS typically have rotary wings; however, some fixed-wing and airships UAS (i.e., blimps) are also in use (Aleshin et al., 2020; Zheng et al., 2021a) (see Table 1-3 for
specifications and Figure 1-2 (F – through I) for examples). These UAS subcategories include: NAV – nano air vehicle or MAV – micro air vehicle (< 0.3 kg); VTOL – vertical take-off and landing (small (< 3kg) and large (< 30 kg)); LASE – low altitude, short endurance; and LASE Close – longer endurance than LASE. Usually NAV, MAV, and VTOL UAS have rotary wings, while LASE and LASE Close UAS have fixed wings. Light UAS have significant military applications (i.e., reconnaissance) as well as commercial (i.e., inspections, surveying, etc.), and personal applications (i.e., photography, videography, and entertainment). Flexible UAS (Figure 1-2 – E) are not typical and are limited to applications for aeromagnetic surveying or, more broadly, geoscience purposes. These UAS can exhibit different modes of flight styles, some take inspiration from birds and insects, while others are a hybrid or can convert between fixed- and rotary-wings (Gupta et al., 2013). Finally, there is the airship UAS (Figure 1-2 – J) class, which includes blimps and balloons. These UAS tend to be large but light weight and have long endurance.

Rotary-wing UAS have become the primary platform used for most recreational, and commercial applications, with each having 84% and 58% market share, respectively (Simonsen et al., 2019) (Table 1-4). The advancement of flight control and autopilot hardware and software has allowed for easy control and automated flight of both single rotor and multi-rotor UAS. Single rotor UAS provide higher efficiency and stability over multi-rotor aircraft. They can also be powered with battery (i.e., lithium polymer (LiPo)) or gas; each having their own advantages and disadvantages (e.g. flight endurance vs vibrational noise). In general, single-rotor
UAS are more complex, with a complicated main rotor assembly, and main and
tail rotor drivetrains. There have been only a few case histories featuring their use
for aeromagnetic surveying. These UAS are listed in Table 1-4.

Multi-rotor UAS platforms are easier to use than their single-rotor counterparts,
so they have a larger user base (Table 1-4). They use multiple motors, one for
each rotor, so do not need servo motors to control rotor blade tilt or a transmission
system to control main- or tail-rotor speeds. These aircraft are supported by on-
board autopilot, which assists in providing smoother flight control when taking over
manually. Because of this, there are off-the-shelf single-rotor UAS commercially
available that can be adapted for aeromagnetic surveying. These tend to come in
various designs, such as quadcopter (four rotor arms), hexacopter (six rotor arms),
octacopter (eight rotor arms), X6 (three arms, each with two motors and rotors)
and X8 (four arms, each with two motors and rotors).

For both single-rotor and multi-rotor UAS, the magnetic sensors have been
installed using two different mounting methods: towed magnetometer (Figure 1-3
- left), either hanging the sensor below, or towing a pre-built shell, such as the
MagArrow, which allows for the minimization of UAS magnetic noise at the cost of
sensor stability; or hard mounted sensors (Figure 1-3 - right), with a forward or
backward stinger/boom, or dual side arms (for gradiometry) allowing for a more
stable sensor orientation, but with an increase in more UAS noise.

Early aeromagnetic surveying was focused on fixed-wing UAS; however, the
large area or other equipment, such as a catapult, required for take-off and landing
made operations difficult. Fixed-wing UAS do provide a more stable, faster flight,
and options for improved sensor mounting locations. Unlike rotary-wing UAS, fixed-wing UAS for aeromagnetic surveying are typically custom designed or modified versions of remote-controlled aircraft (Table 1-5).

There has been limited development on flexible and airship style UAS for aeromagnetic surveying (Table 1-6). Like rotary-wing UAS, flexible UAS have the ability of VTOL while also being able to fly at similar speeds to fixed-wing UAS. The KapetAir VTOL is an example of a flexible aircraft for aeromagnetic surveying (Jirigalatu et al., 2021), where its main rotors can move from vertical points (for VTOL) and forward facing (forward flight), like the inhabited Bell Boeing V-22 Osprey or the Harrier Jump Jet. Similarly, only a few airship style UAS have been demonstrated for aeromagnetic surveying. These UAS are blimps, which are lifted by gas (i.e., helium); this enables them to carry heavier payloads than other platforms, but it is more difficult for them to follow a planned flight path due to wind, and air pressure changes, and they tend to have slower survey speeds. A group in Korea, from the Korea Institute of Geoscience and Mineral Resources (KIGAM) has successfully tested a blimp for aeromagnetic surveying (Kim, Lee, et al., 2021).

Of the aeromagnetic UAS platforms discussed above (Table 1-4, Table 1-5, and Table 1-6), many of them present the capabilities of their system, survey results in an area of interest or focus on a specific research aspect (noise characterisation, compensation, platform development) but few compare results to industry accepted platforms and systems at large scale. Cunningham et al. (2018) mathematically modelled and predicted the impact of surveying at decreased flight altitudes (100 m, 50 m, and 2 m AGL), highlighting improved detection of small
Figure 1-2: Examples of each UAS class. Left column (A-D) are heavy UAS, where: A – LALE, the Sky-Sailor (Noth, 2008); B – TUAV, the Watchkeeper UAS (Watchkeeper Tactical UAV, 2021); C – MALE, NASA’s Ikhana Predator B (Conner, 2019a); and D – HALE, NASA’s Global Hawk (Conner, 2019b). The right column (F - I) are light UAS, where: F – NAV, the Back Hornet 3 (Teledyne FLIR, 2021); G – VTOL, Stratus Aeronautic’s SkyLance 600 (Cunningham, 2016; Cunningham et al., 2018, 2021, 2022); H – LASE, Geoscan-201 (Cherkasov & Kapshatan, 2018); and I – LASE Close, Stratus Aeronautic’s Venturer UAS (Cunningham, 2016; Wood et al., 2016). The bottom row UAS are: E – Flexible, KapetAir UAS (Jirigalatu et al., 2021); and J – Airship, KIGAM Airship (Kim, Lee, et al., 2021).
Figure 1-3: Sketches (side view) of a multi-rotor UAS carrying a towed magnetometer (left) and a multi-rotor UAS carrying a stinger mounted magnetometer (right). Arrows indicate direction of flight. Sketches are not to scale.
structures with decreased altitude and increased spatial sampling. A 50 m AGL UAS flight was also compared with 100 m AGL fixed-wing and 2 m AGL ground aeromagnetic surveys further showing the improved detection capabilities. Malehmir et al. (2017) compared a UAS survey (70 m AGL) with a fixed-wing survey flown at 30 m AGL over a 2 km² area. They showed the two datasets had similar results, but the UAS demonstrated an improved ability to resolve closely spaced magnetite and hematite mineralization zones due to the orientation of flight lines. Jackisch et al. (2019) reported that a UAS survey flown at three altitudes (15 m, 40 m, 65 m AGL) compared well with ground (1.7 m AGL) and fixed-wing (40 m AGL) datasets, respectively over an area (approx. 0.05 km²). Walter et al. (2020), le Maire et al. (2020), Shahsavani et al. (2021), de Smet (2021), and Schmidt et al. (2020) all performed similar studies on small survey regions showing that UAS perform well in comparison to ground magnetic or traditional aeromagnetic surveys. These comparison surveys are limited in the size (0.35 km² to 1.00 km²), are typically performed over geomagnetically uninteresting locations (except Walter et al. (2020)) and tend to be show results under unrealistic survey parameters (i.e., flight altitudes of 2 m in open flat fields). Comparisons between each dataset focus primarily demonstrating qualitative, descriptive differences, and provide minimal quantitative comparisons.
<table>
<thead>
<tr>
<th>Classification</th>
<th>Type</th>
<th>Flight Altitude</th>
<th>Flight Endurance</th>
<th>Typical Style</th>
<th>Weight (kg)</th>
<th>Application(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Heavy</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LALE</td>
<td>&lt; 3,000 m</td>
<td>Up to 2 days</td>
<td>Fixed-Wing</td>
<td>15 – 25</td>
<td>Surveillance, Patrolling, Data Gathering</td>
<td></td>
</tr>
<tr>
<td>TUAV</td>
<td>&lt; 3,000 m</td>
<td>Up to 2 days</td>
<td>Fixed-Wing</td>
<td>150 – 600</td>
<td>Surveillance, Patrolling, Data Gathering</td>
<td></td>
</tr>
<tr>
<td>MALE</td>
<td>&lt; 14,000 m</td>
<td>Days or weeks</td>
<td>Fixed-Wing</td>
<td>&gt; 600</td>
<td>Surveillance, Cargo Transportation</td>
<td></td>
</tr>
<tr>
<td>HALE</td>
<td>&lt; 20,000 m</td>
<td>Days or weeks</td>
<td>Fixed-Wing</td>
<td>&gt; 600</td>
<td>Surveillance, Patrolling, Data Gathering, Signal Relay</td>
<td></td>
</tr>
<tr>
<td>NAV and/or MAV</td>
<td>&lt; 100 m</td>
<td>5 – 30 minutes</td>
<td>Rotary-Wing</td>
<td>&lt; 0.3</td>
<td>Entertainment</td>
<td></td>
</tr>
<tr>
<td>VTOL</td>
<td>&lt; 1,000 m</td>
<td>30 min</td>
<td>Rotary-Wing</td>
<td>&lt; 3 or &lt; 30 (large)</td>
<td>Videography, Photography, Agriculture, Surveying, Inspection</td>
<td></td>
</tr>
<tr>
<td>LASE</td>
<td>&lt; 1,000 m</td>
<td>1 – 2 hours</td>
<td>Fixed-Wing</td>
<td>≈ 2</td>
<td>Aerial Photography, Surveying</td>
<td></td>
</tr>
<tr>
<td>LASE Close</td>
<td>&lt; 1,000 m</td>
<td>&gt; 2 hours</td>
<td>Fixed-Wing</td>
<td>&lt; 30</td>
<td>Patrolling, Surveying</td>
<td></td>
</tr>
<tr>
<td><strong>Flexible</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Flexible</td>
<td>Flexible</td>
<td>Variable</td>
<td>Variable</td>
<td>Hybrid, Convertible, Flexible, Morphing</td>
<td>Variable</td>
<td>Reconnaissance, Data Gathering</td>
</tr>
<tr>
<td><strong>Airship</strong></td>
<td>Airship</td>
<td>Variable</td>
<td>Long endurance</td>
<td>Balloons, blimps, airships</td>
<td>Light</td>
<td>Low Speed Applications</td>
</tr>
</tbody>
</table>
Table 1-4: Rotary-wing UAS used for geophysical surveying. ‘N/A’ designates specification not applicable or provided.

<table>
<thead>
<tr>
<th>UAS</th>
<th>UAS Style</th>
<th>Weight (kg)</th>
<th>Max. Width (m)</th>
<th>Power</th>
<th>Max. Payload (kg)</th>
<th>Max. Endurance (h)</th>
<th>References</th>
<th>Case study</th>
</tr>
</thead>
<tbody>
<tr>
<td>Geoscan 401</td>
<td>Multi-Rotor</td>
<td>1.9</td>
<td>1.5</td>
<td>Battery</td>
<td>2.5</td>
<td>0.75</td>
<td>(Cherkasov et al., 2018; Cherkasov &amp; Kapshtan, 2018; Sterligov et al., 2018)</td>
<td>Aeromagnetic Survey</td>
</tr>
<tr>
<td>DJI M210</td>
<td>Multi-Rotor</td>
<td>4.69</td>
<td>0.883</td>
<td>Battery</td>
<td>1.2</td>
<td>0.5</td>
<td>(Døssing et al., 2021)</td>
<td>Aeromagnetic Survey</td>
</tr>
<tr>
<td>Scout B1-100</td>
<td>Single-Rotor</td>
<td>30</td>
<td>3.2 m</td>
<td>Fuel</td>
<td>15</td>
<td>1.5</td>
<td>(Eck &amp; Imbach, 2012; Stoll, 2013)</td>
<td>Aeromagnetic Survey;</td>
</tr>
<tr>
<td>Mavic Pro2</td>
<td>Multi-Rotor</td>
<td>0.907</td>
<td>0.322</td>
<td>Battery</td>
<td>N/A</td>
<td>0.5</td>
<td>(Gailler et al., 2021)</td>
<td>Aeromagnetic Survey</td>
</tr>
<tr>
<td>IT-180 UAV by ECA Robotics</td>
<td>Single-Rotor</td>
<td>16</td>
<td>N/A</td>
<td>Fuel</td>
<td>5</td>
<td>2.0</td>
<td>(Gavazzi et al., 2016)</td>
<td>Aeromagnetic Survey; Fluxgate magnetometer; UXO and archaeological Detection</td>
</tr>
<tr>
<td>DJI Matrice 100</td>
<td>Multi-Rotor</td>
<td>2.4</td>
<td>0.65</td>
<td>Battery</td>
<td>1.2</td>
<td>0.37</td>
<td>(Gavazzi et al., 2019)</td>
<td>Aeromagnetic Survey; Fluxgate magnetometer; Survey Comparison</td>
</tr>
<tr>
<td>GEM Hawk</td>
<td>Single-Rotor</td>
<td>12.4</td>
<td>N/A</td>
<td>Battery</td>
<td>4</td>
<td>0.83</td>
<td>(GEM Systems, 2017)</td>
<td>Aeromagnetic Survey</td>
</tr>
<tr>
<td>Yamaha Rmax-G1</td>
<td>Single-Rotor</td>
<td>16</td>
<td>3.63</td>
<td>Fuel</td>
<td>10</td>
<td>1.5</td>
<td>(Hashimoto et al., 2014)</td>
<td>Aeromagnetic Survey</td>
</tr>
<tr>
<td>Custom</td>
<td>Multi-Rotor</td>
<td>5.5</td>
<td>N/A</td>
<td>Battery</td>
<td>1.0</td>
<td>0.33</td>
<td>(Heincke et al., 2019)</td>
<td>Aeromagnetic Survey; Hyperspectral; Multispectral</td>
</tr>
<tr>
<td>UAS</td>
<td>UAS Style</td>
<td>Weight (kg)</td>
<td>Max. Width (m)</td>
<td>Power</td>
<td>Max. Payload (kg)</td>
<td>Max. Endurance (h)</td>
<td>References</td>
<td>Case study</td>
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</tr>
<tr>
<td>SU-H2M</td>
<td>Single-Rotor</td>
<td>65</td>
<td>3.81</td>
<td>Fuel</td>
<td>35</td>
<td>2</td>
<td>(D. Jiang et al., 2020)</td>
<td>Aeromagnetic Survey; Attitude Compensation; Magnetic Inversion Modelling</td>
</tr>
<tr>
<td>DJI Matrice 600 Pro</td>
<td>Multi-Rotor</td>
<td>1.668</td>
<td>10.0</td>
<td>Battery</td>
<td>5.5</td>
<td>0.5</td>
<td>(Kaub, Glen, et al., 2021; Kaub, Keller, et al., 2021)</td>
<td>Aeromagnetic Survey; Attitude Compensation;</td>
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<tr>
<td>DJI M210 RTK</td>
<td>Multi-Rotor</td>
<td>4.69</td>
<td>0.883</td>
<td>Battery</td>
<td>1.2</td>
<td>0.5</td>
<td>(Kim, Jeong, et al., 2021)</td>
<td>Aeromagnetic Survey; Survey Comparison; Magnetic Inversion Modelling</td>
</tr>
<tr>
<td>DJI Wind 4 quadcopter</td>
<td>Multi-Rotor</td>
<td>11</td>
<td>0.860</td>
<td>Battery</td>
<td>10</td>
<td>0.5-0.8</td>
<td>(Kolster et al., 2022; Kolster &amp; Døssing, 2020)</td>
<td>Aeromagnetic Survey; UXO Detection; Attitude Compensation; Magnetic Inversion Modeling</td>
</tr>
<tr>
<td>Aerialis X825</td>
<td>Multi-Rotor</td>
<td>N/A</td>
<td>N/A</td>
<td>Battery</td>
<td>N/A</td>
<td>N/A</td>
<td>(Kotowski et al., 2022)</td>
<td>Electromagnetic Survey</td>
</tr>
<tr>
<td>YAMAHA FAZER R G2</td>
<td>Single-Rotor</td>
<td>81</td>
<td>3.665</td>
<td>Fuel</td>
<td>35</td>
<td>1.67</td>
<td>(Koyama et al., 2021)</td>
<td>Aeromagnetic Survey; Magnetic Inversion Modelling</td>
</tr>
<tr>
<td>UAS</td>
<td>UAS Style</td>
<td>Weight (kg)</td>
<td>Max. Width (m)</td>
<td>Power</td>
<td>Max. Payload (kg)</td>
<td>Max. Endurance (h)</td>
<td>References</td>
<td>Case study</td>
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<td>----------------------------------------------------------------------------</td>
</tr>
<tr>
<td>DJI Matrice 210</td>
<td>Multi-Rotor</td>
<td>4.69</td>
<td>0.883</td>
<td>Battery</td>
<td>1.2</td>
<td>0.5</td>
<td>(le Maire et al., 2020)</td>
<td>Aeromagnetic Survey; Multi-Altitude Vertical-Gradient; Attitude Compensation</td>
</tr>
<tr>
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<td>1.4</td>
<td>N/A</td>
<td>Battery</td>
<td>1.8</td>
<td>0.25</td>
<td>(Lipovský et al., 2021)</td>
<td>Aeromagnetic Survey; Fluxgate Magnetometer; Indoor Application</td>
</tr>
<tr>
<td>DJI Matrice 600 Pro</td>
<td>Multi-Rotor</td>
<td>1.668</td>
<td>10.0</td>
<td>Battery</td>
<td>5.5</td>
<td>0.5</td>
<td>(Luoma &amp; Zhou, 2020)</td>
<td>Aeromagnetic Survey; Towed Gradiometer</td>
</tr>
<tr>
<td>3DR X8+</td>
<td>Multi-Rotor</td>
<td>2.6</td>
<td>0.5</td>
<td>Battery</td>
<td>0.8</td>
<td>0.25</td>
<td>(Macharet et al., 2016)</td>
<td>Aeromagnetic Survey; Magnetic Interference Characterisation</td>
</tr>
<tr>
<td>DJI S1000 Premium Folding Octocopter</td>
<td>Multi-Rotor</td>
<td>6</td>
<td>0.337</td>
<td>Battery</td>
<td>5</td>
<td>0.25</td>
<td>(Malehmir et al., 2017)</td>
<td>Aeromagnetic Survey; Radio-Magnetotelluric; Survey Comparison</td>
</tr>
<tr>
<td>DJI MG1</td>
<td>Multi-Rotor</td>
<td>22.5</td>
<td>1.520</td>
<td>Battery</td>
<td>2.0</td>
<td>0.4</td>
<td>(Mu et al., 2020; Zheng et al., 2021b)</td>
<td>Aeromagnetic Survey; Vertical Gradiometry; Magnetic Noise Reduction</td>
</tr>
<tr>
<td>UAS</td>
<td>UAS Style</td>
<td>Weight (kg)</td>
<td>Max. Width (m)</td>
<td>Power</td>
<td>Max. Payload (kg)</td>
<td>Max. Endurance (h)</td>
<td>References</td>
<td>Case study</td>
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</tr>
<tr>
<td>DJI Matrice 600</td>
<td>Multi-Rotor</td>
<td>1.668</td>
<td>10.0</td>
<td>Battery</td>
<td>5.5</td>
<td>0.5</td>
<td>(de Smet et al., 2021; Nikulin &amp; de Smet, 2019)</td>
<td>Aeromagnetic Survey; LiDar; cultural object detection</td>
</tr>
<tr>
<td>SibGIS</td>
<td>Multi-Rotor</td>
<td>15</td>
<td>N/A</td>
<td>Battery</td>
<td>N/A</td>
<td>0.5</td>
<td>(Parshin et al., 2018, 2020; Parshin, Morozov, et al., 2021)</td>
<td>Aeromagnetic Survey; Radiometric; Multispectral; LiDar</td>
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<tr>
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<td>1</td>
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<td>0.42</td>
<td>(Parvar, 2016; Parvar et al., 2017)</td>
<td>Aeromagnetic Survey</td>
</tr>
<tr>
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<td>Multi-Rotor</td>
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<td>0.46</td>
<td>Battery</td>
<td>3.5</td>
<td>0.3</td>
<td>(Parvar, 2016; Parvar et al., 2017)</td>
<td>Aeromagnetic Survey</td>
</tr>
<tr>
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<td>Multi-Rotor</td>
<td>7.9</td>
<td>1.219</td>
<td>Battery</td>
<td>6.5</td>
<td>N/A</td>
<td>(Parvar, 2016; Parvar et al., 2017)</td>
<td>Aeromagnetic Survey</td>
</tr>
<tr>
<td>Z3</td>
<td>Single-Rotor</td>
<td>67</td>
<td>3.200</td>
<td>Fuel</td>
<td>25</td>
<td>1.5</td>
<td>(Pei et al., 2017)</td>
<td>Aeromagnetic Survey; Gradiometry; Attitude Compensation</td>
</tr>
<tr>
<td>V750</td>
<td>Single-Rotor</td>
<td>545</td>
<td>7.24</td>
<td>Fuel</td>
<td>80</td>
<td>4.0</td>
<td>(Pei et al., 2017)</td>
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<td>0.5</td>
<td>(Pisciotta et al., 2021)</td>
<td>Aeromagnetic Survey</td>
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<tr>
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<td>1.133</td>
<td>Battery</td>
<td>6.0</td>
<td>0.63</td>
<td>(Porras et al., 2021)</td>
<td>Aeromagnetic Survey; Magnetic Inversion Modeling</td>
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<tr>
<td>DJI Matrice 600 Pro</td>
<td>Multi-Rotor</td>
<td>9.5</td>
<td>1.133</td>
<td>Battery</td>
<td>6.0</td>
<td>0.63</td>
<td>(Romero et al., 2021)</td>
<td>Aeromagnetic Survey</td>
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<tr>
<td>UAS</td>
<td>UAS Style</td>
<td>Weight (kg)</td>
<td>Max. Width (m)</td>
<td>Power</td>
<td>Max. Payload (kg)</td>
<td>Max. Endurance (h)</td>
<td>References</td>
<td>Case study</td>
</tr>
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<tr>
<td>DJI S1000+</td>
<td>Multi-Rotor</td>
<td>6</td>
<td>0.337</td>
<td>Battery</td>
<td>5</td>
<td>0.25</td>
<td>(Schmidt et al., 2020)</td>
<td>Aeromagnetic Survey</td>
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<tr>
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<td>Multi-Rotor</td>
<td>0.6</td>
<td>0.68</td>
<td>Battery</td>
<td>N/A</td>
<td>0.25</td>
<td>(Shahsavani, 2021)</td>
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<tr>
<td>T-Rex 600E Pro</td>
<td>Single-Rotor</td>
<td>5.2</td>
<td>1.58</td>
<td>Battery</td>
<td>N/A</td>
<td>N/A</td>
<td>(Tuck, 2019; Tuck et al., 2021)</td>
<td>Aeromagnetic Survey; Magnetic Interference Characterisation</td>
</tr>
<tr>
<td>DYS D800 X4</td>
<td>Multi-Rotor</td>
<td>0.8</td>
<td>2.8</td>
<td>Battery</td>
<td>6.5</td>
<td>0.25</td>
<td>(Tuck, 2019; Tuck et al., 2021)</td>
<td>Aeromagnetic Survey; Magnetic Interference Characterisation</td>
</tr>
<tr>
<td>DJI S800 EVO</td>
<td>Multi-Rotor</td>
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<td>3.7</td>
<td>Battery</td>
<td>2.3</td>
<td>0.33</td>
<td>(Tuck, 2019; Tuck et al., 2021)</td>
<td>Aeromagnetic Survey; Magnetic Interference Characterisation</td>
</tr>
<tr>
<td>Renegade</td>
<td>Single-Rotor</td>
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<td>2.5</td>
<td>Fuel</td>
<td>11</td>
<td>1.0</td>
<td>(McAnuff et al., 2019; Tuck, 2019; Tuck et al., 2019)</td>
<td>Aeromagnetic Survey; Attitude Compensation</td>
</tr>
<tr>
<td>DJI S900</td>
<td>Multi-Rotor</td>
<td>4.7</td>
<td>0.46</td>
<td>Battery</td>
<td>3.5</td>
<td>0.3</td>
<td>(Walter, 2021; Walter et al., 2019b, 2019a, 2020, 2021)</td>
<td>Aeromagnetic Survey; Magnetic Interference Characterisation; Survey Comparison</td>
</tr>
<tr>
<td>Taro T960</td>
<td>Multi-Rotor</td>
<td>4.0</td>
<td>0.96</td>
<td>Battery</td>
<td>4.0</td>
<td>0.37</td>
<td>(Walter, 2021; Walter et al., 2021)</td>
<td>Aeromagnetic Survey; Magnetic Interference Characterisation; Survey Comparison</td>
</tr>
<tr>
<td>UAS</td>
<td>UAS Style</td>
<td>Weight (kg)</td>
<td>Max. Width (m)</td>
<td>Power</td>
<td>Max. Payload (kg)</td>
<td>Max. Endurance (h)</td>
<td>References</td>
<td>Case study</td>
</tr>
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<td>-----------------------------------------------</td>
</tr>
<tr>
<td>Custom</td>
<td>Multi-Rotor</td>
<td>4.225</td>
<td>1.0</td>
<td>Battery</td>
<td>0.775</td>
<td>N/A</td>
<td>(Yoo et al., 2020, 2021)</td>
<td>Aeromagnetic Survey; UXO Detection</td>
</tr>
<tr>
<td>Unicorn</td>
<td>Single-Rotor</td>
<td>65</td>
<td>3.81</td>
<td>Fuel</td>
<td>35</td>
<td>2</td>
<td>(P. Yu et al., 2022)</td>
<td>Aeromagnetic Survey; Attitude Compensation; Machine Learning</td>
</tr>
<tr>
<td>Custom</td>
<td>Multi-Rotor</td>
<td>19</td>
<td>N/A</td>
<td>Battery</td>
<td>5</td>
<td>0.58</td>
<td>(Zheng et al., 2021b)</td>
<td>Aeromagnetic Survey; Magnetic Noise Characterisation</td>
</tr>
<tr>
<td>SkyLance 6200</td>
<td>Multi-Rotor</td>
<td>15</td>
<td>1.0</td>
<td>Battery</td>
<td>5</td>
<td>0.5</td>
<td>(Cunningham, 2016; Cunningham et al., 2016, 2018, 2021, 2022)</td>
<td>Aeromagnetic Survey; Survey Comparison</td>
</tr>
<tr>
<td>Tholeg Tho-R-PX8-12</td>
<td>Multi-Rotor</td>
<td>5.5</td>
<td>0.7</td>
<td>Battery</td>
<td>4.5</td>
<td>0.417</td>
<td>(Jackisch et al., 2019)</td>
<td>Aeromagnetic Survey</td>
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</table>
Table 1-5: Fixed-wing UAS platforms used for geophysical surveying. ‘N’ designates specification not provided.

<table>
<thead>
<tr>
<th>Aircraft</th>
<th>Weight (kg)</th>
<th>Wingspan (m)</th>
<th>Power</th>
<th>Max. Payload (kg)</th>
<th>Max. Endurance (h)</th>
<th>Paper(s)</th>
<th>Demonstration</th>
</tr>
</thead>
<tbody>
<tr>
<td>GeoSurv II</td>
<td>92.25 h</td>
<td>4.88</td>
<td>Fuel</td>
<td>N</td>
<td>N</td>
<td>(Forrester, 2011; Forrester et al., 2014; Huq et al., 2015; Wells, 2008)</td>
<td>Aeromagnetic Survey, Magnetic Interference Characterisation (servo)</td>
</tr>
<tr>
<td>Ant-Plane 1, 2, 3, 4, 5, 6</td>
<td>9 (AP3)</td>
<td>2.76 (AP3)</td>
<td>Fuel</td>
<td>0.5 (AP3)</td>
<td>3 (AP3)</td>
<td>(Funaki et al., 2014; Funaki &amp; Hirasawa, 2008)</td>
<td>Aeromagnetic Survey</td>
</tr>
<tr>
<td>GEM MONARCH</td>
<td>10</td>
<td>3.2</td>
<td>Battery</td>
<td>N</td>
<td>1.5</td>
<td>(GEM Systems, 2017)</td>
<td>Aeromagnetic Survey; Gradiometry</td>
</tr>
<tr>
<td>Sierra UAS</td>
<td>N</td>
<td>N</td>
<td>Fuel</td>
<td>N</td>
<td>3.5</td>
<td>(Glen et al., 2013)</td>
<td>Aeromagnetic Survey</td>
</tr>
<tr>
<td>Albatros VT</td>
<td>4</td>
<td>2.8</td>
<td>Fuel</td>
<td>2</td>
<td>3</td>
<td>(Heincke et al., 2019; Jackisch et al., 2020, 2022)</td>
<td>Aeromagnetic Survey; multispectral, inversion</td>
</tr>
<tr>
<td>senseFly eBee Plus</td>
<td>0.8</td>
<td>1.16</td>
<td>Battery</td>
<td>0.5</td>
<td>0.67</td>
<td>(Jackisch et al., 2020)</td>
<td>Visible Light; Multispectral</td>
</tr>
<tr>
<td>ICE-powered UAV</td>
<td>N</td>
<td>N</td>
<td>Fuel</td>
<td>N</td>
<td>N</td>
<td>(Ge et al., 2021)</td>
<td>Aeromagnetic Survey; Magnetic Interference Characterisation</td>
</tr>
<tr>
<td>CH-3</td>
<td>495</td>
<td>8</td>
<td>fuel</td>
<td>145</td>
<td>10</td>
<td>(W. Li et al., 2014)</td>
<td>Aeromagnetic Survey; Radiometric Survey; Attitude Compensation;</td>
</tr>
<tr>
<td>Geoscan-201</td>
<td>8.5</td>
<td></td>
<td>Battery</td>
<td>1.5</td>
<td>3.0</td>
<td>(Cherkasov et al., 2016; Sterligov &amp; Cherkasov, 2016)</td>
<td>Aeromagnetic Survey; Magnetic Interference Characterisation</td>
</tr>
<tr>
<td>Piper Pawnee</td>
<td>17.25</td>
<td>0.33</td>
<td>Battery</td>
<td>5</td>
<td>N</td>
<td>(Tuck et al., 2021)</td>
<td>Aeromagnetic Survey; Magnetic Interference Characterisation</td>
</tr>
<tr>
<td>Corvus</td>
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<td>3.66</td>
<td>Battery</td>
<td>5</td>
<td>N</td>
<td>(Tuck et al., 2018)</td>
<td>Aeromagnetic Survey; Magnetic Interference Characterisation</td>
</tr>
<tr>
<td>Aircraft</td>
<td>Style</td>
<td>Weight (kg)</td>
<td>Length (m)</td>
<td>Power</td>
<td>Max. Payload (kg)</td>
<td>Endurance (h)</td>
<td>Paper(s)</td>
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</tr>
<tr>
<td>KapetAir VTOL</td>
<td>Hybrid: VTOL &amp; fixed-wing</td>
<td>6.5</td>
<td>3.3</td>
<td>Battery</td>
<td>1.0</td>
<td>N/A</td>
<td>(Jirigalatu et al., 2021)</td>
</tr>
<tr>
<td>KIGAM Blimp</td>
<td>Airship</td>
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<td>11</td>
<td>Battery</td>
<td>10</td>
<td>N/A</td>
<td>(Kim, Lee, et al., 2021)</td>
</tr>
</tbody>
</table>
1.2.2 Magnetic characterisation and compensation

The characterisation and compensation of magnetic interference from various sources has been a significant focus of research in aeromagnetic surveying since Tolles and Lawson (1950) first identified that the effects related to the survey platform itself was sometimes making it difficult to achieve low noise levels due to aircraft attitude variations while in flight (Bickel, 1979). Research on UAS magnetic interference has concentrated on: (1) the characterisation and mitigation of effects due to on-board hardware and (2) compensating magnetic survey data by modelling and removing magnetic interference due to aircraft attitude variations.

Magnetic interference due to the survey platform was identified as a combination of three separate sources: permanent magnetization, induced magnetization, and eddy current fields. Wells (2008), Forrester (2014), Sterligov and Cherkasov (2016), Cherkasov and Kapshtan (2018) and Tuck et al. (2018) have identified motors and servos as significant sources of permanent magnetic interference due to the presence of iron alloys. Electronic systems, such as electronic speed controllers, motors, servos, and batteries all can contribute changing magnetic field signals by changing the amount of current flow in the circuitry; an increase in current, increases the magnetic field strength. Magnetic interference from eddy currents have not been as thoroughly or widely investigated because this effect is more complicated to measure; these currents are induced by time-varying external magnetic field acting on the conductive material, such as having the aircraft platform move through the Earth’s magnetic field during flight (Leliak, 1961; Teskey et al., 1991; Tuck et al., 2018). Typically eddy currents are
minimized through the use of non-conductive airframe materials; however, UAS airframes, particularly off-the-shelf brands (DJI, Yamaha, etc.) primarily use conductive materials, such as carbon fibre reinforced epoxy and/or aluminum make replacement or substitution without completely replacing the airframe difficult (Cunningham et al., 2018; de Smet et al., 2021; Eck & Imbach, 2012; D. Jiang et al., 2020; W. Li et al., 2014; Nikulin & de Smet, 2019; Pei et al., 2017; Romero et al., 2021; Wood et al., 2016; Yoo et al., 2020, 2021).

1.2.2.1 Magnetic characterisation of UAS and on-board components

Hansen (2018), Sterligov and Cherkasov (2016), Tuck et al. (2018, 2021), Walter et al. (2021) have developed techniques to identify sources of magnetic interference on UAS and provide clues to where optimal placement of components might be. Hansen (2018) performed pull-away magnetic field measurements over various components of a UAS, as well as the full UAS, and identified VTOL and servos were the primary sources of magnetic interference. Sterligov and Cherkasov (2016) identified that electro-engine, servos, and ferromagnetic elements were the primary sources of magnetic interference. Tuck et al. (2018) identified that the strongest sources of magnetic interference were power cables that connect batteries to motors and servos and identified that a magnetic sensor needs to be at least 0.5 m away from a fixed-wing UAS wingtip to reduce magnetic interference below a 2 nT threshold, a level that should ensure the 4th difference noise envelope is below the industry standard of 0.1 nT. Tuck (2019) further
demonstrated that magnetic interference is reduced with a sensor placement of 1.7 m from the center of a rotary-wing UAS. Tuck et al. (2021) developed a magnetic field scanner that allowed for mapping of four different UAS platforms (fixed-wing, single-rotor, quad-rotor, and hexa-rotor aircraft). Scanning was possible with motors engaged and this identified peak magnetic interference resulting from ferromagnetic and electrical current sources such as near servos, motors, and/or batteries with ranges between 21.4 and 574.2 nT.

Wells (2008), Forrester (2011), Hansen (2018), Forrester et al. (2014), and Huq et al. (2015) developed mathematical models to help predict, and thus attenuate, on-board magnetic interference sources through improved platform design. Wells (2008) concluded that high frequency fields could be attenuated with Faraday cages, and that Modified Dipole Ellipse Modelling (MoDEM) was successful at helping attenuate, stabilize, and equalize magnetic noise produced by interference sources. Hansen (2018) modelled a UAS as a combination of six magnetic dipoles in three dimensions. From the models, the optimal position magnetic sensors were found to be over 0.35 m away from both the end of the tail or wingtips. Forrester (2011) and Forrester et al. (2014) employed a genetic algorithm to find optimal configurations for servo motor positions on a UAS and demonstrated the improvements of changing configurations. Forrester (2011) and Huq (2015) developed the Permanent Magnetic Dipole (PMaD) and Dual Permanent Magnetic Dipole (DuPMaD) schemes to help model simple magnetic field sources and reduced magnetic noise of servo actuators.
1.2.2.2 Attitude compensation of UAS aeromagnetic datasets

Variations in aircraft attitude can create magnetic interference and are primarily managed by the application of attitude compensation techniques that were first outlined in the 1950s. Compensation can be applied during or after a survey, and typically requires a FOM, a set high-altitude of manoeuvres that can be used to model the magnetic signal generated from the motions of the aircraft due to permanent, induced, and eddy current elements. Since Tolles and Lawson (1950) identified that aircraft attitude variation creates magnetic interference, significant developments have been made on a least square modelling approach (Leliak (1961), Leach (1979), Bickel (1979), Groom et al. (2004), Han et al. (2017), Jianjun (2014), FitzGerald (2015)). Additional work, listed in Table 1-7 has focused on handling other on-board components, such as strobe and beacon lights (Du et al., 2019), or physical components with linear variations in magnetic interference (G. Zhao et al., 2019; X. Zhao et al., 2021). Adaptive filtering has been developed to further improve least squares fitting (Dou et al., 2016b; Noriega & Marszalkowski, 2017), and allow for handling electrical currents from on-board avionics, hydraulic pump controls, intercoms, and other instrumentation that is not accounted for by conventional methods.

Aircraft attitude compensation was initially developed for fixed-wing aircraft. Chen (2018) proposed second-stage, coherent noise suppression compensation method to reduce effects from helicopter aircraft components, such as helicopter engine, avionics systems, and other sources. Noriega (2011, 2013, 2015) presented performance metrics, such as improvement ratio, cross-correlation...
index, and profile similarity index, to assist in evaluating the effectiveness of aircraft attitude compensation. Noriega (2015), and Yin (2019) suggested approaches to compensate gradiometer systems, both three-axis and tensor, respectively. With the accessibility of machine learning, novel approaches to attitude compensation with neural networks have been presented by Williams (1993), Ma et al. (2018) Zhao et al. (2021), Jiao et al. (2022), Yu et al. (2021, 2022), and Zhang et al. (2022).

Although attitude compensation on UAS has not received as much attention as for other platforms, a few research projects (Table 1-7) have investigated the issue. Zhang et al. (2011) simulated an aeromagnetic survey with a UAS and found that permanent and induced components produced significant interference and concluded that eddy-currents were negligible. However, Li et al. (2018) performed Tolles-Lawson compensation on a FOM flight flown by a hexacopter and a towed sensor and identified that only considering permanent and induced components did not compensate for attitude as well as when eddy currents were also accounted for; improvement ratios were 3.80 and 6.86, respectively. Tuck et al. (2019) employed a real-time compensator on a gas powered single-rotor UAS and obtained IRs of between 1.77 and 3.99 on FOM flight manoeuvres. The machine learning attitude compensation outlined by Yu et al. (2021, 2022) was applied to a FOM collected by an UAS. The results were compared to a recursive least-squares algorithm (IR = 10.95), principal component analysis (10.82), least squares (IR = 7.37), and ridge regression (IR = 7.73).
Machine learning is being actively researched for its application to attitude compensation for aeromagnetic surveying (Table 1-7). Williams (1993) first presented an approach for compensating aeromagnetic data with neural networks; implementing a network that concatenated positional, diurnal, and attitude effects. Ma et al. (2018) presented an updated neural network model that employs a stochastic gradient variational Bayes estimator and a variational autoencoder. The model considers nine positional and 16 attitude components, and successfully compensated a synthetic dataset. They showed that the aeromagnetic compensation problem is well-conditioned from a neural network point of view, and that a consistent and robust neural network solution was viable. Zhao et al. (2021) applied a 5-layer deep autoencoder (DAE) that was activated with the sigmoid function and showed an IR of 22.73 for a FOM flight whereas Tolles-Lawson least squares compensation only achieved 12.66. Yu et al. (2021, 2022) presented machine learning approaches to attitude compensation based off the structure outlined by Williams (1993). The modified structures were a generalized regression neural network (GRNN) and the DAE proposed by Zhao et al. (2021). The GRNN and DAE returned IRs of 10.5 to 11.5 and 11.22 to 11.75, while least squares and principal component analysis produced results of 10.95 and 10.82, respectively. The DAE was found to better handle multicollinearity than least squares compensation. The methods mentioned above have all been proposed and demonstrated on small FOM flights.
Table 1-7: Summary of aeromagnetic compensation publications. ‘N/A’ designates specification was not provided in publication.

<table>
<thead>
<tr>
<th>Reference</th>
<th>Method</th>
<th>Platform</th>
<th>Flight Altitude AGL (m)</th>
<th>FOM Used?</th>
<th>Applied to low altitude data?</th>
<th>IR</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>(L. Chen et al., 2018)</td>
<td>Tolles-Lawson coherence noise suppression</td>
<td>Helicopter Stinger</td>
<td>N/A</td>
<td>Yes</td>
<td>N/A</td>
<td>11.15 to 23.6</td>
<td>Reduced residual interference from 0.065 nT to 0.045 nT</td>
</tr>
<tr>
<td>(Dou et al., 2016b)</td>
<td>Tolles-Lawson adaptive filtering</td>
<td>Simulation</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>Effectively reduced standard deviation.</td>
</tr>
<tr>
<td>(Dou et al., 2016a)</td>
<td>Tolles-Lawson coefficient estimation</td>
<td>Simulation</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>Helped consider horizontal and vertical gradients to improve attitude compensation performance</td>
</tr>
<tr>
<td>(Dou et al., 2021)</td>
<td>Tolles-Lawson real-time adaptive filtering</td>
<td>Inhabited Aircraft</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>Demonstrated that it can adapt and compensate for quiet data, but struggled with magnetic anomalies</td>
</tr>
<tr>
<td>(Han et al., 2017)</td>
<td>Modified Tolles-Lawson</td>
<td>Simulation</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>Effective when three-axis fluxgate magnetometer has low measurement accuracy</td>
</tr>
<tr>
<td>(Jiao et al., 2022)</td>
<td>Neural networks with compressed and accelerated networks</td>
<td>UAS</td>
<td>N/A</td>
<td>Yes</td>
<td>N/A</td>
<td>N/A</td>
<td>Improved standard deviation from 0.221 nT for ridge regression approach to 0.194 nT and 0.195 nT</td>
</tr>
<tr>
<td>(H. Li et al., 2018)</td>
<td>Tolles-Lawson least squares compensation</td>
<td>UAS</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>6.86</td>
<td>Demonstrated an IR of 6.86 and a reducing in noise from ±15 nT to ±1 nT</td>
</tr>
<tr>
<td>(Ma et al., 2017)</td>
<td>Neural networks with unscented Kalman filtering</td>
<td>Towed Bird</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>Reduced overfitting by 60%</td>
</tr>
<tr>
<td>Reference</td>
<td>Method</td>
<td>Platform</td>
<td>Flight Altitude AGL (m)</td>
<td>FOM Used?</td>
<td>Applied to low altitude data?</td>
<td>IR</td>
<td>Results</td>
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</tr>
<tr>
<td>(Ma et al., 2018)</td>
<td>Neural network and stochastic gradient variational bayes</td>
<td>Simulation</td>
<td>N/A</td>
<td>Yes</td>
<td>N/A</td>
<td>N/A</td>
<td>Demonstrated correlation between true residual error and estimated standard deviation</td>
</tr>
<tr>
<td>(Noriega, 2015)</td>
<td>Tolles-Lawson based compensation in gradiometry</td>
<td>N/A</td>
<td>N/A</td>
<td>Yes</td>
<td>N/A</td>
<td>15 to 65</td>
<td>Showed effective compensation with IR ranging from 16 to 65</td>
</tr>
<tr>
<td>(Tuck et al., 2019)</td>
<td>Tolles-Lawson based compensation with hardware compensator</td>
<td>Single-rotor UAS</td>
<td>120</td>
<td>Yes</td>
<td>Yes</td>
<td>1.6 to 8.1</td>
<td>Showed compensation of aeromagnetic data collected by UAS with IR ranging from 1.6 to 8.1</td>
</tr>
<tr>
<td>(Williams, 1993)</td>
<td>Artificial neural network</td>
<td>Inhabited Aircraft</td>
<td>1000</td>
<td>Yes</td>
<td>No</td>
<td>N/A</td>
<td>Showed that neural networks can provide a solution to attitude compensation</td>
</tr>
<tr>
<td>(Yin, 2019)</td>
<td>Tolles-Lawson tensor gradiometric compensation with non-linear least squares</td>
<td>Simulated</td>
<td>N/A</td>
<td>Yes</td>
<td>No</td>
<td>260</td>
<td>Showed that non-linear compensation can be beneficial to tensor gradiometry compensation</td>
</tr>
<tr>
<td>(P. Yu et al., 2021)</td>
<td>Generalised regression neural network compensation</td>
<td>UAS</td>
<td>50</td>
<td>Yes</td>
<td>Yes</td>
<td>7.3 to 11.5</td>
<td>Showed compensation of low-altitude FOM compensation with a GRNN on UAS data</td>
</tr>
<tr>
<td>(P. Yu et al., 2022)</td>
<td>Deep auto encoder neural network attitude compensation</td>
<td>UAS</td>
<td>50</td>
<td>Yes</td>
<td>Yes</td>
<td>2.5 to 9.7</td>
<td>Showed that a deep auto encoder can be used to compensate UAS data</td>
</tr>
<tr>
<td>(B. Zhang et al., 2011)</td>
<td>Simplified Tolles-Lawson</td>
<td>UAS</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>Eddy-current fields can be ignored for UAS</td>
</tr>
<tr>
<td>Reference</td>
<td>Method</td>
<td>Platform</td>
<td>Flight Altitude AGL (m)</td>
<td>FOM Used?</td>
<td>Applied to low altitude data?</td>
<td>IR</td>
<td>Results</td>
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</tr>
<tr>
<td>(D. Zhang et al., 2022)</td>
<td>Convolution neural network</td>
<td>Fixed-wing</td>
<td>3000</td>
<td>Yes</td>
<td>N/A</td>
<td>21.3 to 50.8</td>
<td>Improved IR compared to classical Tolles-Lawson and Tolles-Lawson gradient compensated</td>
</tr>
<tr>
<td>(G. Zhao et al., 2019)</td>
<td>Tolles-Lawson multimodal compensation for mitigating multicollinearity</td>
<td>Fixed-wing</td>
<td>3000</td>
<td>Yes</td>
<td>N/A</td>
<td>3.8</td>
<td>Showed multimodal compensation can mitigate multicollinearity, and performed better than classical Tolles-Lawson least squares compensation</td>
</tr>
<tr>
<td>(X. Zhao et al., 2021)</td>
<td>Deep auto encoder neural network compensation</td>
<td>UAS</td>
<td>N/A</td>
<td>Yes</td>
<td>N/A</td>
<td>12.7</td>
<td>DAE helped reduce the problem of multicollinearity in classical Tolles-Lawson least squares compensation</td>
</tr>
<tr>
<td>(Zhou et al., 2014)</td>
<td>Tolles-Lawson least mean squares (LMS)</td>
<td>Simulation and Inhabited Aircraft</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>Visually compared compensation results, concluding LMS is effective</td>
</tr>
</tbody>
</table>
1.2.3 Advanced processing of magnetic data acquired with UAS

Magnetic gradiometry is the rate of change of magnetic intensity between two points in space (either from a pair of sensors recording simultaneously or between two successive measurements) divided by the separation distance. The possibility of doing gradiometry with data acquired using UAS has been discussed in literature since Trammell III (2005) presented simulated studies on the topic. In 2014, Caron et al. (2014) presented gradiometry results from a survey with a simulated UAS (a towed bird with similar characteristics to a fixed-wing UAS) showing higher resolution gradient maps than traditional surveys by flying at a lower altitude. Some UAS have been developed for gradiometry but have not been demonstrated in literature. Cunningham (2016), GEM Systems (2017), Pei et al. (2017) and Mu et al. (2020) each present aircraft that are capable of gradiometry but have not presented any results. Cunningham (2016) described a fixed-wing UAS capable of gradiometry and provided theoretical estimations on the capabilities of gradiometry for UAS anomaly detection. Two publications present gradiometry results from a UAS survey. First, Luoma et al. (2020) flew a DJI Matrice 600 Pro UAS with a towed vertical gradiometer using three-axis fluxgates and showed that the use of a gradiometer was feasible with a UAS but results contained significant noise. Walter et al. (2020) performed a series of UAS surveys at different altitudes, 35 m, 45 m, and 70 m, and the presented vertical gradient results between 35 m and 45 m AGL. This paper showed that the gradient between these two datasets were similar to upward continuation calculations practiced throughout industry and highlighted a local shear zone. The margin of errors
identified were due to ±2.5 m variation in flight altitude for both the 35 and 45 m AGL surveys.

Similarly, advanced processing of magnetic datasets acquired by UAS are limited; only recently has there been published studies of magnetic inversion of UAS data. Walker (2018) provided an overview of magnetic inversion steps with the use of a UAS dataset, but no detailed information on the dataset or region were provided. Jiang et al. (2020) presented a helicopter UAS dataset with inversion results successfully identifying 3D magnetically susceptible targets over a 3 km x 3 km region. Koyama et al. (2021) provided horizontal and vertical slices through a magnetic susceptibility model over the main crater of Mt. Motoshirane in Japan, with limited success due to the size of the area covered by the survey compared to the total area of the mountain. Porras et al. (2021) presented 3D inversion results from a Mavic Matrice 600 Pro hexacopter over a 1.0 km x 0.3 km area, successfully highlighting the location of two magnetic bodies of interest along a normal fault cutting through the survey area.

1.2.4 Other applications

Aeromagnetic surveying has been the primary application of UAS within the field of geophysics, particularly for mineral exploration. The use of aeromagnetic surveying with UAS within enclosed spaces, such as buildings or mines, is also being investigated. Lipovský et al. (2021) reported findings from an aeromagnetic survey with a small UAS to map magnetic interference within smart cities and
buildings, while also noting potential for surveying hazardous areas, such as caves or mines. Other fields of research have also investigated the use of aeromagnetic surveying with UAS, some notable examples are UXO (Kolster et al., 2022; Kolster & Døssing, 2020; Trammell III et al., 2005; Versteeg et al., 2010) or archeological (Gavazzi et al., 2016; Pisciotta et al., 2021; Schmidt et al., 2020) detection.

Beyond magnetics, UAS are also being developed for other applications as well, most notably for multi- and hyper-spectral, radiometric, and electromagnetic surveying. Heincke et al. (2019) and Jackisch et al. (2019, 2022) have published results from multispectral and hyperspectral surveys with UAS and integrated results with magnetic data collected by an UAS to provide a comprehensive and geologically interpretable product. Li et al. (2014) and Parshin et al. (2021) showed successful radiometric surveys with a scintillator attached to a UAS produce over 1 km² areas. Parshin, Bashkeev et al. (2021) and Parshin, Morozov, et al. (2021) have presented novel applications for time-domain electromagnetic surveying with the use of an UAS. A large ground EM transmitter loop is deployed, and data is collected by a UAS carrying a receiver loop. Results identified potentially conductive targets; however, many improvements to the system were suggested.

1.3 Research problem statement

As discussed in Sections 1.1 and 1.2, UAS studies have primarily focused on introducing new UAS and showing their capabilities on small case studies, typically covering areas of under 1 km². Studies that present direct comparisons with
traditional surveys are rare and typically provide minimal quantitative comparisons. Studies featuring advanced application of UAS surveys are even rarer, where magnetic data from only three small UAS surveys have been inverted (D. Jiang et al., 2020; Koyama et al., 2021; Porras et al., 2021). Some research has been made in identifying which components on UAS are magnetic interference sources (Forrester, 2011; Forrester et al., 2014; Hansen, 2018; Huq et al., 2015; Sterligov & Cherkasov, 2016; Tuck et al., 2018, 2021; Walter et al., 2021; Wells, 2008) but few have explored methods of effectively compensating magnetic interference due to the aircrafts changing attitude (H. Li et al., 2018; Tuck et al., 2019; P. Yu et al., 2021, 2022) and none of these approaches handle limitations in flight altitude due to government regulations or aircraft hardware. This suggests that further efforts are needed to not only show the level of quality UAS data can achieve, both in comparison to traditional survey methods, as well as in terms of final deliverables. Furthermore, methods are needed to effectively remove aeromagnetic interference from aircraft attitude variations, without requiring high-altitude FOM flights.

The overarching challenge for the use of UAS for aeromagnetic surveys can be broken down as three research questions:

1) For commercial surveying, how do UAS platforms perform qualitatively and quantitatively in comparison to traditional magnetic surveying methods at similar or lower altitudes above ground level?

2) Can aeromagnetic datasets collected by a UAS produce realistic and informative inversion results?
3) Is it possible to effectively compensate UAS aeromagnetic data without requiring a high-altitude FOM flight?

1.4 Research objectives

The overarching objective of this thesis is to evaluate and improve aeromagnetic surveying capabilities of UAS. To achieve this, the research presented in this integrated thesis is organized into three studies, corresponding to Chapters 3, 4, and 5. The objectives of each study are:

Chapter 3 - To provide quantitate and qualitative comparisons between three different magnetic datasets – ground, helicopter, and UAS – to demonstrate the maturity of UAS magnetometry over a practical and geomagnetically interesting location: The first study in this thesis aims to address problem (1) by performing direct comparison between a UAS aeromagnetic dataset with two datasets from traditional methods, upward continued ground magnetic and helicopter aeromagnetic datasets. Qualitative comparisons detail visual differences between the three magnetic datasets, including amplitude variations and the locations and continuity of structures. Quantitative comparisons investigate cell-by-cell absolute differences, percent differences, and coherence between the datasets and compare overall image mean absolute difference, mean percent difference, structural similarity index, mean squared error, and peak signal-to-noise ratio metrics.
Chapter 4 - To demonstrate the advanced use of aeromagnetic data collected by an UAS by performing 3D inversion: The second study in this thesis aims at addressing problem (2) by providing a greater insight into the geological subsurface using unconstrained and constrained magnetic 3D inversion using an aeromagnetic dataset that was collected by an UAS. The dataset was collected over a geomagnetically and geologically interesting region that hosts gold mineralization zones.

Chapter 5 - To develop a method for attitude compensation of aeromagnetic data collected by an UAS that does not require a high-altitude figure-of-merit flight: The third study in this thesis aims to address problem (3) by presenting a novel approach to attitude compensation based on recurrent neural networks, an aspect of machine learning. The network presented has the ability to separate positional and attitude components of the aeromagnetic data without the requirement of a high-altitude FOM test flight. The RNN attitude compensation is performed on data from (1) an 80 m AGL traditional fixed-wing airplane survey, (2) a 120 m AGL test single-rotor UAS survey, and (3) a 50 m AGL multi-rotor UAS survey. Comparisons with hardware- and software-based least squares attitude compensation, based off the methods proposed by Tolles and Lawson (1950), are provided.

1.5 Originality of research

As outlined in Section 1.2 there have been previous demonstrations of aeromagnetic surveying with UAS; however, there have been limited
developments in qualitative and quantitative comparisons with traditional survey platforms, minimal demonstrations of advanced uses, and few efforts in compensating attitude effects.

The aeromagnetic surveys with UAS used for comparison with traditional ground and airborne surveys have been performed over small regions: Walter et al. (2020) covered 0.35 km²; le Maire et al. (2020) covered 1.0 km²; Shahsavani et al. (2021) covered 0.1 km²; de Smet (2021) covered 1.1 km²; and Schmidt et al. (2020) covered 0.0012 km². These surveys are too limited in extend to provide robust comparisons with both traditional ground and airborne methods. The associated case studies do not feature advanced processing and analysis of UAS collected datasets. The two studies presented in this thesis, Chapters 3 and 4, expand on the qualitative and quantitative comparisons between magnetic surveying with UAS and traditional methods as well as present advanced data processing and analysis. They show a realistic survey environment where tradition magnetic surveys have been completed. The survey results cover a geologically complex region with an area of 4.96 km². Comparisons are between total magnetic intensity and three calculated gradients (in-line, transverse, and vertical gradients). The methods outlined by the two studies presented in Chapters 3 and 4 provide approaches that could be used to further evaluate the performance of their own UAS.

Magnetic inversion has only recently been demonstrated using UAS datasets; at the time of publishing Cunningham et al., (2021) there was only a conference paper detailing magnetic inversion with UAS collected data, Walker (2018), which
was limited in detail and results. The publications, Jiang et al. (2020), Koyama et al. (2021), and Porras et al. (2021) were all received or published after Cunningham et al. (2021). The second study of this thesis, Chapter 4, detailed both unconstrained and constrained magnetic inversion of UAS collected data. It discussed the steps for both unconstrained and constrained inversion to guide other research projects on how to reproduce the work. The results of this study filled a gap in demonstrating the use cases for aeromagnetic surveying with UAS, showed the robustness of the data collected by a UAS, and provided guidance for further mineral exploration on the Nelligan, QC property.

To date, little research into magnetic compensation for UAS platforms has been performed or described in the literature. The research presented by Li et al. (2018) and Tuck et al. (2019) apply standard industry approaches and Yu et al. (2021, 2022) present novel machine learning approaches to perform aeromagnetic compensation; none attempt to tackle effective aeromagnetic compensation without requiring a high-altitude FOM flight. As discussed in Sections 1.1 and 1.2, in many countries UAS flights are heavily regulated, including their maximum flight altitudes; in Canada UAS can only fly below 122 m above ground level, unless specific permission is provided. This low flight altitude limits the capability of effectively flying a high-altitude FOM and performing magnetic compensation. The third study of this thesis, Chapter 5, proposes a novel machine learning algorithm, with the use of recurrent neural networks, to model and compensate magnetic interference generated by the UAS during or after an aeromagnetic survey without the need for high-altitude test flights. This magnetic compensation method is
demonstrated on a traditional fixed-wing aeromagnetic survey as well as on high-altitude UAS and low-altitude UAS surveys.
2. Background

2.1 Overview

This research uses a standard methodology for collecting and processing aeromagnetic datasets as well as standard tools for developing machine learning algorithms but applied to model attitude effects in magnetic data. The next three chapters, 3, 4, and 5, in this thesis represent standalone manuscripts and each chapter is written to fully describe the methodological approach used in each case. A concise summary of aspects of: aeromagnetic surveying methodologies (Section 2.2) including upward continuation and magnetic inversion; magnetic noise sources and compensation (Section 2.3); as well as a machine learning overview including details on multi-layer perceptron and long-short-term memory networks (Section 2.4) are provided below to expand on the material discussed in Chapters 3, 4, and 5.

2.2 Magnetic surveying and processing methods

Because the Earth’s metallic outer core is an electrically conductive fluid rotating and convecting, it functions as an electrical generator converting kinetic energy into electrical and magnetic energy (Ranalli, 1995). Due to chemical and radioactive heating, the outer core is in a continual state of convection, which induces electrical currents within itself, which in turn generate their own magnetic field, creating a self-sustaining feedback loop. This magnetic field can interact with
magnetically susceptible minerals that are below their Curie temperature within the crust of the Earth (Kearey et al., 2002).

Magnetic surveying is used to investigate subsurface geology by using a magnetometer to record the local magnetic field. Magnetometers can measure the total strength of the magnetic field or its magnitude and direction, the vector field. It allows for remote mapping and delineation of geological structures and assists in locating and identifying potential mineral resources. The measured field is the vector sum of the contribution from local geology, diurnal effects, and attitude signals, induced from motions of the survey platform. For aeromagnetic surveying, processing of survey data involves the removal of effects that are not due to geological contributions from magnetic minerals in the subsurface.

Geological contributions are related to the underlying rocks and minerals, where magnetic signal is a function of the unit’s magnetic susceptibility, a ratio between the induced magnetization and the inducing field. Most common rock-forming minerals exhibit low magnetic susceptibility, where a typically small proportion of magnetic minerals can contribute to large variations in the local magnetic field; particularly minerals belonging to the iron-titanium-oxygen (e.g., magnetite (Fe₃O₄)) or the iron-sulphur (e.g., pyrrhotite (Fe₁₋ₓS, 0 < x < 0.2)) geochemical groups. Magnetic susceptibility is dependant on the size and shape of mineral grains, so a wide range of susceptibilities is possible for a given mineral content in a rock. Values of magnetic susceptibility vary by orders of magnitude from below 10⁻⁵ SI (e.g., shales) to over 10² SI (e.g., massive magnetite); Figure 2-1 presents a range of magnetic susceptibility values for common minerals and rock types.
Some magnetic susceptibilities of materials can also be negative, such as bismuth (-1.6 x 10^{-4} SI), gold (-3.4 x 10^{-5} SI), silver (-2.4 x 10^{-5} SI), and water (-9 x 10^{-6} SI) (Griffiths, 1999).

The Earth’s magnetic field experiences temporal variations, either long- or short-period. Long-period variations have periods of over a year and are primarily associated with changes in the electric currents producing the internal field. Shorter period variation, less than a year, are due to sources external to the Earth and are known as diurnal variations. Diurnal variations are primarily due to currents flowing in the ionosphere due to ionising radiation from the Sun generating magnetic interference with the Earth’s field. Values typically vary up to 30 nT in a day, as well as with latitude, and are at a minimum during the night, when the region is shielded from the Sun’s radiation. Magnetic storms can create rapid variation in the magnetic field, with periods of milliseconds to minutes and can cause amplitude changes of over 100 nT. These storms are transient disturbances that are associated with the 11-year sunspot cycle and can last from hours to several days. Magnetic surveys are not performed during magnetic storms as they can significantly affect measurements which cannot be corrected for with base station corrections.

To remove diurnal variations from a magnetic survey, a base station magnetic sensor is deployed near the survey area and records the magnetic field variations during the project. This magnetic field data is typically filtered with a moving average window of 60 s and interpolated to the sampling rate of the survey.
platforms magnetometer (e.g., to 1 or 10 Hz). Differences from the average field are then subtracted from the survey platform’s dataset.

Magnetic datasets can also contain effects due to variations in the survey platform’s orientation in the Earth’s magnetic field. For aeromagnetic surveying, effort is made to minimise the amount of magnetically susceptible material on the platform, but some components cannot be removed, such as motors, wires/cables, electronics, and all of these can produce their own magnetic field and will contribute to the measured field. The first model of the magnetic interferences from the survey platform was presented by Tolles and Lawson (1950) using a 16-coefficient equation which is associated to a change in attitude of an aircraft. This model assumes that the interference from the aircraft is composed of three magnetic components: (1) permanent magnetization, (2) induced magnetization, and (3) eddy-currents. Effective compensation of these aircraft effects is typically performed by solving for the 16-coefficients using least squares fitting, and then subtracting the modelled effects from the measured magnetic field (See Section 2.3).

The steps to process aeromagnetic data are listed below in their typical order of application:

1. **Data collection** with the aeromagnetic survey platform.

2. Magnetic aircraft **attitude compensation** corrections (in real-time or post-processing).
3. **Manual editing** of magnetic data is performed to remove spurious data, such as spikes from sensor loss-of-lock.

4. A **lag correction** which applies a shift to the sample time to account for synchronization issues as well as the horizontal spatial offsets between the GPS antenna and the magnetic sensor (Coyle et al., 2014).

5. A **heading correction** which adjusts the magnetic data to remove a small residual magnetic response related to the platforms heading, its flight direction (Dentith & Mudge, 2014).

6. An **IGRF** (International Geomagnetic Reference Field) **correction** which removes magnetic variations attributable to the theoretical undisturbed magnetic field of the Earth due to circulation patterns within the outer core (Kearey et al., 2002). This will provide residual magnetic intensity (RMI) results, reflecting variations from the modeled IGRF magnetic field across the area of interest.

7. **Line levelling** which adjusts magnetic field values along survey lines due to temporal variation of Earth’s magnetic field by using intersection points between tie and traverse lines (Coyle et al., 2014; Dentith & Mudge, 2014).

8. **Micro-levelling** which is applied to isolate and remove low amplitude anomalies that are parallel to flight line direction to minimize line levelling issues that were not removed with the line levelling procedure (Coyle et al., 2014).
9. Gridding and further processing and analysis can then be applied. Gridding the data is done to interpolate the magnetic data such that maps can be made for further interpretation. Bidirectional gridding, minimum curvature interpolation, and kriging are industry standard methods of data gridding (Guo et al., 2012; Naprstek & Smith, 2019). Filtering of the data can be performed to give information on horizontal (in-line) gradients, first or second vertical derivatives, analytical signal, etc. Advanced data processing and analysis can also be performed (i.e., upward continuation, magnetic inversion modelling).
Figure 2-1: Magnetic susceptibility ranges for different minerals and rocks. Dark shading indicates the most common parts of the range. From Dentith & Mudge (2014).
2.2.1 Upward continuation

When two or more magnetic surveys are performed at different altitudes, upward continuation can be performed to bring each dataset magnetic field readings up to a consistent altitude above ground level. It can also be applied to attenuate small, shallow anomalies and enhance ones that are from deeper, larger sources (Blakely, 1995). This method is typically performed by converting the magnetic data into the frequency domain, typically via the Fast Fourier Transform, and multiplying by an exponential, upward continuation filter \( f \) (equation 2.1), with a change in altitude of \( \Delta z \) and wavenumber of \( k \), and then transforming back to the time domain, via the inverse Fast Fourier Transform.

\[
f = e^{-\Delta z |k|}
\]  

(2.1)

2.2.2 Magnetic inversion

Magnetic inversion is used to obtain an estimate of the magnetic susceptibility distribution in the subsurface. Several inversion techniques exist for potential field data using both linear and non-linear techniques (Soulaimani et al., 2020). The non-uniqueness of the solution is the primary challenge with all inversion procedures, thus more information allows for improved models. Inversion typically follows a form of the minimisation algorithm originally developed in 1970 (Soulaimani et al., 2020). Model parameters are varied to minimize an error function until a model best satisfies the data. Unconstrained inversion is the
modelling of the dataset without the input of other constraints, whereas constrained inversion imposes restriction to the model with known information, such as borehole data and magnetic susceptibility readings to provide a more realistic estimation of the subsurface structures.

The magnetic inversion presented in Chapter 4 employs Seequent’s (formerly Geosoft) Oasis Montaj voxel-based inversion, VOXI Earth Modelling™. Rectangular cells are initialized with a single magnetic susceptibility value which is then varied to reduce the difference between the calculated magnetic field from the voxel model with that of the input magnetic field map. Depth weighting is also applied, to attenuate the effects from deep voxels. VOXI Earth Modelling is based on the cartesian cut cell inversion algorithm developed by Ingram et al. (2003) and improved upon by Ellis & MacLeod (2013) using cloud data storage and computing systems (Soulaïmani et al., 2020).

2.3 Magnetic sources and compensation

2.3.1 Magnetic noise sources

Under an external magnetic field, matter will become magnetized, where tiny dipoles will align along some preferential direction (Griffiths, 1999). The magnetization of a material is determined by the sum of the contributions from each magnetic domain within that material, where each has a magnetic moment ($m$). The magnetization ($M$) of a material is the magnetic dipole moment per unit
volume of that material. It can be described in terms of the superposition of two different magnetizations; the permanent \((M_p)\) and induced \((M_i)\) magnetizations (equation 2.2).

\[
M = M_p + M_i
\]  (2.2)

As a molten material cools below its Curie temperature, the interatomic distances are decreased to separations where electron coupling is possible, allowing for a permanent field to become stored in, or locked into, the material, \(M_p\).

The domains of the material align in such a way to resist the external magnetic field \((H)\). Electron orbits within atoms are normally random but \(H\) causes each atom to pick up a little extra dipole moment, because of electron charge, these increases are opposite of the applied field (Griffiths, 1999). For materials that can exhibit permanent magnetization, their strength and orientation of magnetization is related to the external field at the time of the materials formation and is considered constant for most purposes but can change very slowly over geological time scales (Dentith & Mudge, 2014). \(M_i\) is a temporary field, where the magnetic domains in the material will align with the external field until the external field is removed. Under weak magnetic fields, like the Earth’s, the \(M_i\) is proportional to \(H\):

\[
M_i = \chi_M H
\]  (2.3)

where \(\chi_M\) is the magnetic susceptibility of the material, which is a measure of how magnetized a material will become in an external field. It is closely related to the
permeability of a material; a measure of a material's ability to support a magnetic field. Materials that follow equation 2.3 are considered linear media. In that case, the induced magnetic field ($B_i$) is described as:

$$B_i = \mu_o (H + M_i) = \mu_o (1 + \chi_M) H$$

where $\mu_o$ is the permeability of free space ($4\pi \times 10^{-7}$ N·A$^{-2}$) (Griffiths, 1999).

The permanent magnetic ($B_p$) field from a material, can be modelled as a series of magnetic dipoles ($B_{dip}$) at a distance, $r$, in the direction of vector $\hat{r}$ (Griffiths, 1999):

$$B_{dip}(r) = \frac{\mu_o}{4\pi} \frac{3\hat{r} (m \cdot \hat{r}) - m}{r^3}$$

The Biot-Savart law (Griffiths, 1999) describes the magnetic field generated from electric current:

$$B_{et}(r) = \frac{\mu_o}{4\pi} \int_C \frac{ldl \times \hat{r}}{r^2}$$

where $dl$ is the vector along the path $C$ with a magnitude that is the length of the element of wire in the current ($I$) direction.

Magnetic fields can also occur on the surface of conductive materials that are within a varying magnetic field, known as the eddy current magnetic field, and can contribute to magnetic noise (FitzGerald & Perrin, 2015). The eddy current magnetic field ($B_{ed}$) is (Griffiths, 1999):
\[ B_{ed} = \frac{-1}{\sigma} \int \nabla \times J_{ed} dt \]  

(2.7)

where \( J_{ed} \) is the eddy current density that is induced from a time-varying \( H \) which is described by Lenz’s Law:

\[ J_{ed} = -\mu \sigma \frac{d}{dt} \int_S H \cdot dS \]  

(2.8)

where \( \sigma \) is the electrical conductivity and \( S \) is the magnetic flux surface.

### 2.3.2 Magnetic attitude model

Tolles and Lawson (1950) first proposed a 16-coefficient equation for modelling the magnetic field noise from platform attitude and motional changes with Leliak (1961) demonstrating a solution with least squares using data from figure-of-merit flight patterns and manoeuvres.

The Tolles-Lawson (TL) model assumes that the magnetic field produced from aircraft attitude (\( B_A \)) is composed of the vector sum of three different noise sources: (1) \( B_P \) – permanent magnetization; (2) \( B_I \) – induced magnetization; and (3) \( B_E \) – eddy-currents.

\[ B_A = B_P + B_I + B_E \]  

(2.9)

The TL model requires the projection of noise from each source type along the transverse, longitudinal, and vertical axes of the aircraft (\( T, L, \) and \( V \), respectively)
onto the direction of the geomagnetic field \((B_g)\). When \(B_g\) and \(B_A\) are the only sources considered (i.e., no diurnal effects), the measured magnetic field produced by the survey platform \((B_M)\) is the vector sum:

\[
B_M = B_g + B_A
\]  
(2.10)

For many aeromagnetic surveys, including the ones in this thesis, \(B_M\) is measured using a total-field magnetometer providing its magnitude value only \((B_M)\), whereas the direction of the field is usually measured by a second magnetometer (e.g., three-axis fluxgate).

Bickel (1979) described the original TL model with 16 coefficients as a combination of: three permanent magnetization components \((B_p)\), five induced sources (reduced from nine) components \((B_i)\), and eight (reduced from nine) eddy current components \((B_e)\).

\[
B_p = \sum_{i=1}^{3} c_i u_i
\]
(2.11)

\[
u_1 = \cos(\alpha) = \frac{T}{F}
\]
(2.12)

\[
u_2 = \cos(\beta) = \frac{T}{F}
\]
(2.13)

\[
u_3 = \cos(\gamma) = \frac{T}{F}
\]
(2.14)
where $c_i$ is the coefficient associated with $u_i$, the directional cosine of the angles $\alpha$, $\beta$, and $\gamma$ between $B_o$ and $T$, $L$, and $V$. Leach (1979) proposed that a three-axis fluxgate magnetometer can describe the direction cosines using:

\[
F = \sqrt{T^2 + L^2 + V^2} \tag{2.15}
\]

Nine coefficients from $(B_i)$ can be reduced to five by removing three due to symmetry and another via high-pass filtering (Bickel, 1979).

\[
B_i = \sum_{i=1}^{3} \sum_{j=1}^{3} c_{ij}u_iu_j \tag{2.16}
\]

The magnetic field from eddy currents $(B_e)$ produces a field that is proportional to the time derivative of the directional cosines $(u_i')$. By Assuming $\frac{\partial H}{\partial t} \approx 0$, then $u_1u'_1 + u_2u'_2 + u_3u'_3 \approx 0$, one of the components where $i = j$ can be removed.

\[
B_e = \sum_{i=1}^{3} \sum_{j=1}^{3} c_{ij}u_iu'_j \tag{2.17}
\]

FitzGerald and Perrin (2015) presents nomenclature that was used in Chapter 5, adapted from the version discussed above. It follows the form outlined by employing the magnitude of each axis of a three-axis fluxgate magnetometer ($T$, $L$, and $V$). $T$, $L$, and $V$ is mapped to the inputs of $B_p$. The multiplication of data from each fluxgate axis, $TT$, $TL$, $TV$, $LT$, $LL$, $LV$, $VT$, $VL$, and $VV$, maps to the inputs of $B_i$ with $TT$, $LT$, $VT$, and $VL$ removed. The multiplication of data from each fluxgate
axis with the derivatives, Tt, TI, Tv, Lt, LI, Lv, Vt, VL, and Vv maps to the inputs of $B_e$ with Tt removed.

A solution for determining the TL coefficient is (Bauer, 1965; P. Yu et al., 2021):

$$b_t = Xc$$

(2.18)

$$c = (X^T X)^{-1} X^T b_t$$

(2.19)

where $b_t$ and $c$ are both column vectors. Variable $b_t$ is composed of $N B_A$ readings, where $B_A$ is approximated by the filtering the FOM’s $B_M$ to minimize $B_G$. The $c$ values correspond to the 16 TL coefficients. Variable $X$ is an $N \times 16$ matrix comprised of $N$ of the 16 TL inputs (T, L, V, TT, TL, etc.). Variable $c$ is determined by applying least squares fitting to the FOM data, and then is used to calculate and remove $B_A$ to determine $B_G$ from $B_M$.

FitzGerald and Perrin (2015) identified shortcomings of the solution Leliak (1961) first proposed: (1) the use of low altitude magnetic vector data will contain second order effects on sensors due to aircraft movements in a magnetic field gradient; (2) Leliak (1961) ignores vertical gradient terms for pitch corrections; (3) eddy currents neglect the noise from moving parts such as the rudder, EM effects from moving through a large magnetic gradient and magnetotellurics, and varying EM signals from electronic components and electrical use. They highlighted that ‘black box’ attitude compensation tools will perform better than the mathematical approach described above because the hardware has been refined over many
years. Improvements to the model could involve considering exponential decay of vertical terms and consider the third order orientation terms from the magnetic field tensor.

### 2.4 Machine learning and neural networks

In general, machine learning is a branch of artificial intelligence and computer science that focuses on the use of data and algorithms to imitate the way in which humans learn by gradually improving accuracy. It is a powerful tool can be used to make predictions or classifications based on input data using the previously trained algorithm. The results can be optimized by evaluating an error function (e.g., the mean-squared error as done in Chapter 5) and iteratively adjusting weights of each node to minimize the error between the model and an accepted value through backpropagation, repeating the iterative process until a threshold has been met. It allows for a system to learn and enhance itself from experience automatically without being specifically programmed and for extraction of new information from a dataset (Sarker, 2021).

There are four main types of machine learning techniques (Figure 2-2) (Sarker, 2021):

1. **Supervised** learning is a task driven approach to learning a function that maps an input to an output based on sample input-output pairs. It is most commonly applied to classification, the separation of data, and
regression, the fitting of data. Examples include the labelling of text (i.e., spam detection) or speech recognition.

2. **Unsupervised** learning is a method for analysing unlabeled datasets without the need for human interference. This is used for extracting generative features, meaningful trends, and grouping results. Examples include data clustering, rule finding, and anomaly detection.

3. **Semi-supervised** is a hybridisation of supervised and unsupervised learning methods. It operates on labeled and unlabeled data with the objective to better predict outcomes than using labeled data alone. Examples include fraud detection, text classification, and machine translation.

4. **Reinforcement** is an algorithm that enables software agents and machines to automatically evaluate the optimal behaviour in a particular context or environment to improve efficiency. It can help increase automation or optimize operational efficiency of sophisticated systems. Example applications include autonomous driving tasks, and manufacturing and supply change logistics.
Machine learning applications that aim to perform sequence modelling, signal separation, and forecasting typically employ RNN units (Hewamalage et al., 2021; Issa & Al-Irhaym, 2021; Liu et al., 2021; Pineau et al., 2020; M. Zhao et al., 2021). These architectures include the: multi-layer perceptron network (Section 2.4.1); long short-term RNN (Section 2.4.2); Elman Recurrent Neural Network (ERNN) (Section 2.4.3); and Gated Recurrent Unit (GRU) (Section 2.4.4). The recurrent neural network (RNN) presented in Chapter 5 falls within the supervised learning category of machine learning approaches (Figure 2-2). It employs both a multi-layer perceptron network and long-short term memory RNN to model magnetic signal from aircraft attitude and local geology, respectively. Alternative RNN architectures were investigated, such as the ERNN and GRU, but were ultimately not selected due to excessive training time requirements and performance considerations. These architectures are typically employed for time series forecasting and signal source separation analysis.
2.4.1 Multi-layer perceptron

A multi-layer perceptron is a fully connected network that consists of an input, an output, and one or more hidden layers. Its architecture contains multiple individual perceptrons in a single layer that are all connected to each perceptron in the next layer. Each perceptron in one layer has an associated weight that is adjusted by the network through backpropagation (Sarker, 2021). The network is iteratively trained by comparing the output model (based of a set of inputs) to the expected value and adjusts weights accordingly. Mathematically, a single perceptron is the weighted sum (equation 2.20) of each input (Staudemeyer & Morris, 2019).

\[ s = w_o + \sum_{i=1}^{n} w_i x_i \]  

(2.20)

where \( s \) is the weighted sum with bias (\( w_o \)), weights \( w_i \) and inputs \( x_i \) for \( n \) inputs.

The output \( (y) \) of the perceptron is governed by an activation function to determine whether that perceptron is ‘on’ or ‘off’ (binary step activation – equation 2.21) or some range in value following a specified function (such as hyperbolic tangent – equation 2.22).

\[
y = \begin{cases} 
1 & \text{if } s > 0; \\
-1 & \text{otherwise}
\end{cases} \tag{2.21}
\]

\[
y = \frac{e^s - e^{-s}}{e^s + e^{-s}} \tag{2.22}
\]

2.4.2 LSTM recurrent neural network

Long short-term memory (LSTM) is a type of RNN and is considered one of the most powerful dynamic classifiers publicly available and used (Alghazzawi et al., 2022; Staudemeyer & Morris, 2019). An LSTM has feedback connections, allowing for the processing of not only a single point of data but also a sequence. A single data sample is input and manipulated by a series of gates; the forget gate, input gate, and output gate. An LSTM contains a cell state that is modified to influence a model based on past measurements. The general architecture of an LSTM is described in Chapter 5, but more background on a single LSTM unit (Figure 2-3) is detailed in this subsection. Each LSTM unit is connected across a time window, where the output and cell state of past and future samples transferred and manipulated (Figure 2-4).

The forget gate ($F$) is used to remove irrelevant information by adding inputs with weights ($v$, and $w$) from the current time step ($X_t$) as well as the output from the previous time step ($H_{t-1}$) and passed through an activation function ($a_F$):

$$ F = a_F(v_{Ft}X_t + w_{Ft}H_{t-1}) $$

(2.23)

where $a_F$ is a sigmoid function and sets $F$ to be between (0,1). To remove values from the cell state, $F$ is then piecewise multiplied with the previous cell state $C_{S_{t-1}}$, where if $F$ approaches 0, its values tend to be removed from the cell state.

The input gate is a two-operation function, with $I$ and $G$, that sets the values stored in the cell state. It determines which information is added to the cell state.
Figure 2-3: Architecture of an LSTM cell, modified from Figure 5-1 – right. The cell is connected to past and future times (Figure 2-4), tracking the cell state. The cell state and output of the LSTM is modified through a series of gates.

Figure 2-4: Overall structure of an LSTM RNN, with inputs ($X_t$), hidden states ($H_t$), and cell state ($C_{St}$). Each LSTM cell shares updated hidden states and cell states with the next sample, while also outputting the hidden state to the next network layer. One LSTM cell is detailed in Figure 2-3.
\[ I = a_I(v_{It}X_t + w_{It}H_{t-1}) \]  
\[ G = a_G(v_{Gt}X_t + w_{Gt}H_{t-1}) \]

where \( a_I \) is a sigma function that sets \( I \) to be between \((0, 1)\) and \( a_G \) is a hyperbolic tangent function that sets \( G \) to be between \((-1, 1)\). Variable \( I \) is responsible for setting the cell state while \( G \) is a candidate state. The piecewise multiplication of these states determines which values are set in memory with values trending towards 1 being stored, and those trending towards -1 being removed.

The final cell state \((C_{S_t})\) value is determined as:

\[ C_{S_t} = C_{S_{t-1}} \odot F + I \odot G \]  
\[ (2.26) \]

where \( \odot \) represents the element-wise operation product of two matrices.

The output gate \( O \) is responsible for finding the final hidden state, or output, \( H_t \) of the LSTM by multiplying the new inputs with the memory cell:

\[ O = a_O(v_{Ot}X_t + w_{Ot}H_{t-1}) \]  
\[ (2.27) \]

\[ H_t = O \odot a_H(C_{S_t}) \]  
\[ (2.28) \]

where \( a_O \) is a sigma function and \( a_H \) is the hyperbolic tangent, allowing for the final output range to be \((-1,1)\). This gate decides which of the information from the updated cell state ends up in the next hidden state, or output. \( H_t \) transferred to the next layer of the network or LSTM cell.
2.4.3 Elman recurrent neural network

The ERNN is the most basic RNN unit (Figure 2-5) and was initially proposed by Elman (1990). It is a simple structure that inputs new data, $x_t$, as well as information from the previous hidden state, $h_{t-1}$, with

$$H_t = \sigma(W_i \cdot H_{t-1} + V_i \cdot x_t + b_i)$$

(2.29)

$$H_t = \tanh(W_o \cdot H_t + b_o)$$

(2.30)

where $W$ and $V$ are weight matrices, and $b_i$ is a bias term. The sigmoid function is used as the activation function for the hidden state and hyperbolic tangent as the output activation function (Hewamalage et al., 2021).

The ERNN suffers from vanishing or exploding gradient problems (Hewamalage et al., 2021), so it is not typically employed for ML tasks. When sequences are long, the gradients diminish (vanish), and the weights do not get updated adequately. If the gradient is instead very large, the weights may explode over long sequences resulting in unstable weighting for the model. This hinders the ERNN functionality in capturing long term dependencies and handling highly non-linear and abrupt changes. The LSTM and GRU RNN expand on the capabilities of the ERNN to address these issues.
2.4.4 GRU Recurrent Neural Network

The GRU was introduced in 2014 (Cho et al., 2014) and is simpler than the LSTM unit; it employs only two gates instead of three. The GRU (Figure 2-6) uses an update gate and a reset gate. The update gate functions as a combination of the forget gate and input gate from the LSTM while the reset gate is used to decide how much of the previous state contributes to the current state. Unlike the LSTM, the GRU only contains one component to its state, the hidden state. The following equations describe the functionality of the GRU cell:

\[
u_t = \sigma(W_u \cdot H_{t-1} + V_u \cdot x_t + b_u)
\]  

(2.31)

Figure 2-5: Architecture of an ERNN cell. The cell is connected to the hidden state of previous ERNN cells.
\[ r_t = \sigma(W_r \cdot H_{t-1} + V_r \cdot x_t + b_r) \] (2.32)

\[ \tilde{H}_t = \sigma(W_u \cdot H_{t-1} + V_u \cdot x_t + b_u) \] (2.33)

\[ H_t = u_t \odot \tilde{H}_t + (1 - u_t) \odot H_{t-1} \] (2.34)

where \( u_t \) and \( r_t \) are the update and reset gates, respectively. \( \tilde{h}_t \) is the candidate hidden state and \( h_t \) is the current state at time step \( t \). \( W \) and \( V \) are weight matrices and \( b_u \) a bias term.

The GRU has been demonstrated to provide similar results as the LSTM but, because of its simpler architecture, it can have smaller overhead requirements (Hewamalage et al., 2021). It does not, however, allow for control over the memory content, which can hinder its functionality (Petneházi, 2018).
Machine learning has shown promise in early proof-of-concept studies in the field of geophysics; however, the community has been slow to adopt its use broadly (Bergen et al., 2019). With the advances of the past 5 to 10 years, including advances in deep learning, and the availability of easy-to-use toolboxes (i.e., TensorFlow, Keras, scikit-learn), there has been a renewed interest in its use. Researchers in geophysics are beginning to employ machine learning for a diverse range of tasks including automation, simulation, modeling, and inversion (Bergen et al., 2019).
Traditionally, research follows a model-driven approach to data analysis, where physical principles are used deduce the cause of measured geophysical phenomena. Machine learning instead employs a data-driven analysis, where the algorithm will not consider physical relationships when making inferences. Examples of both model-driven and data-driven methods are listed in Table 2-1 (S. Yu & Ma, 2021).

Machine learning is now in use across several subfields of geophysics. Within exploration geophysics focus has primarily been on seismic data interpolation, seismic velocity model prediction, and geological structure prediction (Helmy et al., 2010; Huang et al., 2006; Jia & Ma, 2017; Reichstein et al., 2019; C. Zhang et al., 2014). Researchers in earthquake hazard analysis are using machine learning for earthquake localization, aftershock pattern analysis, noise classification, and wave arrival picking (DeVries et al., 2018; Mousavi et al., 2016). Researchers in remote sensing (e.g., hyperspectral imagery) rely on image classification and feature extraction techniques (S. Chen et al., 2016; Cheng et al., 2016; K. Jiang et al., 2019; S. Li et al., 2019; Maggiori et al., 2017; Mou et al., 2017; Z. Zhang et al., 2017). A significant effort is focused on Earth system analysis, which includes: soil moisture and acidity predictions (Fang et al., 2020; Reichstein et al., 2019); temperature reconstruction (Kadow et al., 2020); air pollution analysis (T. Li et al., 2017; Shen et al., 2018; Tang et al., 2018); weather forecasting (Bonavita & Laloyaux, 2020; Fang et al., 2017; Scher & Messori, 2021); and hurricane and typhoon tracking (G. Jiang et al., 2018).
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3. Comparison between ground, helicopter, and uninhabited aircraft system magnetic datasets: a case study from the Abitibi Greenstone Belt, Canada

*This chapter has been peer-reviewed and was published in the Journal of Pure and Applied Geophysics. It should be sited as:*


This paper is included in this thesis with minor formatting changes and variable renaming (for consistency between chapters). Within academia and industry, the terms 'manned' and 'unmanned' are being replaced with the non-gendered terms 'inhabited' and 'uninhabited'; as such these changes have been made throughout this paper except in the above reference.

This paper was co-authored by: the thesis author, Michael Cunningham; his co-supervisors, Dr. Claire Samson and Prof. Jeremy Laliberté; the chief geophysicist from IAMGOLD Corporation, Mark Goldie; the Engineering Manager, Alan Wood, and Chief Executive Officer, David Birkett, from Stratus Aeronautics Inc. M.
Cunningham, provided guidance and input into the design of the aeromagnetic survey flown with the UAS. He led data processing, analyzed the three datasets (ground, helicopter, and UAS), performed data comparison and magnetic inversion, and wrote the manuscript. C. Samson assisted in establishing research objectives and provided extensive comments on the technical results and the manuscript. J. Laliberté provided valuable guidance on UAS and comments on the manuscript. M. Goldie provided access to the survey area, previous datasets, and geological information on the property as well as comments on the manuscript. A. Wood and D. Birkett piloted and maintained the UAS platform, oversaw operations, provided the merged UAS dataset (which included GPS position, altitude, and raw total magnetic intensity), and provided technical support for the aeromagnetic survey planning as well as provided comments on the manuscript.

3.1 Paper context

This study aims to provide quantitate and qualitative comparisons between three different magnetic datasets – ground, helicopter, and UAS – over a geologically interesting location. At the time of its publication there was limited realistic studies directly comparing magnetic surveys with UAS at areas of interest larger than ≈1 km² at an active gold mineral exploration project. This study presents qualitative and quantitative comparisons where it was shown that aeromagnetic surveying with a UAS provides data at the same or better quality as traditional ground and helicopter techniques, where the UAS had improved
resolution than the helicopter due to tighter line spacings. Overall, it was
determined that UAS have reached a level of technical maturity such that they
have become a competitive tool in the geophysics industry, and it was suggested
that UAS could find a role in performing small targeted high-resolution surveys.

3.2 Abstract

This paper presents a direct platform-to-platform comparison of ground,
helicopter, and uninhabited aircraft system (UAS) magnetic data acquired over a
4.96 km² prospective gold area in the Abitibi Greenstone Belt of the Canadian
Precambrian Shield. Qualitative comparison focused on visual inspection of
residual and gradient magnetic maps, focusing mainly on features associated with
iron formations. Quantitative comparison employed maps of cell-by-cell absolute
difference, percent difference, and coherence, as well as three global image
similarity parameters: the structural similarity index, the mean squared error, and
the peak signal-to-noise ratio. The qualitative comparison revealed that lateral
continuity along the dominant E-W structural geological trend was better captured
in the ground and UAS data than in the helicopter data. The UAS data had the
additional advantage over the ground data of having undergone minimal
processing. The quantitative comparison metrics were the same between all three
datasets. This study showed that UAS technology is delivering the same data
quality as traditional survey techniques in addition being an attractive economic
and safety choice.
3.3 Introduction

Magnetic surveying is a classic survey technique in mineral exploration used to delineate structural features and trends by mapping the spatial distribution of magnetically susceptible rocks in prospective environments. Magnetic exploration surveys are performed over a wide range of scales, from medium/large-scale (typically up to ≈150 km$^2$) to small-scale (≈10 km$^2$). Large-scale surveys are usually flown using helicopter or fixed-wing aircraft to cover large territories at reasonable cost (helicopter-borne aeromagnetic surveys in North American currently range between $35/line-km to over $100/line-km depending on survey size) albeit at lower resolution. Small-scale helicopter and ground surveys are executed to provide high-resolution data for focused regions. Surveys using uninhabited aircraft systems (UAS) are increasingly being used to bridge the gap between large- and small-scale surveys and have been suggested as replacement or complement to ground surveys. UAS are known for their versatility: they can be launched in nearly all locales, fly in terrains with rough topography, have lower weight and higher manoeuvrability, and are safer to personnel. UAS operations are often subject to location-specific regulations and flight operation approvals processes, however, these are less complex and associated costs are similar or less than for traditional platforms.

Fixed-wing (Cherkasov et al., 2016; Funaki et al., 2014; Wood et al., 2016; B. Zhang et al., 2011) or rotary-wing (Bian et al., 2021; Cunningham et al., 2018,
UAS can carry magnetic sensors. Presently, most research efforts focus on rotary-wing UAS due their smaller size (and therefore less stringent regulations) and reduced take-off and landing constraints. Payloads onboard UAS consist of either total magnetic intensity (TMI) or fluxgate sensors, that are mounted rigidly (Cunningham et al., 2018; Eck & Imbach, 2012; Stoll, 2013; Tuck et al., 2019; Wood et al., 2016) or are suspended beneath the platform (Malehmir et al., 2017; Parshin et al., 2018; Parvar et al., 2017; Sterligov et al., 2018; Walter et al., 2019b).

Only a few studies comparing magnetic data from UAS and traditional platforms have been published (Cunningham et al., 2018; Walter et al., 2020). The purpose of this paper is to provide detailed qualitative and quantitative comparisons between three different datasets – ground, helicopter, and UAS – over the same location in the Abitibi Greenstone Belt of the Canadian Precambrian Shield. These comparisons are aimed at unraveling the differences between each platform and, more specifically, at highlighting the merits of UAS surveying for targeted mineral exploration.

3.4 Comparison study area

The comparison study area is part of the Nelligan property (Figure 3-1), which is owned by IAMGOLD Corporation and Vanstar Mining Resources. The property is located in the Province of Quebec, approximately 35 km south-east of Chapais.
and 55 km south-west of Chibougamau (a regional geological map detailing rock types, structures, and mineral ore zones is presented in Figure 3-2). It lies within the Caopatina-Desmaraisville volcano-sedimentary segment of the Abitibi Greenstone Belt of the Archean Superior Province of the Canadian Precambrian Shield. The Caopatina-Desmaraisville segment is primarily composed of the Deloro Assemblage (2,734-2,724 Ma) and shows evidence of multiple volcanic cycles. Pre-deformational regional folds (orientated N-S to NNW-SSE) are preserved and related to the Kenorean Orogeny (Carrier et al., 2019) which also caused regional schistosity (Guha et al., 1991). Following this orogeny, the primary deformational event is a N-S shortening producing E-W tectonic fabric and a deformation corridor indicated by longitudinal faulting (Carrier et al., 2019). The Druillettes Syncline and two groups of faults (E-W and SE-NW trending) are associated with this shortening event (Guha et al., 1991) (Figure 3-1). Two younger fault groups are also observed; a NE-SW trending group cutting regional schistosity and a NNE-SSW group associated with the Grenville Orogeny. The north and south limbs of the Druillettes syncline are subvertical, striking approximately east-west and dipping 80° on average. Metasediments of the Caopatina formation are found within the center of the syncline, and primarily consists of metamorphosed units with protoliths of feldspathic wackes, siltstones-mudstones-argillites, greywackes, conglomerates, and layers of iron formation. On either side of the syncline (northward and southward) are metavolcanics and metasediments which primarily consist of basalts and gabbros of tholeiitic composition.
Three separate magnetic surveys were performed over the Nelligan property – ground, helicopter, and UAS (Figure 3-1, Table 3-1). The 4.96 km$^2$ UAS survey area was selected as the comparison study area. The comparison study area is generally flat with some rolling hills ($\leq$ 30 m elevation change). There are thick glacial deposits within the area, which is covered by the boreal forest, and no known outcrop.

The comparison study area features four different gold mineralization zones (Renard, Zone 36, Liam, and Dan) (Figure 3-1). The mineralization zones are hosted in metasedimentary rocks of the Deloro assemblage, which is atypical of gold mineralization for Abitibi type deposits (typically gold mineralization is hosted in the metavolcanic rocks). They are generally located at the boundary between upper greenschist and amphibolite facies, and are adjacent to first-order crustal faults.

Previous magnetic surveys have been performed over the Nelligan property to map and delineate structural trends. Along with past drilling projects, these surveys have identified local iron formations (IF) as the sources of the strongest magnetic responses in the area. The IF layers have been used to develop the property's structural framework (Carrier et al., 2019). Inversion of the UAS aeromagnetic data produced models that are consistent with the presence of near-vertical structures or thin sheets steeply dipping towards the north and south (Cunningham et al., 2021), further supporting this interpretation.
Figure 3-1: Location maps. Top left: Eastern Canada; top right: central Quebec; and bottom: three aeromagnetic survey areas. Gold zones overlain on elevation in yellow: R – Renard; Z – Zone 36; L – Liam; and D – Dan. Elevation data from Government of Canada (2017).
**Table 3-1: Magnetic survey parameters.**

<table>
<thead>
<tr>
<th>System</th>
<th>Ground</th>
<th>Helicopter</th>
<th>UAS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Line-km (km)</td>
<td>95.7</td>
<td>587.7</td>
<td>319.7</td>
</tr>
<tr>
<td>Line Spacing (m)</td>
<td>100</td>
<td>Traverse: 100</td>
<td>Traverse: 50 and 25</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Tie: 1000</td>
<td>Tie: 150</td>
</tr>
<tr>
<td>Average Speed (km/h)</td>
<td>4.5</td>
<td>80</td>
<td>30</td>
</tr>
<tr>
<td>Altitude (AGL) (m)</td>
<td>2</td>
<td>Traverse: 0 / 180</td>
<td>Traverse: 0 / 180</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Tie: 90 / 270</td>
<td>Tie: 90 / 270</td>
</tr>
<tr>
<td>Line Azimuth (°)</td>
<td>0 / 180</td>
<td>Traverse: 0 / 180</td>
<td>Traverse: 0 / 180</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Tie: 90 / 270</td>
<td>Tie: 90 / 270</td>
</tr>
<tr>
<td>Sensor</td>
<td>GEM GSM-19 Proton Precession Overhauser</td>
<td>Geometrics Caesium Vapour</td>
<td>Geometrics G-823A Caesium Vapour</td>
</tr>
<tr>
<td>Sampling frequency (Hz)</td>
<td>1</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>Spatial Sampling (m)</td>
<td>12.5</td>
<td>2.2</td>
<td>0.8</td>
</tr>
<tr>
<td>Time to complete survey</td>
<td>1 month</td>
<td>3 days</td>
<td>3 days</td>
</tr>
</tbody>
</table>

**Figure 3-2: Geological map of the Nelligan survey area. Local geological map adapted from Carrier et al. (2019) and SIGEOM (2020).**
3.5 Magnetic survey descriptions

3.5.1 Ground survey

The ground TMI survey was conducted between July and August 2013. This survey employed a GEM GSM-19 proton precession Overhauser magnetometer and covered an area of 14.11 km$^2$ and 95.7 line-km. Traverse lines were oriented in a N-S direction with a line spacing of 100 m. TMI data was recorded at station intervals of 12.5 m. Approximately 46.5 line-km were completed within the comparison study area at 2 m above ground level (AGL) (Figure 3-3 - left).

3.5.2 Helicopter survey

The helicopter TMI survey was conducted between 8 July 2015 to 10 July 2015. This survey was a combined time-domain electromagnetic and magnetic survey. The helicopter was instrumented with two caesium vapour sensors (spaced 12.5 m apart) allowing for TMI and cross-line gradient surveying. An area of 52.70 km$^2$ was covered at a nominal altitude of 50 m AGL by draping topography, corresponding to 587.7 line-km. Traverse lines were oriented in a N-S direction with a line spacing of 100 m and tie lines were spaced at 1,000 m intervals. TMI data from each sensor was recorded at a sampling frequency of 10 Hz and compensated for aircraft attitude. A total of 51.6 line-km (46.5 traverse line-km and 5.1 tie line-km) were completed within the comparison study area (Figure 3-3 - middle).
3.5.3 UAS survey

Between September 29, 2018, to October 3, 2018, Stratus Aeronautics flew a UAS survey with the prototype SkyLance 6200 hexacopter (Figure 3-4). A total of area of 4.96 km$^2$ was covered, corresponding to 319.7 line-km, by holding a constant altitude above sea level, corresponding approximately to 50 m AGL. A subset of 129.1 line-km (97.4 traverse line-km and 31.7 tie line-km) are considered in the present study (Figure 3-3 - right). Traverse lines were oriented in a N-S direction with a traverse and tie line spacing of 50 m and 150 m, respectively. Uncompensated TMI data was recorded at a sampling frequency of 10 Hz. A repeatability test executed along a N-S oriented line showed that the UAS was very stable in flight with average standard deviations from nominal altitude and easting being 1.8 m and 0.7 m, respectively (Cunningham et al., 2021).

The SkyLance 6200 hexacopter employs an autopilot that is capable of automatic take-off and landing, as well as following predetermined waypoints. The platform weights approximately 15 kg excluding the payload. It carries a payload weighing approximately 5 kg primarily consisting of a Geometrics G-823A caesium vapour magnetometer. The UAS has a flight endurance of approximately 30 minutes and can fly at an average of 32 km/h ground speed. Typically, 3 people are required on the ground for UAS survey operations.
Figure 3-3: Survey line paths for each survey platform with the comparison survey area is outlined in red and gold ore zones are highlighted in yellow. Left – 2013 ground magnetic survey. Middle – 2015 helicopter survey. Right – 2018 UAS survey. Magenta lines, labelled A-A’ and B-B’, highlight the profiles presented in Figure 3-5.

Figure 3-4: Stratus Aeronautics SkyLance 6200 with front-mounted caesium vapour magnetometer.
3.6 Results

3.6.1 Residual magnetic intensity and gradients

Processing of each dataset followed a typical workflow, using Seequent’s (formerly Geosoft) Oasis Montaj processing software, and included: diurnal correction, lag corrections, line levelling, and interpolation. Diurnal corrections were performed by subtraction of base station data. Base station data was collected at a sampling frequency of 1 Hz. A moving average with a 60 s window was applied and the data was linearly interpolated to a frequency of 10 Hz. The interpolated data was then subtracted from the raw magnetic data collected by each survey platform. Further lag corrections and line levelling was applied to the helicopter and UAS datasets. Lag corrections apply a temporal or positional shift in the datasets to account for the positional offset between the positional sensor and the magnetic sensor. Line levelling redistributes corrugations within parallel traverse lines to reduce line-by-line errors by using intersection points between traverse and tie lines. Minimum curvature interpolation at ¼ the flight line spacing was then applied, following standard industry practice (Lee & Morris, 2013), to produce magnetic maps of cell size 25 m x 25 m (note that interpolation of the UAS data was performed at ½ of the flight line spacing to match the spatial resolution of ground and helicopter data). In-line, cross-line, and vertical gradients were calculated from the residual magnetic intensity (RMI) data.

Magnetic intensity profiles along two lines highlighted in Figure 3-3, are shown in Figure 3-5. Profile A-A’, oriented west to east and crossing Feature 3 (described
below), shows less intensity variations since it is parallel to structural trends. Profile B-B’, oriented south or north and intersecting perpendicularly Features 1, 3, and 4 (described below), exhibit larger intensity variations. Overall, Figure 3-5 shows that the magnetic profiles for the 3 datasets from a 50 m altitude (either calculated or directly recorded) match closely.

Figure 3-6, Figure 3-7, Figure 3-8, and Figure 3-9 show the original ground data, the ground data upward continued (UC) to 50 m above ground level (AGL), the helicopter data, and the UAS data, respectively.

The magnetic intensity maps from each survey (Figure 3-6, Figure 3-7, Figure 3-8, and Figure 3-9 (top left)) reveal a structurally complex region exhibiting several known and inferred IF units. Feature 1 is located along the northern edge of the comparison study area and might correspond to two parallel E-W trending IF units. Feature 2 is interpreted as a continuation of Feature 1 but was displaced by a series of faults (striking SW-NE and E-W) causing an offset between the features. Feature 3, located in the center of the comparison survey area, follows the same local (SW-NE) fault. This region is where the Liam and Dan gold mineralization zones are located. Feature 4 is an E-W trending IF and coincides with the axis of the Druillete Syncline. It is the only IF in the comparison study area that is featured on regional geological maps (Carrier et al., 2019; SIGEOM, 2020). The northern segment of Feature 4 appears as though it may have been displaced from the southern segment through secondary faulting or folding.

To allow a direct comparison between the three magnetic datasets, the ground data was upward continued to 50 m AGL which is the nominal altitude of the
helicopter and UAS surveys. The original ground data (Figure 3-6) has captured fine structural details, especially within the IF units, but does exhibit artifacts presumably due to uneven spacing coverage. These artifacts are particularly prominent in the gradient maps. Applying upward continuation to the data (Figure 3-7) gives a smoother appearance to the data but some details are lost. Feature 2, for example, appears as three distinct parallel structures truncated by a NE-SW

Figure 3-5: Profile plots of residual magnetic intensity from each survey dataset along two survey lines that are highlighted in Figure 3-4. A-A’ is a tie line, from west to east across the center of the survey area. B-B’ is a traverse line from south to north. The crossover point (COP) between the two lines is marked by a dashed vertical line. Key features are numbered according to the regions marked in Figure 3-6, Figure 3-7, Figure 3-8, Figure 3-9, and Figure 3-10 and their extents are highlighted in grey. The ground TMI profile is linked to the right axis, the other profiles are RMI and linked to the left axis.
Figure 3-6: Ground magnetic maps of the comparison survey area. Black lines delineate the gold zones. Dashed lines are local faults. Dash-dot lines are folds (syncline). Arrows point to the key features described in Section 3.6.1.
Figure 3-7: Upward continued to 50 m AGL ground RMI maps of the comparison survey area. Black lines delineate the gold zones. Dashed lines are local faults. Dash-dot lines are folds (syncline). Arrows point to the key features described in Section 3.6.1.
Figure 3-8: Helicopter RMI maps of the comparison survey area. Black lines delineate the gold zones. Dashed lines are local faults. Dash-dot lines are folds (syncline). Arrows point to the key features described in Section 3.6.1.
**Figure 3-9:** UAS RMI maps of the comparison survey area. Black lines delineate the gold zones. Dashed lines are local faults. Dash-dot lines are folds (syncline). Arrows point to the key features described in Section 3.6.1.
fault to the west in the original ground data, but only appear as two faint parallel E-W trending structures in the upward continued ground data.

Visually comparing the upward continued ground, helicopter, and UAS RMI maps (Figure 3-7, Figure 3-8, and Figure 3-9 (top left)) reveals some notable differences in terms of amplitude and lateral continuity. The amplitude of the magnetic anomalies associated with the four key features described above are strongest in the upward continued ground data. Lateral continuity along the dominant E-W structural trend is better expressed in the upward continued ground and UAS data than in the helicopter data. In the case of the upward continued ground data, however, continuity might be a product of mathematical operations. On the other hand, the continuity of the UAS data can be interpreted as a genuine geological signature since the data has undergone minimal processing. The helicopter data suffers from resolution effects due to the large traverse line spacing used during data acquisition (25-50 m for the UAS data versus 100 m for the helicopter data (Table 3-1)). Consequently, it did not capture details of the internal structure of Features 1 and 4 as well as the upward continued ground data and the UAS data.

In-line, cross-line and vertical gradient maps (Figure 3-7, Figure 3-8, and Figure 3-9 (top right, bottom left, bottom right)) highlight the structural boundaries between the key features and surrounding geology. The four features discussed above can be easily identified in the in-line and vertical gradient maps and, to a lesser extent, on the cross-line gradient map. The cross-line gradient maps tend to be of lesser quality due to presence of resolution artifacts associated with interpolation effects
for the upward continued ground data and to lower spatial sampling in the E-W direction (traverse lines) for the helicopter and UAS datasets.

3.6.2 Quantitative dataset comparison

Two metrics assessing the differences between each dataset were employed. First, the absolute difference between each dataset was calculated on a grid cell by grid cell basis. Second, the percent difference between each normalized dataset on a grid cell by grid cell basis was determined, where the percent difference is calculated as the difference between two datasets in each grid cell divided by the average value in that grid cell.

The first metric provides a direct measure of the differences between each dataset whereas the second method provides a normalized comparison. The first method highlights regions where there is more difference but ignores the possibility that this could be due to the fact that the magnetic intensity might be stronger locally. The percent difference reduces the effects of local variations in magnetic intensity.

Figure 3-10 presents the absolute (left) and percent differences (middle) between the UAS and helicopter datasets (top), UC ground and UAS datasets (middle), and UC ground and helicopter (bottom) datasets, respectively. Higher absolute differences are primarily situated over higher gradient regions (Features 1, 3, and 4) surrounding the IF units. This is probably the consequence of small variations in altitude and/or positioning between the platforms, an effect that is
Figure 3-10: Left - Absolute differences between the three datasets. Middle - Percent difference between the three datasets. Right - Level of confidence in coherence between the three datasets. Black lines delineate the gold zones. Labelled black arrows point to the key features described in Section 3.6.1.
exacerbated in high gradient regions. Percent difference does not emphasise the regions of higher gradient to the same extent. Higher percent differences are found in the center of the survey area and mainly associated with the UAS dataset. This is likely because the UAS was held a constant altitude with respect to sea level (no draping), whereas both the helicopter and ground are effectively following topography; the center is lower in elevation than the edges of the survey area (Figure 3-1).

A statistical test was also performed to determine the coherence between each dataset (Sampietro et al., 2013). Assuming each survey provides independent maps, $m_j, m_k$, of the local magnetic field, $T$, where $j$ and $k$ correspond to the two datasets being compared, we have for each grid cell, $i$:

$$\Delta T_i^{m_j, m_k} = T_i^{m_j} - T_i^{m_k}$$

(3.1)

with the variance $\sigma^2$ given by:

$$\sigma^2(\Delta T_i^{m_j, m_k}) = \sigma^2(T_i^{m_j}) + \sigma^2(T_i^{m_k})$$

(3.2)

Statistical interference can be used to test that the hypothesis that:

$$\Delta T_i^{m_j, m_k} = 0$$

(3.3)

is true for multiple confidence intervals. The resultant coherence maps, for multiple confidence intervals, are presented in Figure 3-10 (right) and summarized in Table
3-2. For each comparison set, over 93% of the survey area shows coherence within or higher than the 80% - 90% confidence interval. However, regions of lower coherence are observed for all three platforms near the key features previously identified. Feature 4 has the lowest coherence in all three comparisons and low coherence is also observed along the eastern flank of Feature 1.

A series of additional quantitative comparison metrics were also employed: (1) the structural similarity index (SSIM); the mean squared error (MSE); and the peak signal-to-noise ratio (PSNR). Each metric was computed from normalized datasets so that they range between 0 and 1.

<table>
<thead>
<tr>
<th>Confidence Interval</th>
<th>UAS vs. Helicopter</th>
<th>UAS vs. UC Ground</th>
<th>UC Ground vs. Helicopter</th>
</tr>
</thead>
<tbody>
<tr>
<td>0%-25%</td>
<td>0.21%</td>
<td>0.04%</td>
<td>0.22%</td>
</tr>
<tr>
<td>25%-50%</td>
<td>0.41%</td>
<td>0.26%</td>
<td>0.71%</td>
</tr>
<tr>
<td>50%-60%</td>
<td>0.41%</td>
<td>0.54%</td>
<td>0.83%</td>
</tr>
<tr>
<td>60%-70%</td>
<td>0.61%</td>
<td>1.31%</td>
<td>1.46%</td>
</tr>
<tr>
<td>70%-80%</td>
<td>1.74%</td>
<td>3.10%</td>
<td>2.92%</td>
</tr>
<tr>
<td>80%-90%</td>
<td>11.66%</td>
<td>23.71%</td>
<td>15.76%</td>
</tr>
<tr>
<td>90%-100%</td>
<td>84.95%</td>
<td>71.02%</td>
<td>78.08%</td>
</tr>
</tbody>
</table>

The SSIM is a strategy used in image analysis to measure the similarity between two images (Wang et al., 2004); a SSIM value of 0 means there is no similarity between the images, and a value of 1 means the images are identical.
\[ SSIM(x, y) = [l(x, y)^a] \cdot [c(x, y)]^b \cdot [s(x, y)]^y \] (3.4)

with

\[ l(x, y) = \frac{2\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1} \] (3.5)

\[ c(x, y) = \frac{2\sigma_x\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2} \] (3.6)

\[ s(x, y) = \frac{\sigma_{xy} + C_3}{\sigma_x\sigma_y + C_3} \] (3.7)

where \( \mu_x, \mu_y, \sigma_x, \sigma_y, \) and \( \sigma_{xy} \) are local means, standard deviation, and cross-variance for images \( x \) and \( y \). \( C_1, C_2, \) and \( C_3 \) are constants that are included to avoid instability when \( \mu_x \) and \( \mu_y \) and/or \( \sigma_x \) and \( \sigma_y \) are very close to zero:

\[ C_1 = (K_1L)^2 \] (3.8)

\[ C_2 = (K_2L)^2 \] (3.9)

\[ C_3 = \frac{C_2}{2} \] (3.10)
where \( K_1 \) and \( K_2 \) are very small (\( \ll 1 \)) constants and \( L \) is the dynamic range of the cell.

Mean squared error (MSE) and peak signal-to-noise ratio (PSNR) were also employed as comparison metrics. The MSE is computed by averaging the squared intensity differences between two cells (Wang et al., 2004),

\[
MSE = \frac{1}{MN} \sum_{n=1}^{N} \sum_{m=1}^{M} [g(n,m) - h(n,m)]^2
\]  

(3.11)

where \( n \) and \( m \) are the x-axis and y-axis cell number in each dataset, \( g(n,m) \) and \( h(n,m) \), with a total of \( N \) and \( M \) x-axis and y-axis cells, respectively. MSE is simple to calculate and interpret; the smaller the value, the closer the two datasets match. However, with larger dataset sizes and range in data values, the MSE does not scale well, and becomes difficult to interpret (Wang et al., 2004).

The PSNR avoids the problematic scaling issues of the MSE by adding a scaling term:

\[
PSNR = \log_{10} \frac{P}{MSE}
\]  

(3.12)

where \( P \) is the peak value of the image. With the datasets scaled between 0 and 1, a PSNR value of 0 implies no similarities between the two datasets and a PSNR of 1 implies the datasets are identical.
As with the absolute difference and percent difference results, the SSIM, MSE, and PSNR, all reveal that the different datasets are nearly indistinguishable from one another (Table 3-3).

Table 3-3: Quantitative comparison between datasets using absolute difference (with standard deviation), percent difference (with standard deviation), SSIM, PSNR, and MSE.

<table>
<thead>
<tr>
<th>Datasets</th>
<th>UAS vs. Helicopter</th>
<th>UAS vs. UC Ground</th>
<th>UC Ground vs. Helicopter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Absolute Difference</td>
<td>-16.1 ± 69.8 nT</td>
<td>0.8 ± 80.2 nT</td>
<td>16.6 ± 83.7 nT</td>
</tr>
<tr>
<td>Mean Percent Difference</td>
<td>1.9 ± 3.5 %</td>
<td>2.4 ± 3.3 %</td>
<td>1.5 ± 2.1 %</td>
</tr>
<tr>
<td>SSIM</td>
<td>0.90</td>
<td>0.91</td>
<td>0.87</td>
</tr>
<tr>
<td>MSE</td>
<td>0.0024</td>
<td>0.0034</td>
<td>0.0036</td>
</tr>
<tr>
<td>PSNR</td>
<td>26.28</td>
<td>24.79</td>
<td>24.50</td>
</tr>
</tbody>
</table>

3.7 Concluding remarks

3.7.1 Discussion

This study provided a direct comparison of three magnetic survey datasets – ground, helicopter, and UAS – from a forested area typical of the Canadian Precambrian Shield. Comparison metrics, absolute difference, percent difference, coherence, and structural similarity indices were almost the same for the three datasets taken as a whole. This indicates that the UAS technology is delivering data of the same quality as the traditional ground and helicopter techniques. With autopilot and waypoint navigation, UAS have an additional advantage. They are capable of flying survey lines more tightly spaced than achieved in this study (e.g., 5-10 m line spacing). This opens the possibility of filling niche roles in exploration.
surveying. UAS are ideal for flying small, very targeted ‘surgical’ surveys, offering quick turn-around of results in the support of near real-time decision making in the field during exploration campaigns. Furthermore, they could have a role in sensitive survey regions, such as: areas populated by people or livestock; environmental protected areas; or regions near international borders.

Geologically complex regions, such as the Druillettes syncline, are examples of locations where lower altitude and tighter line spacing could improve delineation of geological features. Cunningham and co-authors (2018) show that it is theoretically possible to distinguish between two structures with a limiting depth of 40 m and a width of 10 m when they are spaced 67.5 m, 45 m, and 22.5 m apart perpendicular to strike at survey altitudes of 100 m, 50 m, and 2 m AGL, respectively. Improved delineation would also be possible with tighter line spacing allowing for the detection of potential discontinuities (e.g., faulting) or structures near-parallel the survey direction. The Geological Survey of Canada recommends a standard altitude to line spacing ratio of 1:2.5 (Coyle et al., 2014); however, this will vary depending on specific client needs and it is common to see a 1:1 ratio (e.g., an altitude of 50 m and line spacing of 50 m). If it were possible to fly a UAS as low as possible, down to a 2 m AGL (vegetation ignored) it would not be unreasonable to design a survey with a 10 m line spacing. Close examination of the RMI maps presented (Figure 3-7, Figure 3-8, Figure 3-9) revealed subtle differences between the datasets. Features related to IF (Features 1 and 4) are crisply defined in the UAS data, especially near-parallel internal structures that follow the dominant E-W structural trend. The upward continued ground data has
also captured these fine details but there remains the issue of not knowing which data has been directly observed versus which data has been generated in interpolation and upward continuation. In contrast to UAS and upward continued ground data, helicopter data is adversely affected by its lower resolution, due to an increased line spacing and higher spatial sampling interval. Notwithstanding economic and safety considerations, the results of this study reinforce the fact that UAS magnetometry has now reached a level of technical maturity such that it has become a competitive tool in comparison with traditional survey techniques.

3.7.2 Recommendations for future work

Building on the results presented in Cunningham and co-authors (2018) and this paper, future work could address broader issues in survey design. A study, including both modelling and experimental surveying, could investigate the impact of the following variables on data quality: (1) lateral resolution limits as a function of line spacing; (2) in-line resolution as a function of the sampling interval (changing flight speed or sampling rate); (3) flight altitude and tightness of terrain draping; (4) signal to noise ratio; and (5) economic competitiveness in relation to survey planning, platform endurance, and processing workflows.

Since the UAS platform is an emerging technology, in contrast to the well-established ground and airborne methods, it offers more potential for improvement. In particular, the issue of compensation (Tuck et al., 2019) should be examined carefully. A standard practice of airborne magnetic surveying is the use of aircraft
attitude compensation, the removal of in-flight magnetic noise from the changing position and orientation of the aircraft in space. Traditionally, this is performed by flying a high-altitude compensation flight pattern (box or cloverleaf) to remove the effects of local geology, and then by performing a linear least squares analysis to model the aircraft attitude effects. Due to government regulations, in Canada and other countries, UAS are limited to low altitude flying only, so traditional attitude compensation modelling is not an option. Alternative attitude compensation methods need to be developed to quantify and reduce the aeromagnetic noise from aircraft motions during UAS surveying.

3.8 Acknowledgements

The authors thank NSERC (Natural Sciences and Engineering Research Council) for providing the Engage grant to Dr. Claire Samson and scholarship to Michael Cunningham.
4. Inversion of magnetic data acquired with a rotary-wing uninhabited aircraft system for gold exploration

This chapter has been peer-reviewed and was published in the Journal of Pure and Applied Geophysics. It should be sited as:


Within academia and industry, the terms ‘manned’ and ‘unmanned’ are being replaced with the non-gendered terms ‘inhabited’ and ‘uninhabited’; as such these changes have been made throughout this paper except in the above reference.

This paper was co-authored by: the thesis author, Michael Cunningham; his co-supervisors, Dr. Claire Samson and Prof. Jeremy Laliberté; the chief geophysicist from IAMGOLD Corporation, Mark Goldie; the Engineering Manager, Alan Wood, and Chief Executive Officer, David Birkett, from Stratus Aeronautics Inc. M. Cunningham, provided guidance and input into the design of the aeromagnetic survey flown with the UAS. He led data processing, analyzed the three datasets (ground, helicopter, and UAS), performed data comparison and magnetic inversion, and wrote the manuscript. C. Samson assisted in establishing research
objectives and provided extensive comments on the technical results and the manuscript. J. Laliberté provided valuable guidance on UAS and comments on the manuscript. M. Goldie provided access to the survey area, previous datasets, and geological information on the property as well as comments on the manuscript. A. Wood and D. Birkett piloted and maintained the UAS platform, oversaw operations, provided the merged UAS dataset (which included GPS position, altitude, and raw total magnetic intensity), and provided technical support for the aeromagnetic survey planning as well as provided comments on the manuscript.

4.1 Paper context

At the time of this study’s publication, there was only one found article in the literature, a conference proceeding, showing magnetic inversion of data collected by a UAS with very limited details. The study presented in this chapter aims to further develop the capabilities of UAS for aeromagnetic surveying by performing 3-D magnetic inversion on a dataset collected by a UAS. The dataset was collected over a geologically interesting region that hosts gold mineralization zones and was actively being investigated. In this study, it demonstrated the repeatability of the UAS collected magnetic data. Both unconstrained and constrained inversion were completed with details provided to assist in future endeavours to reproduce results and/or to invert similar datasets. Both methods produced very similar results. It was found that unconstrained inversion of magnetic data required minimal data handling and with short run times it could be possible to perform
inversion during an active magnetic survey project to assist in the exploration process. The results of this study further reinforced the fact that UAS magnetometry has reached a level of technical maturity such that it has become a useful and effective operational tool for mineral exploration.

4.2 Abstract

A hexacopter uninhabited aircraft system instrumented with a caesium vapour magnetometer recorded total magnetic intensity over a 5.0 km² prospective gold area in the Abitibi Subprovince of the Canadian Precambrian Shield. The survey also included a N-S repeatability line which showed that the uninhabited aircraft system was very stable in flight with average standard deviations from nominal altitude and easting being 1.8 m and 0.7 m, respectively. The total magnetic intensity map revealed the structural framework of the banded iron formations present in the survey area and showed that the gold ore zones are not directly associated with magnetic highs but rather with steeply dipping faults. The total magnetic intensity data was inverted in 3-D using unconstrained and constrained approaches with 12.5 m (northing) x 12.5 m (easting) x 5 m (depth) cells and a maximum of 20 iterations. The processed (after diurnal corrections, heading correction, and tie-line levelling) total magnetic intensity data was input directly in the unconstrained inversion algorithm. Initial model building for the constrained inversion was a much more laborious process involving the inclusion of 15 synthetic structures based on borehole magnetic susceptibility measurements and knowledge of the local geology. The results of both inversion approaches were very similar. They revealed the presence of near-vertical thin sheets, individually
resolvable down to approximately 400 m. In this particular case, the straightforward unconstrained inversion yielded a realistic and detailed model of the subsurface in approximately 1 hour of runtime. Uninhabited aircraft system total magnetic intensity data could therefore be processed and inverted almost immediately after acquisition and have an impact on decisions made in the field while a survey is still in progress.

4.3 Introduction

With the rapid technological development of uninhabited aircraft systems (UAS) over the past decade, UAS are an alternative to conventional aircraft for numerous applications (e.g. photography, surveillance, site inspection, and geophysical surveying). UASs have become a valuable option within the mineral exploration industry as an aeromagnetic survey platform. They are capable of providing high-quality and high-resolution data by flying slower, at lower altitudes, and with improved maneuverability than traditional platforms. Moreover, they can fly during the day and at night, in jurisdictions where it is permitted, with no risk of pilot fatigue or injury.

Recent research has primarily focused on demonstrating the capabilities of different aeromagnetic survey systems (Cunningham et al., 2018; Parvar et al., 2017; Pei et al., 2017; Walter et al., 2020; Wood et al., 2016), as well as quantifying and reducing noise levels (Cherkasov et al., 2016; Huq et al., 2015; Tuck et al., 2018, 2019; Walter et al., 2019b, 2019a).
Aeromagnetic surveying with UASs is primarily performed using a single rotor helicopter or multi-rotor style uninhabited aircraft (Cunningham et al., 2018; Malehmir et al., 2017; Parshin et al., 2018; Parvar et al., 2017; Sterligov et al., 2018; Stoll, 2013; Tuck et al., 2019; Walter et al., 2020) with only a few exceptions (Cherkasov et al., 2016; Wood et al., 2016). Helicopter and multi-rotor UASs typically use a single magnetic sensor either mounted rigidly to the platform or hanging beneath it. Although each strategy has its own potential drawback (e.g. data acquired with a rigidly mounted sensor is mostly affected by vibrational noise whereas data acquired with a hanging sensor suffers mostly from rotational noise), UASs have been demonstrated to provide high-quality data, such that their fourth difference noise levels are within the airborne industry standard (0.1 nT) (Coyle et al., 2014).

Total magnetic intensity (TMI) and gradiometric results from aeromagnetic surveys can give insight into the geological subsurface, terrain and structure (Dentith & Mudge, 2014). Furthermore, using magnetic data inversion, a greater understanding of constraints can be achieved (Vallée et al., 2019). The objective of this paper is to demonstrate how UAS aeromagnetic data that was acquired above tree canopy (50 m above ground level (AGL)) in the boreal forest, near Chibougamau, Quebec, Canada, can be successfully inverted in three dimensions (3-D), with a minimum amount of pre-processing and constraints, to yield a realistic model of the subsurface in support of gold exploration. This paper includes unconstrained and constrained inversion models over a prospective region and provides commentary into the added benefit of inverting UAS aeromagnetic data.
4.4 Geology of the survey area

The survey area is a section of the Nelligan property (Figure 4-1), owned by IAMGOLD Corporation and Vanstar Mining Resources. The property is located approximately 55 km southwest of Chibouganau, Quebec, Canada in the Abitibi Subprovince of the Late Archean Superior Province of the Canadian Precambrian Shield. The Abitibi Subprovince extends for 500 km from east to west and is bounded by the Grenville Province (east), Wawa Sub Province (west), Quetico and Opatica Subprovinces (north) and the Pontiac Subprovince (south). The Abitibi Subprovince is composed of east-trending synclines of primarily volcanic rocks and intruding domes with synvolcanic and/or syntectonic plutonic rock cores (Daigneault et al., 2004). Primary rock compositions include gabbro-diorite, tonalite, and granite. Most of the strata (volcanic and sedimentary) are vertically dipping and separated by eastward trending faults of variable dips.

More precisely, the Nelligan property is located within the Caopatina-Desmaraisville segment of the Abitibi Subprovince which features four groups of faults based on their direction (ordered from oldest to youngest): E-W, S-E, N-E, and NNE (Carrier et al., 2019). The E-W and S-E faults are related to the primary episode of deformation, while the N-E faults cut regional schistocity and the E-W faults and the NNE faults are related to Grenvillian orogeny. The Caopatina-Desmaraisville segment is primarily composed of volcanic rocks from the Deloro Assemblage (2734-2724 Ma) where several volcanic cycles have occurred (Carrier et al., 2019; Chown et al., 1991).

The Nelligan property is centered on an E-W syncline bounded to the north and
Figure 4-1: Location and geological maps. Top: Eastern Canada overview. Middle: Regional map. Bottom: Local geological map adapted from Carrier et al. (2019) and SIGEOM (2020). Base map source: ESRI, HERE, Garmin.
south by the Obatogamau Formation volcanic rocks. Diamond borehole data has
determined that the local geology is composed of strongly altered sedimentary
rocks hosted in the Caopatina formation sediments (Carrier et al., 2019) belonging
to the North Volcanic Zone of the Abitibi Subprovince. There are several preserved
folding events oriented N-S to NNW in the Nelligan property. The main deformation
occurred following these folds. This deformation is primarily characterized by N-S
regional shortening (Carrier et al., 2019) and is the origin of the E-W tectonic
structure identified by: large fold axes; regional schistosity (E-W trending); and
longitudinal faults. This deformation is followed by a deformation episode causing
shear cleavages that cut or fold the main regional schistosity or crenulation
cleavages affecting regional schistosity (Chown et al., 1991). The northern region
of the Nelligan property also contains numerous regional and local structures and
deformation zones, and hosts granodioritic to tonalitic intrusions. Previous
exploration efforts (VTEM; ground magnetics; helicopter-borne magnetics; and
borehole data) has allowed for the identification and inference of deformed
segments of banded iron formation (BIF).

The Nelligan property has atypical gold mineralization for Abitibi type deposits,
as it is hosted in sedimentary basins, more specifically in the sedimentary rocks of
the Caopatina Formation, which overlay earlier volcanic cycles. These
sedimentary rocks are composed of feldspathic wacke, turbidites, greywackes,
conglomerates, and iron formation layers. Furthermore, there are basalts and
gabbro sills interwoven between beddings. The property contains four different
known gold mineralization zones grouped by their mineralization style (Figure 4-2):
Figure 4-2: UAS survey area digital elevation (ASL) map. Brown lines are elevation contours at 2 m increments. Black lines are flight lines (traverse lines are oriented north-south, tie lines are oriented east-west). The pink line is the repeatability test flight line (Figure 4-4). Black encircled regions highlight known gold ore zones. Red points represent borehole collars.
• **Renard Zone** – Silicified units with phlogopite zones (length: 1100+m; width: 150-250m);

• **Zone 36** – Silicified zones in the east, and silicified and hematized tectonic breccias in the west (length: 200-300m; width: 5-10m);

• **Liam Zone** – Schists and silicified zones with pseudo iron formations (length: 700m; width: 20-30m);

• **Dan Zone** – Silicified and hematized isolated conglomerate lenses (length: 300-500m; width: 10-20m).

The mineralization zones are generally located at the boundary between upper greenschist and amphibolite facies and are adjacent to first-order crustal faults.

The Nelligan property contains overburden between 10 to 50 m in thickness. There are no known outcrops, making geophysics a very important aspect of mineral exploration. The topography is generally flat with some rolling hills; there is a total elevation change of less than 40 m over the survey area (Figure 4-2).

### 4.5 UAS Survey

#### 4.5.1 Description of the rotary-wing UAS

The SkyLance 6200, developed by Stratus Aeronautics Inc., is an updated version of the original SkyLance described in Cunningham et al. (2018). It is a prototype hexacopter UAS with a magnetometer front-mounted on a non-magnetically susceptible boom to minimize the magnetic interference from the
UAS frame on the sensor data (Figure 4-3 and Table 4-1). It employs six motors mounted on radially orientated arms to ensure stable flight. Avionics include an autopilot system, a differential RTK GPS, radio link for streaming data, and a barometric altimeter for altitude above sea level (ASL) measurements. The main payload is a Geometrics G-823A caesium vapour magnetometer, which records scalar aeromagnetic data at a frequency of 10 Hz.

![Figure 4-3: Stratus Aeronautics SkyLance 6200.](image)

**Table 4-1: Specifications of the SkyLance 6200 UAS.**

<table>
<thead>
<tr>
<th>Specification</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>UAS type</td>
<td>Hexacopter</td>
</tr>
<tr>
<td>Crew size</td>
<td>3</td>
</tr>
<tr>
<td>Total mass</td>
<td>≈15 kg (excluding payload)</td>
</tr>
<tr>
<td>Payload mass</td>
<td>5 kg</td>
</tr>
<tr>
<td>Endurance</td>
<td>30 min at 32 km/h</td>
</tr>
<tr>
<td>Maximum flight speed</td>
<td>37 km/h</td>
</tr>
<tr>
<td>Sensor</td>
<td>Geometrics G-823A caesium vapour magnetometer</td>
</tr>
</tbody>
</table>
4.5.2 UAS flights

The SkyLance 6200 UAS performed flights between September 29, 2019, and October 3, 2019. During the UAS survey it was partially cloudy, with temperatures ranging between -1°C to +7°C, and wind speeds between 5 km/h and 30 km/h. Space Weather Canada reported quiet to unsettled solar activity for the sub-auroral zone where the survey was located; minimal magnetic noise would be due from solar activity.

Over the UAS survey area a total of 319.7 line-km were flown; however, for this study only a total of 131.5 line-km was considered. Figure 4-2 shows the 50 traverse lines flown at a 50 m line spacing with a N-S heading (97.7 line-km) and the 14 tie lines flown at a 150 m line spacing with a E-W heading (33.8 line-km). To ensure the UAS flew safely above the trees and to ensure visual line of sight operations, the survey grid was flown at a nominal altitude of 50 m AGL (395 m ASL). The UAS flew at a speed of approximately 38 km/h. Since the sampling frequency of the magnetometer is 10 Hz, this corresponds to a spatial sampling interval of approximately 1 data point per metre.

The pink line in Figure 4-2 was flown four times at three nominal flight altitudes to assess repeatability, 395 m, 400 m, and 405 m ASL. The 405 m line was flown twice for direct altitude comparison. The TMI variation (top left), altitude variation (bottom left), and flight line positional variation (right) are presented in Figure 4-4 and summarised in Table 4-2. The mean altitudes (ASL) for each flight were all within 1.8 m of their nominal altitudes. Altitude variations had a total range of 5.8 m or less (ASL), and an average standard deviation of 0.8 m. The mean eastings
for each flight were within 1.6 m from their nominal eastings; variations had a total range of 4.5 m or less, and an average standard deviation of 0.7 m. Data from flights with a south heading showed less altitude variation, but no significant change in easting variation was observed, suggesting that wind was from the north to the south, and caused minimal effects on flight.

The residual magnetic intensity (RMI) map from the UAS survey area is presented in Figure 4-5; processing included diurnal correction, heading correction, and tie-line levelling. Minimum curvature interpolation at ¼ the flight line spacing (Lee & Morris, 2013) was applied as part of standard practice, producing a cell size of 12.5 m x 12.5 m using Geosoft’s Oasis Montaj. The four gold ore zones are circled in black. Magnetic highs do not coincide with the gold ore zones; instead, the highs are related to BIFs and give insight into the structural framework of the area.

4.63-D inversion

Inversion, also known as inverse modelling, is an automated, iterative, modelling process that employs computer algorithms to create a model of a geophysical property by linking observation and a computed response (Dentith & Mudge, 2014). The ‘goodness of fit’ between the model and observed response is described by an objective function, where inversion is tasked to iteratively adjust model parameters to minimize this objective function. Inversion can be run either unconstrained or constrained, where unconstrained inversion is simpler, as it
involves no operator input and is allowed to converge at whichever model best fits the problem. Constrained inversion requires an input of constraints such as surrounding geology, borehole data, and data from other geophysical techniques to limit the possibilities of solutions. This additional information steers the constrained inversion process towards a more realistic model of the subsurface than the unconstrained inversion and assists in avoiding the non-uniqueness problem, a well-known (ill-posed) issue, where there are infinite possibilities that can fit the data.
Figure 4-4: Repeatability flights along a single survey line (pink line in Figure 4-2). Top left – Magnetic intensity variation for each flight with focussed region for direct comparison between 405 m nominal altitude flights; Bottom left - flight altitude for each of the flights; and Right – positional variation along the flight lines. Each colour (dark blue (1), light blue (2), red (3), and yellow (4)) represent different flights. The dark and light blue flights were flown at a nominal altitude of 405 m, the red flight at a nominal altitude of 400 m, and the yellow flight at a nominal altitude of 395 m.
Figure 4-5: RMI map of the UAS survey area. Black lines outline known gold ore zones: R – Renard; Z – Zone 36; L – Liam; and D – Dan. Arrows point to east-west trending structures: (1) two discontinuous linear structures producing a high magnetic anomaly along the northern edge of the survey area; and (2) two linear structures that are slightly offset in northing, potentially from structurally deformed BIFs, along the southern edge of the survey area. Contours are every 100 nT.
Table 4-2: Variation from nominal altitude ASL and easting for the four flights along the repeatability flight line (Figure 4-2).

<table>
<thead>
<tr>
<th>Repeatability Line</th>
<th>Heading</th>
<th>Altitude ASL (m)</th>
<th>Deviation from nominal easting (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Nominal Mean Maximum Minimum Standard Deviation</td>
<td>Nominal Mean Maximum Minimum Standard Deviation</td>
</tr>
<tr>
<td>1</td>
<td>North</td>
<td>405.0 406.8 408.6 404.9 0.7</td>
<td>0.0 1.6 3.3 -0.6 0.7</td>
</tr>
<tr>
<td>2</td>
<td>South</td>
<td>405.0 405.0 408.8 403.0 1.0</td>
<td>0.0 0.2 2.2 -2.2 0.7</td>
</tr>
<tr>
<td>3</td>
<td>South</td>
<td>400.0 399.7 401.8 397.9 0.6</td>
<td>0.0 0.7 2.3 -1.2 0.7</td>
</tr>
<tr>
<td>4</td>
<td>North</td>
<td>395.0 393.8 397.3 391.7 1.0</td>
<td>0.0 -1.6 1.1 -3.4 0.7</td>
</tr>
</tbody>
</table>
The RMI data (Figure 4-5) was inverted in 3-D using both (1) unconstrained and (2) constrained inversion to yield magnetic susceptibility models of the subsurface. Both unconstrained and constrained inversion were performed using Geosoft’s Oasis Montaj and the VOXI toolbox which uses Geosoft’s cloud-powered computing. A summary of the inversion parameters is provided in Table 4-3. The cell size used (12.5 m x 12.5 m x 5 m) for inversion corresponded to a 1:1 cell to data point ratio from the input grid (the RMI map was interpolated to a 12.5 m x 12.5 m cell size). This cell size was chosen as it was the closest match to the number of data points. Other cell sizes were tested (10 m x 10 m x 5 m; 20 m x 20 m x 10 m; and 25 m x 25 m x 10 m) and led to similar results, although fine details started to get lost as the cell size increased. The error in the inversion is quantified by calculating the root mean square deviation between the observed and calculated data. Inversions were limited to 20 iterations or until a VOXI default fit error of under 5% of the standard deviation of the magnetic data, or 27.4 nT, was achieved. Both constrained and unconstrained inversions were completed before the reaching the 20-iteration limit. They were completed in approximately 1-3 hours of runtime through cloud computing using Windows Azure.

4.6.1 Unconstrained

The unconstrained inversion used the RMI data (Figure 4-5) and the digital elevation model of the survey area (Figure 4-2). Figure 4-6 presents horizontal slices through the unconstrained magnetic susceptibility model at various depths. Figure 4-7 shows vertical slices (labeled in Figure 4-6 – top left) through the unconstrained magnetic susceptibility model.
Table 4-3: Inversion parameters for both unconstrained and constrained inversion. IGRF – international geomagnetic reference field.

<table>
<thead>
<tr>
<th>Type of data</th>
<th>RMI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cell size (m)</td>
<td>x (northing) = 10</td>
</tr>
<tr>
<td></td>
<td>y (easting) = 10</td>
</tr>
<tr>
<td></td>
<td>z (depth) = 5</td>
</tr>
<tr>
<td>Maximum Number of iterations</td>
<td>20</td>
</tr>
<tr>
<td>Minimum Fit Error (nT)</td>
<td>27.42</td>
</tr>
<tr>
<td>IGRF date (dd/mm/yyy)</td>
<td>01/10/2018</td>
</tr>
<tr>
<td>IGRF field strength (nT)</td>
<td>55298</td>
</tr>
<tr>
<td>IGRF inclination (degree)</td>
<td>73.0</td>
</tr>
<tr>
<td>IGRF declination (degree)</td>
<td>-15.2</td>
</tr>
<tr>
<td>Root Mean Square Deviation (nT)</td>
<td></td>
</tr>
<tr>
<td>Unconstrained</td>
<td>3.30</td>
</tr>
<tr>
<td>Constrained</td>
<td>1.15</td>
</tr>
</tbody>
</table>
Figure 4-6: Unconstrained inversion results. Horizontal slices through the 3-D magnetic susceptibility model at various depths as indicated in the bottom right corners. The grey outlines are the known gold ore zones. The black dashed lines correspond to the vertical slices presented in Figure 4-7. Contours are every 0.1 SI.
Figure 4-7: Unconstrained inversion results. Vertical slices through the 3-D magnetic susceptibility model corresponding to the dashed lines drawn on Figure 4-6. Solid lines show the traces of the sheet structures and associated numbers (Figure 4-9 and Table 4-4).
4.6.2 Constrained

Constrained inversion included borehole magnetic susceptibility data and geological knowledge of the area.

Figure 4-2 shows surface locations of the 27 borehole collars used for the constrained inversion. The spatial distribution of the collars reveals that drilling took place with a primary focus on intersecting gold ore zones. Figure 4-8 shows the 8.4 km of boreholes with magnetic susceptibility data plotted in 3-D (easting, northing, and depth). Magnetic susceptibility measurements were made using a handheld Terraplus SM-30 magnetic susceptibility meter approximately every 3 m along each core. Susceptibility values ranged from 0 SI to 550 SI with a mean, median, and standard deviation of 7 SI, 0.2 SI and 23 SI, respectively. Borehole data was used to create a parameter reference model and a parameter weighting model using Oasis Montaj VOXI; a radius around boreholes of 20 m, a weight attenuation factor of 0.1, and a weight minimum threshold of 0.0001 were used.

*Figure 4-8: Magnetic susceptibility data from 27 boreholes. Circle size is proportional to the magnetic susceptibility value and range from 0 SI to 550 SI.*
A modelling tool was developed in MATLAB to create synthetic geological structures and import them into the initial model (Figure 4-9). The tool is capable of modelling 3-D sheet structures with the following parameters: easting, northing, limiting depth, horizontal and vertical lengths, thickness, strike, dip, and magnetic susceptibility. Table 4-4 lists the parameters used to describe each of the 3-D sheet structures which were inferred from the RMI map (Figure 4-5). For easting, northing, and depth there is a reference position, a known or interpreted location where the structure is built from. There are also minimum and maximum limits to the structure’s extent (east/west and north/south) and depth. For this constrained inversion, the reference position is based on interpretation of magnetic data and grids as well as borehole cross-sections. These geological structures (Figure 4-9) are converted to voxel models in Oasis Montaj and then imported in the VOXI inversion toolbox. To account for varying overburden thickness three separate structures were created: sheet 1 is only 10 m thick, extends from the south-east edge of the survey area to 350 m west of that edge, and ends 300 m from the northern edge of the survey area; sheet 2 and sheet 3 are set to 20 m of overburden and fill the rest of the survey area. A map view of the resulting voxel is shown in Figure 4-9 (right) at an altitude of 250 m ASL.

The results of the constrained inversion, using the same parameters as for the unconstrained inversion (Table 4-3) and incorporating steeply dipping structures (Table 4-4) and the borehole magnetic susceptibility data (Figure 4-8) are shown in Figure 4-10 and Figure 4-11.
Figure 4-9: Synthetic geological structures numbered and further described in Table 4-4. Left – 3-dimensional view. Right – map view at 250 m ASL.

Table 4-4: Parameters describing the 3-D structures used for the constrained inversion.

<table>
<thead>
<tr>
<th>Geological Structure</th>
<th>Figure 4-8 Structure #</th>
<th>Relative Easting (m) Reference</th>
<th>Start</th>
<th>Stop</th>
<th>Relative Northing (m) Reference</th>
<th>Start</th>
<th>Stop</th>
<th>Depth (m) Reference</th>
<th>Limiting</th>
<th>Strike (°)</th>
<th>Dip (°)</th>
<th>Thickness (m)</th>
<th>Susceptibility (SI)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sheet 1</td>
<td>1</td>
<td>13</td>
<td>440</td>
<td>448</td>
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<tr>
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<td>1075</td>
<td>1605</td>
<td>843</td>
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<td>Sheet 4</td>
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<td>745</td>
<td>1610</td>
<td>1316</td>
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<td></td>
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<td></td>
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</tr>
<tr>
<td>Sheet 5</td>
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<td>1837</td>
<td>1700</td>
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<tr>
<td>Sheet 6</td>
<td>6</td>
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<td>2137</td>
<td>1838</td>
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<td>Sheet 7</td>
<td>7</td>
<td>22</td>
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<td>1846</td>
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<tr>
<td>Sheet 8</td>
<td>8</td>
<td>1947</td>
<td>2137</td>
<td>1994</td>
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<td>0</td>
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<tr>
<td>Overburden 1</td>
<td>10</td>
<td>852</td>
<td>1359</td>
<td>809</td>
<td>1755</td>
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<td>Overburden 2</td>
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<td>809</td>
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<td>0</td>
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<td>0</td>
<td>0.1</td>
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<tr>
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<td>1359</td>
<td>809</td>
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<td>20</td>
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<tr>
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<td>809</td>
<td>1755</td>
<td></td>
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</tbody>
</table>
Figure 4-10: Constrained inversion results. Horizontal slices through the 3-D magnetic susceptibility model at various depths as indicated in the bottom right corners. The grey outlines are the known gold ore zones. The black dashed lines correspond to the vertical slices presented in Figure 4-11. Contours are every 0.1SI.
Figure 4-11: Constrained inversion results. Vertical slices through the 3-D magnetic susceptibility model corresponding to the dashed lines drawn on Figure 4-10. Solid lines show the traces of the sheet structures and associated numbers (Figure 4-8 and Table 4-4).
4.6.3 Comparison

Both the unconstrained and constrained inversion results are consistent with structural trends by revealing near-vertical structures or thin sheets steeply dipping towards the north and south as shown when projecting synthetic sheet structures (Table 4-4) into vertical slices through the magnetic susceptibility models (Figure 4-7 and Figure 4-11). The presence of BIFs whom by their nature are typically associated with well-defined linear magnetic anomalies has produced a signature which highlights particularly well the local structural framework. The northern region of the survey area is modelled as two linear sheets trending east-west and steeply dipping southward (structures 5 and 7), down to depths of approximately 400 m beyond which these features are no longer resolvable as two separate structures. The south-western region of the survey area is also modeled as near-vertical sheets down to approximately 400 m but dipping northward (structures 1 and 2). The central region of the survey area is more complicated; there is evidence that both faulting and folding has occurred; the two sheets appear to be dipping south-eastward (structures 3 and 4).

At shallow depths (down to 150 m AGL), the constrained inversion (Figure 4-10) provides more structural details than the unconstrained inversion (Figure 4-6) (in the 350 m and 300 m ASL maps). On the other hand, near vertical structures appear to blend at shallower depths for the constrained inversion (Figure 4-11) than for unconstrained inversion (Figure 4-7). The unconstrained inversion returned magnetic susceptibility values from -0.144 SI to 0.569SI, while the
constrained inversion returned values within a similar range between -0.002 SI to 0.523 SI.

Typical iron formation units range in magnetic susceptibility from $10^{-2}$ SI to $10^2$ SI (Clark, 1997) depending on the formation’s haematite versus magnetite content (Dentith & Mudge, 2014). Taner and Chemam (2015) modelled an iron formation, located 250 km west of the Nelligan property, using 0.6 SI. The difference in magnetic susceptibility between the iron formations at these two locations could be due to varying magnetite content. Taner and Chemam (2015) report between 77% and 89% of the iron oxide minerals being magnetite with the rest primarily being haematite. The iron formations found on the Nelligan property contain centimetric alternations of magnetite and haematite bands but there is no data on the relative abundance of the two minerals.

### 4.7 Discussion and conclusion

A key finding of this study is the similarity between the results of the unconstrained and constrained inversion. The initial model of the constrained inversion, a laborious process, incorporated 13 modelled structures, magnetic susceptibility data from 27 boreholes totalling 8.4 km spaced every 3 m to steer the results towards a model of the subsurface consistent with a priori knowledge of the geology of the survey area. On the other hand, the straightforward unconstrained inversion which simply inputs the processed TMI data gives a detailed model of the subsurface and the results are not biased towards any
preconceived interpretation of the local geology. The convergence of the unconstrained inversion towards a realistic model of the subsurface is attributable to the high density (approximately 12 data points per 12.5 m x 12.5 cell) and high quality (as demonstrated by repeatability statistics (Table 4-2)) both, in turn, being related to the capability of the UAS of flying at low speed in a stable manner.

The minimal data handling required for unconstrained inversion of TMI data acquired by a UAS and the relatively short time needed to run an inversion (approximately 1 hour) makes it possible to envisage that TMI data could be processed and inverted almost immediately after it has been acquired, while the survey team is still in the field. A quick interpretation of the results could impact the continuation of the survey in the following days (e.g., flying lines with tighter spacing over areas of particular exploration interest or perpendicular to the strike of newly identified structures). The results of this research project reinforce the fact that UAS magnetometry has now reached a level of technical maturity such that it has become a useful operational tool for gold mineral exploration surveys.

4.8 Acknowledgements

The authors thank NSERC (Natural Sciences and Engineering Research Council) for providing the Engage grant to Dr. Claire Samson and scholarship to Michael Cunningham.
5. Aeromagnetic attitude compensation for uninhabited aircraft systems without high-altitude calibration patterns using recurrent neural networks

This chapter has been submitted to a peer-reviewed journal on Jul 12, 2022.

Its authors are:


This paper is included in this thesis with minor formatting changes and variable renaming (for consistency between chapters). This paper was co-authored by: the thesis author, Michael Cunningham; his co-supervisors, Dr. Claire Samson and Prof. Jeremy Laliberté; the chief geophysicist from IAMGOLD Corporation, Mark Goldie; the Engineering Manager, Alan Wood, and Chief Executive Officer, David Birkett, from Stratus Aeronautics Inc. M. Cunningham formulated objectives, developed the machine learning algorithm, acquired publicly available fixed-wing airplane datasets (e.g., Shabogamo Lake), evaluated least squares and recurrent neural network compensation results for each dataset, and wrote the manuscript. L. Tuck provided valuable insight into aeromagnetic compensation and machine learning, access to a second aeromagnetic dataset collected by a UAS, and extensive comments on the manuscript. C. Samson provided extensive comments on technical results and the manuscript. J. Laliberté provided guidance on machine
learning and comments on technical results and the manuscript. M. Goldie provided access to the Nelligan, QC survey area and comments on the manuscript. A. Wood and D. Birkett piloted and maintained the UAS platform, oversaw operations, provided the merged UAS dataset (which included GPS position, altitude, and raw total magnetic intensity), and provided technical support for the aeromagnetic survey planning as well as provided comments on the manuscript.

5.1 Paper context

As the level of quality of aeromagnetic data collected by UAS improved, the need to remove magnetic noise from variations in aircraft attitude increased. At the time of this thesis, most solutions require a high-altitude figure-of-merit flight to fit models based on the 16-coefficient Tolle-Lawson model. Due to regulatory and hardware limitations UAS are unable to perform effective figure-of-merit flights. This study proposes a recurrent neural network architecture as an alternative method to perform magnetic attitude compensation. This compensation approach is compared to typical hardware and least-squares based compensation methods for three different survey datasets. It showed that the recurrent neural network compensation method is successful at modelling magnetic noise from aircraft attitude variations and has potential to be used for any platform with a hard-mounted sensor that also carries a three-axis fluxgate magnetometer. The study proposed a method that can be used to perform attitude compensation on UAS
data without the need for a high-altitude figure-of-merit flight thereby further improving the data quality of magnetic data collected by a UAS.

5.2 Abstract

Since the 1950s, Tolles-Lawson based aeromagnetic compensation methods have been used to separate magnetic signal from the aircraft from signal associated with ground geological and cultural features. This is done by performing a high-altitude figure-of-merit (FOM) flight and fit the band-pass filtered magnetic data to determine compensation parameters. This paper describes a supervised recurrent neural network (RNN) algorithm trained on low-altitude survey data to perform aeromagnetic compensation. The proposed RNN attitude compensation method can be employed for aeromagnetic surveys where traditional FOM and compensation are not possible, with particular relevance for UAS surveying. Firstly, the RNN was tested on data from a fixed-wing airplane survey and the results were compared to hardware-based compensation results. The standard deviation of the difference between the two methods for magnetic attitude corrections (MAC) was 0.1 nT for the training region and 0.4 nT for the application region, respectively. Secondly, a UAS FOM flight at the highest permitted altitude in Canada, 120 m above ground level, showed similar improvement ratios for software-based least squares (LS) and the proposed RNN algorithm of 3.5 and 2.6, respectively. The percent change and deviation in differences in MACs from LS to RNN was 0.0% and 0.9 nT across small-box loops and -2.7% and 0.4 nT
across large-box loops. Finally, LS and the proposed RNN algorithm were applied to a 50 m altitude UAS dataset for which no FOM flight was possible. LS did not provide realistic results whereas the RNN demonstrated effective removal of the magnetic signal due to aircraft attitude variations. The modelled RNN MAC had a standard deviation of 2.4 nT.

5.3 Introduction

Compensation methods have long been used in aeromagnetic surveying to model and remove platform attitude and motion signals from the measured local magnetic field, allowing for better identification of lower amplitude geological and cultural features. Attitude compensation removes noise produced by sensor carrying aircraft and was first proposed by Tolles-Lawson (TL) (1950). To effectively model the signal due to aircraft attitude variations, a high-altitude calibration flight is required, often referred to as ‘Figure of Merit’ (FOM) manoeuvre (Coyle et al., 2014; Noriega, 2015; Teskey et al., 1991; Tuck et al., 2019). At high altitude the geological signal is sufficiently attenuated, and the signal from aircraft attitude variations become dominant. By recording aircraft attitude information, it is possible to model the attitude effects using linear least squares (LS) regression and later remove them from survey magnetic data.

Since 1993, machine learning has been investigated as a tool for modelling the aircraft attitude effects in magnetic data, as opposed to employing LS regression. However, as with other compensation methods, all the proposed solutions require
FOM compensation flights that are ideally as high as possible (Jiao et al., 2022; Ma et al., 2018; Tuck et al., 2019; P. Yu et al., 2021, 2022; D. Zhang et al., 2022; X. Zhao et al., 2021). Williams (1993) provided an encouraging framework for employing machine learning to attitude compensation on aeromagnetic datasets, but like other more recent publications, does not provide real-word demonstrations showing the validity of its use.

The recent introduction of uninhabited aircraft systems (UAS) for aeromagnetic surveying poses a new problem for aircraft attitude compensation. Attitude effects for UAS are not as well understood as they are for traditional platforms and vary depending on the UAS type and sensor placement (Accomando et al., 2021; Cunningham et al., 2018; Hansen, 2018; Kim, Jeong, et al., 2021; le Maire et al., 2020; Tuck et al., 2021; Walter et al., 2020; Wood et al., 2016; B. Zhang et al., 2011). Several investigations have been performed to better understand the magnetic characteristics of UAS (Forrester, 2011; Forrester et al., 2014; Huq et al., 2015; Sterligov & Cherkasov, 2016; Tuck et al., 2018, 2021; Walter et al., 2019a, 2021; Wells, 2008) and have informed the development of aircraft attitude compensation for UAS (H. Li et al., 2018; Tuck et al., 2019; B. Zhang et al., 2011). However, a major obstacle in most countries the use of UAS are tightly regulated to minimize the risks to other airspace users and to people and property on the ground (Stöcker et al., 2017). In Canada, UAS are limited to altitudes below 122 m (400 feet) above ground level (AGL) without a special flight operations certificate (SFOC) and permission from NAV Canada (Transport Canada, 2020). UAS are further limited in their ability to fly an FOM because communication range
remote-control capabilities at high altitude are limited, complex manoeuvres are not easily programmed into the UAS autopilot (i.e., performing a series of yaw, pitch, and roll manoeuvres), and physical limitations can prevent them from reaching the typical altitudes required for an FOM. This limits the ability for UAS to perform effective FOM calibration flights for attitude compensation at an altitude sufficiently high for the data not to be affected by geological and cultural signals.

This paper proposes a new algorithm based on recurrent neural networks (RNNs) for performing attitude compensation without the need for high-altitude calibration patterns, which is of particular interest for UAS surveying. The objective is to demonstrate the effectiveness of the algorithm and, in order to accomplish this, the paper presents three case studies illustrating different aspects of attitude compensation with the RNN method: (1) a comparison with industry-standard hardware compensation using data acquired by a fixed-wing airplane, (2) a comparison with LS regression compensation using data from a UAS flown at 120 m AGL, and (3) and its application to data acquired by a UAS flown at 50 m AGL.

5.4 Background

5.4.1 Aeromagnetic compensation

The aircraft attitude effects ($B_A$) are composed of the vector sum of three different sources: (1) $B_p$ – permanent magnetization; (2) $B_i$ – induced magnetization; and (3) $B_E$ – eddy-currents.
\[ B_A = B_P + B_I + B_E \]  

Tolles and Lawson (1950) were the first to propose a 16-coefficient equation for modelling the platform attitude or motion related to magnetic noise of an aircraft. An LS solution for solving the model equation was later attempted by Leliak (1961). Presently, aeromagnetic data recorded using traditional sensor-mounted survey platforms (not towed but boom-mounted to a fixed-wing airplane or helicopter) is compensated via two methods: (1) real-time compensation that uses on-board equipment to remove unwanted signal; or (2) software compensation, applied in post-survey processing. Both methods typically model the bandpass filtered \( B_A \) to provide a model of the three contributions to magnetic noise from the aircraft. The basis of these methods rooted in the LS regression to fit the 16 coefficients, as originally suggested by Tolles-Lawson (1950). The TL model requires the projection of attitude interference from the three sources along the transverse, longitudinal, and vertical axes of the aircraft (T, L, and V, respectively) onto the direction of the geomagnetic field to describe the aircraft’s orientation in space which requires the collection of vector magnetic data using a three-axis fluxgate magnetometer. It also uses the products of these variables and their time derivatives: TT, TL, TV, LL, LV, VV, TI, Tv, Lt, Li, Lv, Vt and Vv (where lower case indicates a time derivative). Variables T, L, and V describe permanent magnetization effects; variables TT, TL, TV, LL, LV, and VV describe induced magnetization effects; and variables TI, Tv, Lt, Li, Lv, Vt and Vv describe eddy currents (Bickel, 1979; FitzGerald & Perrin, 2015; Leliak, 1961).
The linear regression equation takes the form of:

\[ \hat{y} = c_1x_1 + c_2x_2 + \cdots + c_Nx_N = \mathbf{c} \cdot \mathbf{x} \]  

(5.2)

where \( c_n \) are the 16 weighting coefficients, \( x_n \) are input variables, and \( \hat{y} \) is the predicted output. The LS estimation attempts to minimize a loss equation over \( M \) measurements defined as:

\[ L_{S\text{loss}} = \sum_{m=1}^{M} (y_m - [x_{m\times N} \cdot c_{N\times 1}])^2 \]  

(5.3)

Coefficients are calculated from a calibration test with FOM manoeuvres. The test is carried out in a low gradient area at high altitude (typically at or above 2,500 m AGL) with manoeuvres varying between ±10° rolls, ±5° pitches, and ±5° yaws (Coyle et al., 2014; FitzGerald & Perrin, 2015; R. Groom et al., 2004; Noriega, 2015; Teskey et al., 1991; Tuck et al., 2019). The compensation pattern is typically a box pattern having four orthogonal flight directions. Compensation is typically performed at the onset of a survey, at the end of the survey, and/or if any significant changes have been made to the aircraft (Teskey et al., 1991).

Attitude effects are typically within the range of ±10 nT, but can be much larger in noisy datasets, and have a frequency range between 0.008-4 Hz while geological features can be upwards of thousands of nT and have a typical frequency range of 1 Hz or lower for typical mineral exploration surveys (Hardwick, 1984).
The improvement ratio (IR) is a measure of the effectiveness of compensation and is defined as:

\[ IR = \frac{\sigma(BP(M_U))}{\sigma(BP(M_C))} \]  

(5.4)

where \( \sigma(BP(M_U)) \) is the standard deviation (\( \sigma \)) of the bandpass (BP) filtered uncompensated magnetic data (\( M_U \)), and \( \sigma(BP(M_C)) \) is the standard deviation of the bandpass filtered compensated magnetic data (\( M_C \)). The IR calculation is typically only applied to the high-altitude FOM test flight data and if IR is greater than 1 there is an improvement from applying attitude compensation (Noriega, 2011; Tuck et al., 2019).

5.4.2 Recurrent neural networks

Neural networks mimic organic neural connections by developing and reinforcing links between artificial neurons, termed 'perceptrons' in response to an input. A perceptron (Figure 5-1 - left) is a functional unit that encapsulates an \( N \)-term linear regression equation with weights (\( w \)), a bias (\( b \)), and a specified activation (\( a \)) function.

\[ \hat{y} = a(w_1x_1 + w_2x_2 + w_3x_3 + \ldots + w_Nx_N + b) = a(c \cdot x + b) \]  

(5.5)

The bias \( b \) is applied to produce an offset in the sum of all inputs and can improve model prediction by adjusting the level at which the activation function's
threshold is surpassed. The individual weights and bias terms can be adjusted through training iterations. An activation function can be linear or non-linear and determines whether the perceptron is ‘on’ or ‘off’. The activation functions ‘linear’ and ‘hyperbolic tangent’ were used for the proposed algorithm (Figure 5-2) (Vasilev, 2019; Williams, 1993; P. Yu et al., 2022).

This type of artificial neural network (ANN) is known as a feed-forward neural network, where the network learns independently by minimizing a loss function, in this case the mean-squared error (MSE) between a modelled output value and the observed value. To do this \( w \) and \( b \) are iteratively adjusted through backpropogation as a batch; a smaller chunk of data that can use fast-accessed memory. An epoch has been completed once all batches of a dataset have been processed. Variables \( w \) and \( b \) are modified between each batch by an optimizer, such as gradient descent, in incremental steps called the learning parameter \( (l_k) \):

\[
w = w - l_k \frac{\partial\text{Loss}}{\partial w}
\]

\[
l_k = l_i e^{-\lambda k}
\]

with and initial rate \( l_i \) and current epoch \( k \) and decay constant \( \lambda \).

RNN are more complex than the basic ANN, where they are capable of better handling sequences of data by sharing parameters across different time steps. One type that contains and modifies a memory cell is the long-short-term memory (LSTM) RNN. An LSTM has \( N \) connected cells connected across the \( N \) time steps.
being provided; therefore, each LSTM (Figure 5-1 -right) cell has a more complex architecture than a perceptron and is capable of learning and remembering longer patterns by allowing for feedback connections (Géron, 2019). An LSTM cell is capable of processing sequences of data and retaining values over arbitrary time intervals, where gates regulate the flow of information into and out of the cell. LSTMs are ideal for making predictions based on time series data.

Multiple units (perceptrons or LSTMs) can be arranged into a structure featuring an input layer, hidden layer(s), and an output layer. When all units from a layer are fully connected to all the previous layer’s units, this is called a dense layer (Figure 5-3).

Underfitting or overfitting can happen during training. Underfitting occurs when the model does not fit the training data and does not generalize well to new data either; in general, this is simple to detect with good performance metrics and visualization tools. Overfitting occurs when the model becomes unnecessarily too complex relative to the amount of training data and the level of noise present (Géron, 2019). Using a dropout layer is a simple method of reducing the risk of overfitting (Figure 5-3) (Baldi & Sadowski, 2013; Hinton et al., 2012). The dropout layer will temporarily ignore a random unit for an iteration at a specified rate and prevent units from becoming highly dependent on another unit.
Figure 5-1: Architecture of a perceptron (left) and LSTM cell (right). The perceptron contains a bias and input parameters ($X_i$) each with an associated weight $W_i$, that are randomly initiated and then trained by varying the weighted sum of inputs and whether the perceptron activates. The LSTM cell considers a set time window, ‘$t$’, which is connected to time ‘$t-1$’ and ‘$t+1$’. A cell state (CS) is used to track information between all connected cells over a time window and is adjusted from cell to cell. The forget gate determines what information not to keep in a cell state. The input gate determines what information to add to a cell state. The output gate sends the current cell state ($CS_t$) and LSTM output ($H_t$) to the next connected cell. $H_t$ is also output to the next layer. Activations are set by the user, while piecewise addition (large + symbol) and multiplication (large X symbol) are always present.
Figure 5-2: Activation functions used in the proposed RNN algorithm: linear (solid line) and hyperbolic tangent (dashed line).

Figure 5-3: Example of a structure of dense layers with an input layer, two hidden layers, and an output layer. The black units indicates where dropout is applied for this epoch. Modified from Géron (2019).
Neural networks do not perform well when inputs are at very different scales (Géron, 2019); by scaling inputs so that they have similar ranges, it is possible to improve the algorithm’s learning and modelling capabilities.

LS compensation is normally poorly conditioned, it can only provide a first order approximation of some attitude effects, and some effects are not easily calculated unless the exact geometry of the aircraft is known (Williams, 1993). Neural networks, particularly ones with multiple hidden layers (known as a deep networks), can be used to solve complex problems (Géron, 2019) and provide models of potentially non-linear phenomena such as currents, vertical acceleration, motor rotation, etc. For aeromagnetic surveying, they can simultaneously model and separate both $B_C$ and $B_A$ from $B_M$ without the need of high-pass filtering (Williams, 1993).

5.5 Proposed RNN compensation algorithm

5.5.1 Description

The proposed algorithm was developed using Python 3 (version 3.7.13) and Google’s TensorFlow (version 2.8.2) open-source software library (Abadi et al., 2016).

The neural network architecture developed by Williams (1993) uses three branches of input data, for positional, diurnal, and attitude variables, each with three dense layers. This network was used as the basis for the proposed RNN
algorithm (Figure 5-4). The proposed RNN algorithm consists of two neural network branches, with one, an LSTM RNN, to model positional information and the other, a fully connected neural network, to model attitude. The positional branch models the geological response based on the measurement location from global navigation satellite systems. Since the geological response typically occurs at frequencies below 0.1 Hz (Hardwick, 1984), the signal will not vary significantly from one measurement to the next. Past and future measurements should be considered when modelling it; LSTMs (with three layers) are therefore used. As in the case of Williams (1993), testing found that at least three layers were required to successfully model the magnetic response from geology, while more layers significantly increased processing time without improving results. The attitude branch models the magnetic effects from the changing aircraft attitude. For traditional aircraft this signal ranges between 0.01 Hz and 4 Hz (Hardwick, 1984) and can be discontinuous as the aircraft makes sudden adjustments. It is not expected to have the same dependence on past and future measurements as the geological response; fully connected dense layers were therefore selected instead. Testing found that at least two layers were required to successfully model the attitude response, and more layers did not provide significant improvements. The two branches were concatenated to provide one output, the modelled magnetic field with both geology and attitude contributing. Training compared the magnetic model with the measured magnetic field and adjusted the proposed RNN model parameters accordingly.
Since typical aeromagnetic surveys employ a base station, the diurnal branch used by Williams (1993) was not necessary. Instead, the diurnal magnetic field was subtracted from the magnetic survey data prior to training the RNN, reducing the complexity of the algorithm and model.

Input variables into the positional branch are: \( x, x^2, y, y^2, xy, z, z^2, xz, \) and \( yz \), where \( x \) is easting, \( y \) is northing, and \( z \) is altitude. Three LSTMs, that each output 128 values, were used for each layer in the positional branch, with each using a 1.5 s window (15 samples). Testing found this number of outputs and time window size modeled small geological structures well, while not overly smoothing their response. The data inputs for the attitude branch include heading, to help describe a directional dependence in attitude effects, and the 16 TL compensation parameters discussed in Section 5.4.1 (Tolles & Lawson, 1950). Changes in aircraft attitude is not as predictable as aircraft position, but attitude still has a time dependence, so a time distributed set of dense layers was used, each having 36 perceptrons and only considering one time-step (1 sample) at a time. All inputs were scaled to fall between -1 and +1. To reduce the risk of overfitting the training data, both branches had dropouts applied to each hidden layer at a rate of 1%. The positional and attitude branches were concatenated into a single branch and then reduced to one output unit.

Line-by-line geological signal is predictable, structures tend to repeat at similar locations along adjacent lines, whereas aircraft attitude is more irregular and will not vary the same along adjacent lines. With two separate branches, the RNN algorithm can learn how much contribution to the magnetic field is from geology.
Figure 5-4: Flowchart of the proposed two-branch attitude RNN compensation algorithm.
(captured by the positional branch) or aircraft attitude (captured by the attitude branch). The attitude branch has no information provided on position, so no geological signal should be modeled by it. The two branches function as separate models but are updated together through back propagation. After training, the user can restrict the inputs to the RNN algorithm to only retrieve attitude information, providing only a modeled magnetic attitude correction (MAC).

Optimization of the RNN algorithm was done through methodical trial-and-error experimentation with a focus on four aspects (listed in decreasing order of importance): (1) minimizing differences between LS and RNN compensation results (visual comparison and standard deviation calculation); (2) ensuring reproducibility of the model between re-runs using the same input data; (3) minimizing the MSE; and (4) reducing training time to under one hour (a factor dependent on computer components as well the structure and size of datasets). Adjustments were made to the number of layers in each branch, the number of cells and perceptrons in each layer, the method of data scaling (min-max vs standard scaling), the LSTM time window size, the dropout rate, the choice of different activation functions for each layer (i.e., linear, sigmoid, hyperbolic tangent, and rectified linear unit), and alternative layer architectures (i.e., dense, LSTM, and gated recurrent unit). A stopping criterion was used to stop training if no improvement in MSE was observed after 25 iterations.

As for LS compensation, it is expected that RNN compensation will need to be re-run if there are significant changes to the platform, for example, if a hardware
component such as a motor is replaced. The compensation model derived using the proposed RNN algorithm is optimized to a specific platform configuration.

5.5.2 Methodology

To train the proposed RNN algorithm, a survey dataset was separated into three subsets by selecting them in a line-by-line fashion, where the order of the data was not changed; one subset was for training (80-90% of the data), one was for validation (5-10% of data), and one was for testing (10-20% of the data). The training dataset was used to train the RNN model by adjusting model parameters. The validation dataset included data that the model had not been trained on, allowing for an unbiased evaluation of the model’s fit, using the MSE, after each iteration. The testing dataset was a separate dataset used for an unbiased evaluation of the model fit after training had been completed. Final compensation was performed by inputting only attitude data into the trained RNN model which outputs the MAC related to aircraft attitude only. Compensation was achieved through the subtraction of the modeled MAC from the raw magnetic data.

To validate the proposed RNN compensation algorithm, it must be compared with the industry standard methods, hardware- and software-based attitude compensation. For this purpose, one demonstration survey employed hardware compensation while two applied software-based LS compensation.

Training of the algorithm was performed on Google Research’s Collaboratory and their remotely hosted graphical processing units (NVIDIA K80 or better) and
high random-access memory (> 13 GigaBytes) since these systems provide more processing power than consumer-grade desktop graphical processing units.

5.6 Results and discussion

First (Section 5.6.1), a dataset acquired using a fixed-wing airplane, that includes both raw and hardware compensated magnetic data was selected to provide qualitative and quantitative line-by-line comparisons. Second (Section 5.6.2), a 120 m AGL aeromagnetic dataset flown by a single-rotor UAS was selected because it included an FOM calibration flight. Although this survey is limited in its scale and altitude, the FOM flight allows a comparison between LS (software based) and RNN attitude compensation that reflects a typical FOM calibration. Finally, a third dataset (Section 5.6.3) was chosen to illustrate the intended use for the proposed RNN algorithm in compensating low-altitude, 50 m AGL, aeromagnetic data collected by a UAS. Each survey was individually used to train a new RNN model, specific to the survey platform and location.

5.6.1 Compensation of data acquired using a fixed-wing airplane

The aeromagnetic dataset acquired using a fixed-wing airplane chosen to test the proposed RNN compensation algorithm was flown in 2011 and is publicly available from the Government of Canada (Moussaoui, 2011; Natural Resources Canada, 2011) (Table 5-1). The survey area, near Shabogamo Lake, straddles the
border between Québec and Labrador. This dataset was selected because it contained both uncompensated and compensated magnetic data as well as aircraft attitude information from a triaxial fluxgate magnetometer. Two Piper Navajo PA-31 airplanes were used to complete the survey, each carrying a magnetic sensor, in-flight navigation and altitude control equipment, and an RMS Instruments DAARC500 real-time attitude compensation system. The residual magnetic intensity (RMI) map is presented in Figure 5-5 showing the two regions used for training and application of the RNN compensation algorithm; these regions were both flown with the same aircraft.

This dataset was collected over the Ashuanipi subprovince, near the eastern edge of the Superior Province of the Canadian Precambrian Shield. The Ashuanipi subprovince is a high-grade metamorphic terrain that contains predominantly migmatitic paragneiss rocks deriving from sedimentary and igneous protoliths. There are mafic and ultramafic rocks occurring as isolated intrusions, sills, and dykes as well as tonalite and granite plutons. In the survey area, structures with a high magnetic susceptibility correspond to gabbro dykes, tonalites, granites, and metamorphosed iron formations. The eastern edge of the dataset includes geological units of the Labrador Trough, which contains large, banded iron formations (St-Onge et al., 2009; van Nostrand et al., 2016; van Nostrand & Broughm, 2017). The dataset is bordered to the southeast by the Grenville Front. Brittle fault zones transect the survey area, but are poorly constrained in direction and displacement, and may have been reactivated by the compression due to the creation of the Labrador Trough.
Table 5-1: Aeromagnetic survey specifications.

<table>
<thead>
<tr>
<th>Survey Type</th>
<th>Survey Location</th>
<th>Survey Date (Year)</th>
<th>Company</th>
<th>Platform</th>
<th>Sensor</th>
<th>Base Station Sensor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed-wing airplane survey</td>
<td>Shabogamo Lake, Quebec and Labrador (53.6°N, 67.5°W)</td>
<td>2011</td>
<td>Geo Data Solutions Inc</td>
<td>2 x Piper Navajo PA-31</td>
<td>Geometrics Cesium G-822A</td>
<td>GEM GSM-19 Overhauser</td>
</tr>
<tr>
<td>High-altitude UAS survey</td>
<td>N/A</td>
<td>N/A</td>
<td>Stratus Aeronautics Ltd</td>
<td>Single-rotor UAS</td>
<td>Geometrics Cesium G-822A</td>
<td>GEM GSM-19 Overhauser</td>
</tr>
<tr>
<td>Low-altitude UAS survey</td>
<td>Nelligan property, Quebec (49.4° N, 74.7°W)</td>
<td>2018</td>
<td>Stratus Aeronautics Ltd</td>
<td>Multi-rotor UAS</td>
<td>Geometrics Cesium G-823A</td>
<td>GEM GSM-19 Overhauser</td>
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</table>

<table>
<thead>
<tr>
<th>Survey Length (line-km)</th>
<th>Traverse Lines</th>
<th>Tie Lines</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Line Heading (°)</td>
<td>Line Heading (°)</td>
</tr>
<tr>
<td></td>
<td>Line Spacing (m)</td>
<td>Line Spacing (m)</td>
</tr>
<tr>
<td>------------------------------</td>
<td>-----------------------------------------------------</td>
<td>--------------------</td>
</tr>
<tr>
<td>41048</td>
<td>90 / 270</td>
<td>0 / 180</td>
</tr>
<tr>
<td></td>
<td>300</td>
<td>1800</td>
</tr>
<tr>
<td>2.8</td>
<td>70 / 250</td>
<td>160 / 340</td>
</tr>
<tr>
<td></td>
<td>200 (large box)</td>
<td>200 (large box)</td>
</tr>
<tr>
<td></td>
<td>65 (small box)</td>
<td>65 (small box)</td>
</tr>
<tr>
<td></td>
<td>50</td>
<td>150</td>
</tr>
<tr>
<td>319.7</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>80</td>
<td></td>
<td></td>
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<tr>
<td>120 m</td>
<td></td>
<td></td>
</tr>
<tr>
<td>50</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Figure 5-5: RMI map from the Shabogamo Lake fixed-wing aeromagnetic survey. Two boxes show the locations used for training and application of the proposed RNN compensation algorithm. Within the two boxes are flight lines (grey) corresponding to profiles displayed in Figure 5-6 and Figure 5-7.
Training and testing of the proposed RNN algorithm were performed on the training region found in the northwest portion of the survey area (Figure 5-5); this region was selected because it is geomagnetically quiet and therefore less prone to contamination from geological signal. The RNN algorithm produced a model that had a MSE of $1.4 \times 10^{-5}$ on the training subset (29 lines) and $2.5 \times 10^{-6}$ on the testing subset (2 lines) after 249 epochs (Table 5-2).

Table 5-2: Summary of RNN compensation results.

<table>
<thead>
<tr>
<th>Case Study</th>
<th>Fixed-wing airplane survey</th>
<th>120 m AGL UAS survey</th>
<th>50 m AGL UAS survey</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Application</td>
<td>Training</td>
<td>Testing</td>
</tr>
<tr>
<td>Length used (line-km)</td>
<td>418.9</td>
<td>396.0</td>
<td>2.8</td>
</tr>
<tr>
<td>Number of Data Points</td>
<td>41434</td>
<td>N/A</td>
<td>10429</td>
</tr>
<tr>
<td>Number of Data Points</td>
<td>2832</td>
<td>43766</td>
<td>1479</td>
</tr>
<tr>
<td>Training Time (minutes)</td>
<td>25</td>
<td>N/A</td>
<td>10</td>
</tr>
<tr>
<td>Number of Epochs</td>
<td>249</td>
<td>N/A</td>
<td>325</td>
</tr>
<tr>
<td>MSE (nT^2)</td>
<td>Training</td>
<td>1.4 x 10^{-5}</td>
<td>N/A</td>
</tr>
<tr>
<td></td>
<td>Testing</td>
<td>2.5 x 10^{-6}</td>
<td>N/A</td>
</tr>
<tr>
<td>MAC % Difference</td>
<td>11.1</td>
<td>66.7</td>
<td>2.7</td>
</tr>
<tr>
<td>MAC % Change</td>
<td>11.8</td>
<td>100.0</td>
<td>-2.7</td>
</tr>
<tr>
<td>Standard Deviation of MAC Difference (nT)</td>
<td>0.1</td>
<td>0.4</td>
<td>0.4</td>
</tr>
<tr>
<td>IR</td>
<td>N/A</td>
<td>N/A</td>
<td>2.6</td>
</tr>
</tbody>
</table>

Two selected profiles, a traverse line and a tie line, are presented in Figure 5-6, showing the raw, hardware-based compensated, and RNN compensated residual magnetic intensity (RMI), as well as the modelled MACs and the differences between them. The three RMI profiles are almost identical, so Figure 5-6 also includes a zoomed-in segment. Qualitatively, both hardware and RNN compensated MAC profiles are nearly the same, trends and magnitudes are
matched well between the two methods. Over all training lines, the hardware-based compensation MAC has a standard deviation of 0.17 nT, whereas the modeled MAC from the RNN algorithm has a standard deviation of 0.19 nT; producing a percent difference and percent change between the two of 11.1% and 11.8%, respectively. The line-by-line difference between the two MACs has an average of 0.0 nT with a standard deviation of 0.11 nT.

Data from the application region found in the southwest portion of the survey area (Figure 5-5) was compensated using the RNN model from the training region; this region was selected because it is far from the training region, geomagnetically active, and the data was collected by the same aircraft.

Selected profiles from the application region are presented in Figure 5-7. Qualitatively, the RNN compensated MAC is similar to the hardware compensated MAC, trends are the same, but magnitudes of the RNN are larger. Across all lines, the hardware-based compensation MAC had a standard deviation of 0.2 nT, whereas the modeled MAC from the RNN algorithm has a standard deviation of 0.4 nT; producing a percent difference and percent change between the two of 66.7% and 100.0%, respectively. The line-by-line differences between the MACs has an average of 0.0 nT with a standard deviation of 0.4 nT. As expected, because data from the application region was not used for training the RNN algorithm and was acquired at a different date, where hardware changes to the aircraft could have occurred (i.e., significant maintenance), the RNN attitude model deviates more from the hardware-based model. However, as seen in Figure 5-7
Figure 5-6: Profiles along traverse line 11140 (left) and tie line 21120 (right) from the training region indicated in Figure 5-5. Vertical dashed lines are where the two profiles intersect. The top three rows are: Top - raw (solid black), hardware compensator (dashed line) and RNN compensated (dotted line) RMI; Middle – hardware compensator (dashed line) and RNN (dotted line) MAC; and Bottom - the difference between the MACs from the two methods. The bottom three rows are the same for the zoomed-in region shaded in grey.
Figure 5-7: Profiles along traverse line 14610 (left) and tie line 20080 (right) from the application region indicated in Figure 5-5. Vertical dashed lines are where the two profiles intersect. The top three rows are: Top - raw (solid black), LS compensated (dashed line) and RNN compensated (dotted line) RMI; Middle - LS (dashed line) and RNN (dotted line) MAC; and Bottom - the difference between the MACs from the two methods. The bottom three rows are the same for the zoomed-in region shaded in grey.
the RNN still models some of the MAC signal that was identified by the hardware-based compensator.

Overall, this exercise demonstrated that the proposed RNN algorithm is capable of modelling magnetic effects from variations in aircraft attitude. It produced results similar to hardware-based compensation systems for data acquired using a fixed-wing airplane.

5.6.2 Compensation of data acquired using a UAS flying at 120 m AGL

Access to high-altitude UAS surveys is very limited due to regulatory constraints and aircraft limitations; however, data from a small UAS test flight was made available to the authors of this paper (Table 5-1). Details of this test flight are protected under a non-disclosure agreement. The test flight was flown over a region with moderate geological signal. The test included flying two different FOM box-shaped loops, in a clockwise fashion, at an altitude of 120 m AGL (Figure 5-8). A small box, with four 65 m long segments and flown four times, was used for training the RNN compensation algorithm. A second, larger box, with four 200 m long segments, was flown twice. This flight was used to compare results from software-based LS and RNN attitude compensation methods.

The RNN compensation algorithm was trained using the first three of the four small-box loops and the first of the two large-box loops and had a MSE of 2.0 x 10^{-4} after 325 epochs. The last small-box and large-box loops were used to test the algorithm and had an MSE of 1.7 x 10^{-4}. Software-based LS compensation
was also performed in post-processing using all the data from the small box where the data was bandpass filtered between 0.07 Hz and 1.5 Hz to isolate magnetic signal associated with aircraft motions. Both the modeled MACs, from LS and RNN compensation, have a standard deviation of 3.9 nT; producing a percent difference and percent change between the two of 0.0% and 0.0%, respectively. The line-by-line difference between the two MACs has an average of 0.0 nT with a standard deviation of 0.9 nT (Table 5-2). The 16 attitude coefficients for the LS and RNN methods are, for the most part, of the same order of magnitude (Table 5-3).

Attitude compensation results across one full pass of the large box are presented in Figure 5-9. Across both large-box loops, the modelled MAC from the hardware-based LS compensation has a standard deviation of 3.7 nT, whereas the RNN algorithm has a standard deviation of 3.6 nT; producing a percent difference between the two of 2.7% and -2.7%, respectively. LS and RNN compensation produced peak-to-peak correction similar to traditional platforms (±10 nT), with each having a range of 13.3 nT and 12.6 nT, respectively. The line-by-line difference between the two MACs has an average of 0.0 nT with a standard deviation of 0.4 nT.

The filtered raw RMI has a standard deviation of 0.42 nT, whereas the filtered LS RMI has a standard deviation of 0.12 nT and the filtered RNN RMI has a standard deviation of 0.16 nT. The corresponding IRs for LS compensation and RNN are 3.5 and 2.6, respectively (Table 5-2).
This exercise shows that the proposed RNN compensation algorithm is capable of modelling and removing attitude effects from high-altitude UAS data. In this example, software-based LS compensation performs slightly better. The dataset used, however, was relatively small (2.6 line-km in total), so training of the RNN compensation algorithm might not generalized to an attitude model sufficiently.

*Figure 5-8: (Left) Flight paths for training (black line) and application (grey line) flights. Dashed arrows indicate flight direction. Each segment of the pattern is labeled, 1 – northern, 2 – eastern, 3 – southern, and 4 – western. (Top Right) RMI data from the training flight with numbers indicating each segment. (Bottom Right) RMI data from the test flight with numbers indicating each segment. The spotted dark grey highlights correspond to turning manoeuvres. The light grey highlighted region is shown in Figure 5-9.*
Table 5-3: Attitude compensation coefficient comparison for high-altitude UAS dataset.

<table>
<thead>
<tr>
<th>Source of Attitude Effect</th>
<th>Coefficient</th>
<th>LS Compensation</th>
<th>RNN Compensation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Permanent Magnetization</td>
<td>C₁</td>
<td>1.91E+02</td>
<td>1.12E+02</td>
</tr>
<tr>
<td></td>
<td>C₂</td>
<td>-5.01E+00</td>
<td>1.09E+00</td>
</tr>
<tr>
<td></td>
<td>C₃</td>
<td>1.19E+00</td>
<td>1.13E+01</td>
</tr>
<tr>
<td>Induced Magnetization</td>
<td>C₄</td>
<td>1.67E-03</td>
<td>1.04E-03</td>
</tr>
<tr>
<td></td>
<td>C₅</td>
<td>-3.85E-04</td>
<td>-2.75E-04</td>
</tr>
<tr>
<td></td>
<td>C₆</td>
<td>-4.27E-05</td>
<td>1.95E-04</td>
</tr>
<tr>
<td></td>
<td>C₇</td>
<td>-9.26E-07</td>
<td>1.79E-04</td>
</tr>
<tr>
<td></td>
<td>C₈</td>
<td>-1.92E-04</td>
<td>-2.89E-04</td>
</tr>
<tr>
<td>Eddy Currents</td>
<td>C₉</td>
<td>-6.22E+00</td>
<td>-4.71E+01</td>
</tr>
<tr>
<td></td>
<td>C₁₀</td>
<td>-9.19E-01</td>
<td>-8.06E+00</td>
</tr>
<tr>
<td></td>
<td>C₁₁</td>
<td>2.84E+00</td>
<td>7.05E+00</td>
</tr>
<tr>
<td></td>
<td>C₁₂</td>
<td>2.45E+01</td>
<td>-1.44E+02</td>
</tr>
<tr>
<td></td>
<td>C₁₃</td>
<td>-4.39E+00</td>
<td>-3.59E+01</td>
</tr>
<tr>
<td></td>
<td>C₁₄</td>
<td>-1.55E+01</td>
<td>1.84E+02</td>
</tr>
<tr>
<td></td>
<td>C₁₅</td>
<td>1.34E+00</td>
<td>-5.53E+01</td>
</tr>
<tr>
<td></td>
<td>C₁₆</td>
<td>-2.91E+00</td>
<td>-2.53E+01</td>
</tr>
</tbody>
</table>
Figure 5-9: Profile along one pass around the test loop (Figure 5-8 – black) showing RMI (top), MAC (middle) and the difference between the MACs from the two methods (bottom). The four segments of the test flight are numbered at the top. Top - raw (solid black), software LS compensated (dashed line) and RNN compensated (dotted line) RMI; Middle – software LS (dashed line) and RNN (dotted line) MAC; and Bottom - the difference between the MACs from the two methods. The spotted grey highlights correspond to turning manoeuvres. The bottom three rows are the same for the zoomed-in region shaded in light grey.
5.6.3 Compensation of data acquired using a UAS flying at 50 m AGL

The proposed RNN compensation algorithm was applied to aeromagnetic data acquired using Stratus Aeronautics’ SkyLance 6200 UAS (Cunningham et al., 2018) over the Nelligan property (Figure 5-10, Table 5-1) (Cunningham et al., 2021, 2022), flown at 50 m AGL. The property is located approximately 55 km southwest of Chibougamau, Québec, and is owned by IAMGOLD Corporation and Vanstar Mining Resources. It lies within the Caopatina-Desmaraisville volcano-sedimentary segment in the Abitibi Subprovince of the Superior Province of the Canadian Precambrian Shield. The area has experienced significant deformational events, faulting, folding, and metamorphism and is now the host of gold mineralization zones and iron formations. The SkyLance 6200 UAS is a battery powered hexacopter that carries a front boom mounted magnetometer.

The RNN compensation algorithm was trained on 18 traverse lines and three tie lines, where 2 of the traverse lines were used for testing. The lines were selected based on the available fluxgate data; some lines had intermittent three-axis fluxgate data issues that were deemed problematic for effective RNN compensation training. The RNN algorithm produced a model that had a MSE of $2.2 \times 10^{-5}$ on the training data and $2.7 \times 10^{-6}$ after 250 iterations (Table 5-2).

Two selected profiles, a traverse line, and a tie line, are presented in Figure 5-11, showing the raw, software LS compensated and RNN compensated RMI, as well as the modelled MACs and the differences between them. The 16 TL coefficients were modelled with LS compensation using the survey data as no FOM was available. To do this, the data was bandpass filtered between 0.07 Hz
and 1.5 Hz to isolate magnetic signal associated with aircraft motions. The LS MAC does not provide realistic results; over all lines the LS compensation MAC had a standard deviation of 5.9 nT, whereas the RNN algorithm has a standard deviation of 2.4 nT, producing a percent difference and percent change between the two of 84.3% and -59.3%, respectively. LS compensation produced a peak-to-peak correction of 130.6 nT whereas RNN compensation produced a peak-to-peak correction similar to traditional platforms (±10 nT), having a total range of 5.8 nT. The line-by-line difference between the two MACs has an average of 0.0 nT with a standard deviation of 6.5 nT, further emphasising the poor LS MAC results.

Although they do not provide a direct comparison, results from the Nelligan UAS dataset show that the RNN compensation algorithm is a practical alternative to established hardware or software-based LS compensation methods.
Figure 5-10: RMI map from the Nelligan low-altitude UAS aeromagnetic survey. The two profiles displayed in Figure 5-11 are highlighted in grey.
Figure 5-11: Profiles along traverse line 350 (left) and tie line 9080 (right) from the lines highlighted in Figure 5-10 for the low-altitude UAS survey. Vertical dashed lines are where the two profiles intersect. The top three rows are: Top - raw (solid black), hardware compensator (dashed line) and RNN compensated (dotted line) RMI; Middle – hardware compensator (dashed line) and RNN (dotted line) MAC; and Bottom - the difference between the MACs from the two methods. The bottom three rows are the same for the zoomed-in region shaded in grey.
5.7 Concluding remarks and future considerations

The RNN attitude compensation method described in this paper has potential to be used for any aeromagnetic dataset for which the sensor is hard mounted to a platform that is also instrumented to measure the magnetic field vector components. It could be applied to platforms such as fixed-wing airplanes or stinger mounted helicopters, as well as UAS. The advantage of the RNN attitude compensation method is that it removes attitude effects from aeromagnetic data without the need for high-altitude FOM calibration flights.

In the case study comparing software-based LS and RNN compensation methods (Section 5.6.2), the performance of the LS method, as expressed by the IR, was slightly superior to that of the RNN method (3.5 vs 2.6). Two reasons could explain this discrepancy: (1) the RNN may not have generalized sufficiently due to the limited data available, and (2) limitations imposed on the RNN algorithm, such as hardware (i.e., memory, processor), and training time.

Furthermore, because of how compact UAS platforms are, interference from other non-attitude related noise sources could be contaminating the aeromagnetic data. By introducing more input parameters into the RNN algorithm, such as electronic currents, control surface positions, and motor rotation speeds, these issues could be addressed.

Current compensation methods require an FOM pattern to be flown at the onset and completion of a survey and if significant modifications were made on the platform during the survey. Typically, the compensation only applies to surveys
within the same region. With RNN compensation, no pre- and post-survey flights are needed. Nevertheless, it might be interesting to evaluate how frequently the RNN algorithm needs to be trained. Some questions that could be investigated are: (1) Will performance improve if training is completed daily, weekly, or only once per survey? (2) How much data is required to effectively compensate for attitude effects? Can data augmentation for machine learning improve performance for smaller datasets? (3) Will the RNN compensation model apply to future surveys with the same platform if flown in the same region or in another region? (4) How does the RNN compensation algorithm perform in different topographic environments (i.e., flat vs. hilly vs. mountainous)? (5) How does switching on-board hardware (e.g., batteries, motor, rotor blades, etc.) affect the model? (6) Can this approach be applied to more complex aeromagnetic surveying platforms, such as magnetic tensor gradiometers?

Presently, in published literature, attitude compensation on aeromagnetic datasets collected by a UAS, is rarely demonstrated using real-world case studies, and when it is, it requires a high altitude FOM. This paper presented an RNN architecture that provides a practical approach for applying attitude compensation to aeromagnetic datasets collected by a UAS, without the need for high-altitude calibration patterns. Furthermore, the proposed approach is performed in post-survey processing, so it can be applied to previous datasets to potentially improve past UAS surveys.
5.8 Acknowledgements

The authors thank NSERC (Natural Sciences and Engineering Research Council of Canada) for the ENGAGE grant to C. Samson and scholarship to M. Cunningham.
6. Conclusion

6.1 Summary

This research investigated some of the outstanding topics of interest for aeromagnetic survey with UAS. The research described in the first article (Chapter 3) demonstrated the merits of UAS surveying for mineral exploration through quantitative and qualitative comparisons between UAS data and traditional ground and helicopter datasets. Next, the research presented in the second article (Chapter 4) added to those benefits by producing magnetic inversion results from a UAS dataset. The work described in the final article (Chapter 5) improved aeromagnetic attitude compensation approaches using machine learning techniques to be applied to datasets that do not have a figure-of-merit flight, which is of particular interest for UAS surveys. The research presented in these three articles will allow other research groups to use the proposed approaches to evaluate the performance and improve the data quality of their own UAS.

In the first article, quantitative and qualitative comparisons demonstrated that UAS can be used to produce data of the same quality as traditional ground and helicopter survey techniques. Datasets collected by UAS were similar to upward continued ground survey results. Conversely, for the helicopter data it was observed that survey resolution was limited due to line spacing, providing less detailed results than the UAS. Decreasing the line spacing of the helicopter survey is expected to be impractical and unachievable due to increased costs of helicopter use and pilot abilities to stay on tightly spaced flight lines. Cell-by-cell quantitative
comparisons included the computation of absolute and percent differences as well as coherence; differences between the three surveys were highest in regions of strong magnetic gradient, such as near iron formations. Furthermore, it was found that, over 93% of the survey area, the three datasets had a coherence between each other of 80% - 90%. Comparisons for normalized survey data showed that the three datasets are nearly indistinguishable from one another. It was identified that with the precision of UAS flights it could be possible perform highly focused, and tightly spaced (down to 10 m or 5 m line spacing) surveys, providing very high-resolution aeromagnetic maps over regions of particular interest in an exploration project; something that would not be feasible with traditional methods.

As part of the second article, it was found that UAS collected dataset was repeatable and consistent. Over repeat flight lines, the flight altitude and lateral variations were within 5.8 m and 4.5 m of their nominal values, respectively. Both unconstrained and constrained magnetic inversion models were produced, showing that UAS datasets are of a high enough quality to produce reasonable and useful results. The unconstrained magnetic inversion results were very similar to that of the constrained inversion, while requiring minimal data handling. This exercise further reinforced the technical maturity of UAS magnetometry, which has become a useful operational tool for mineral exploration.

An issue identified in the first two articles was that, as for traditional airborne magnetic surveying, UAS surveying could benefit from aeromagnetic attitude compensation to reduce magnetic noise. Industry methods of attitude compensation are not well suited for UAS surveying as they require high-altitude
figure-of-merit flights that cannot typically be performed by a UAS. The third article built upon previous research in both aeromagnetic attitude compensation with machine learning using neural networks and compensation of UAS survey data. A novel recurrent neural network was developed and demonstrated to model the magnetic field produced from local geology and the changes in aircraft attitude. This model was tested on a dataset collected using a traditional fixed-wing airplane that included both raw compensated aeromagnetic data, which showed that the network could model the magnetic effects from aircraft attitude as well as hardware-based compensators that included a high-altitude FOM. The standard deviations in attitude correction applied with the hardware compensator and the RNN were 0.19 nT and 0.17 nT, respectively, with a percent difference of 11.1%. Testing on 120 m AGL UAS survey data showed that standard deviation of least squares and RNN compensation was 3.7 nT and 3.6 nT, respectively, with a percent difference and percent change of 2.7% and -2.7% respectively. Finally, it was shown that the RNN compensation algorithm could compensate 50 m AGL UAS magnetic data, whereas the LS compensation results were not usable. The LS compensation provided a magnetic correction with a standard deviation of 5.9 nT whereas the RNN had a standard deviation of 2.4 nT, having a percent difference and percent change of 84.3% and -59.3%, respectively. The RNN algorithm provided the added benefit of not requiring the filtering of the magnetic data, which could result in losing potentially valuable attitude information, and having the potential to be easily broaden in scope in the future to account for other
inputs, such as electronic current, control surface positions, and motor rotation speeds.

6.2 Future work

This research project contributed information on the use of UAS aeromagnetic data for mineral exploration, including examples of advanced data processing techniques, topics for which there is limited information in the open literature. Nevertheless, further studies over large geologically interesting regions would be beneficial; UAS survey results for geologically complex regions at a scale comparable to that of conventional fixed-wing and helicopter surveys are still relatively uncommon.

Questions surrounding aeromagnetic surveying with an UAS that could benefit from further research include:

1. Are there benefits to performing focused UAS surveys with tightly spaced lines? What is the optimal lateral resolution for different target sizes and depths?

2. What improvements to UAS aeromagnetic datasets could be made, theoretically and in practice, by decreasing flight altitude and improving the tightness of terrain draping?

3. How economically competitive are surveys with UAS, focussing on survey planning, system endurance, and processing workflows? Under
which conditions could UAS surveying compete with traditional surveys at a large scale? Are they only suitable for small high-resolution, focused surveys?

4. What advanced magnetic surveying methods can be applied to UAS’? Can a UAS be used to directly collect horizontal and/or vertical gradient data? How about performing vector magnetic surveying and tensor gradiometric surveying? Is the spatial separation of the sensors that could be achieved in practice large enough to provide reliable results?

An alternative solution to aeromagnetic attitude compensation was presented in Chapter 5 with a particular interest for its use on UAS datasets. Further development and testing of the low-altitude RNN magnetic attitude compensation algorithm could further improve its capabilities. Some outstanding questions include:

1. Could there be improvements when including additional inputs, such as electronic currents, motor rotation speeds, and higher-order attitude terms?

2. How is the RNN model affected by swapping on-board hardware during a survey? Does the RNN need to be retrained? Can the RNN model from a specific survey be applied to another survey flown subsequently by the same platform?

3. During a large-scale UAS survey, is it beneficial to train the algorithm daily? Weekly? Or only at the end of the survey?
4. How much data is needed to effectively perform attitude compensation with the RNN? Is data augmentation an effective means to bypass the issue of low amounts of survey data?

5. How does topography, and the draping of it, affect the quality of the RNN attitude model?

6. Can the proposed RNN algorithm be applied to more complex aeromagnetic survey datasets such as vector field magnetic data, total-field and tensor gradiometry?

Presently, UAS surveying for mineral exploration has focused mainly on its application in aeromagnetic surveying. There have been only a few publications presenting approaches for other geophysical survey methods, which include multi- and hyper-spectral surveying, radiometrics, and electromagnetics. Further development and demonstrations of these applications would further solidify the benefits of UAS within the industry.
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