From Data to DRIVR: connecting sensors in the field with interfaces in the lab using cyclical data ecosystems

by

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Abstract

Recent advances in spatial sensor technology have significantly enhanced the resolution, fidelity, and quantity of spatial data, driving progress in geovisualization. These trends are further extended by improvements in spatial computing and interface technology, creating new opportunities for immersive data visualization. This thesis explores a remote field data production system that integrates data collection, processing, and interpretation in both field and lab settings. A comprehensive review of 3D geovisualization in the geosciences identifies key limitations and potentials, laying the groundwork for a custom LiDAR system to address these issues. The resource utilization and data fidelity of a vehicle-mounted LiDAR system are assessed, highlighting its potential in remote field data collection. Additionally, a new experiential field data visualization interface (DRIVR) is developed, simulating driving through collected data to bridge field and lab experiences. This research emphasizes efficient data management and immersive visualization to enhance decision-making and collaboration in geospatial applications.

Keywords: geovisualization; geoscience; 3D modelling; vehicle-mounted LiDAR; resource utilization; extended reality

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Chapter 1. Introduction

1.1. Background to this research

Geovisualization is rapidly entering a new era, and recent advancements have led to an increase in the variety of applications in fields such as the geosciences. Driven by technological and computational advancements in the past decades, there have been significant strides made in mapping and modelling of the Earth and its 3D and 4D systems (Mossa, Chen, and Wu 2019). The field of 3D geovisualization as we know it developed from 2D cartography (Kraak 2003; Dykes et al. 2005). During this time, there have been significant advancements in both traditional Geographic Information Systems (GIS) and non-traditional tools and interfaces in geovisualization, moving with the progress in the information technology sphere (Song and Wu 2021).

As GIS advances, so do the derivatives of its initial work, like geovisualization. Driven by its technological advancements and increasing data availability, geovisualization draws from disciplines of cartography, scientific visualization, data analytics, and GIScience. From its beginnings built in graphics and information (MacEachren and Monmonier 1992), geovisualization has grown to be about the "people, process, and the acquisition of knowledge and information" (Dykes, MacEachren, and Kraak 2005) blurring the borders between cartography, visualization, and interactive interfaces as technology advances (Çöltekin et al. 2020).

3D geovisualization in geosciences has always been important, as the earth is not a 2D object. Its systems are structurally three-dimensional, and with the element of time impacting many of the systems and structures, four-dimensional. The ability to understand and communicate geophysical space and phenomena as 4D phenomena has certainly always been needed, but been impeded by the limitations of sensors, and more due to the inability (in the past) to integrate data into congruent 4D representations of physical reality. As a result, we have relied upon different representations, abstractions and simplifications of reality. In these circumstances, our ability to derive integrated multidimensional comprehension and insight was perhaps a function of the intellectual talent of those deriving meaning from such abstract representations of reality. Progress in sensor and mapping technologies, data visualization, and human-computer interaction over the past few decades have steadily accelerated us to a point where

3D/4D spatial characterization is feasible and meaningful. Perhaps the continued mainstream use of 2D mapping, while perfectly reasonable for many applications, is to some degree the result of our continued evolution from the legacy (and influence) of planar cartography as the norm for mapping in society.

Now that sensors, data, and visualization workflows are capable of producing robust, reliable reconstructions of spatial reality, commensurate progress in multidimensional, interactive methods are increasingly needed to support the analytical needs of 3- and 4D spatial analysis and visualization (Robinson 2017; Juřík et al. 2017; Hedley, 2017). New opportunities are emerging to create innovative maps and interactive designs in the field of geovisualization (Nelson 2023), and the field of geovisualization has evolved greatly, and 3D and 4D spatial analysis, including mapping and modelling, are continually improving.

Based on recent trends in the literature, the future of 3D geovisualization lies in evolving data generation, data management practices, data mobilization and access, and new models for interactive information experiences (Fitzpatrick and Hedley 2024). The future of 3D geovisualization is linked to XR interfaces. While some of the benefits of 3D/4D geovisualization using XR interfaces have been established in previous works (Shelton and Hedley, 2002; Lochhead et al., 2022), the capabilities of spatial data production, utilization, and immersive, tele-present, tele-sensory visualization will continue to evolve. And as they do, the assessment of systems performance and user capabilities mediated by these methods and technologies will also need to evolve (Rydvanskiy and Hedley 2020; Havenith, Cerfontaine, and Mreyen 2019).

The rapid developments in the sector, fueled by technological advances (Song and Wu 2021), will continue to reveal new limitations in geovisualization, in areas such as data management and computational strength, as time passes; creating a need for its benefits to be identified. This can lead to more targeted research to be performed, focusing on the best way that 3D geovisualizations can aid users. Trends in the past have demonstrated a latency in the capabilities of technology when matched with the volume of data produced (Li et al. 2011). Data management of terabytes of data produced in field scenarios has proven difficult, in addition to the processing of such large amounts of data. Further interactivity is also a key in the future of 3D geovisualization. As interactivity and immersivity become popularized due to both novelty and the ability to improve spatial understanding and recognition (Ahmed, Mahmud, and Tuya 2021; Nordvik et al. 2009), new obstacles emerge. Interaction and collaboration are a key difficulty, with emerging interfaces offering improved options to tackle the creation of interactive and immersive visualizations (Rydvanskiy and Hedley 2020). Future developments of 3D geovisualization will be rooted in interactivity and data management and should be targeted as current growth areas. But they also need to be grounded in sophisticated user experience and interface design, and mindful that advanced data, visualization, and interfaces combine to mediate and potentially transform human relationships with geographic spaces and phenomena (Çöltekin et al. 2020).

The development of geovisualization has been linked to commercial urgency, specifically to the developments in the video game industry. The video game industry has been rapidly growing in the past few decades and is a powerful influence in the entertainment sector (Goh et al. 2023). The technology has evolved, with the game industry spearheading new innovations in game engines, capture logics, and affiliated technology (Lehtonen et al. 2023; Zyda 2023). The same issues that are prevalent in the game industry, are prevalent the geovisualization sector including immersion and interactivity, data mobilization, and power and financial implications of game engines (Gazis et al. 2023; Lehtonen et al. 2023; Zyda 2023). The game industry has developed from being centred around the entertainment industry to intertwining with other sectors such as education and healthcare (Lehtonen et al. 2023). As video games, and their associated technology, become increasingly accepted in the geovisualization and GIScience sectors, innovation is propelled by its subsequent advancements, further connecting the two industries.

Existing development areas in data management and interactivity, illuminated by trends in the literature that demonstrate a rapid influx of data and new ways to interact with it, revealed a need for a remote field data production system. This would support increased field capability and improve the ability to remain in-field while collecting, processing, and interpreting data; creating new opportunities for data to be fed back to the base of the data collector and support all stages of the data collection, processing, and interpretation phases. The generation of a data production cycle would support in-field processing and interpretation, allowing the user in the field to review data, communicate with base, and have those at base be able to experience the data as the collector does. This cyclical data production would have potential benefits in improved in-field decision-making when collecting data, experiential learning, and improved collaboration between all parties.

The creation of iterative data feedback loops can target the development areas in 3D geovisualization, specifically interactivity and large data management. The ability to review and process data in the field, make informed decisions, and be able to experience field data in a lab environment has strong benefits in a variety of use cases. Iterative feedback loops can have applications in the geosciences and mapping geomorphology, mining, civil engineering infrastructure mapping, hazards, field research, Synthetic Aperture Radar (SAR), and navigation, among others. Developing a remote field data production system to manage large datasets in field and lab, and improve interactivity and collaboration when using data not only targets potential growth areas, it also has applications in many use cases and can help fill that gap in the sector.

The field of geovisualization has significantly evolved from traditional 2D cartography to advanced 3D and 4D spatial analysis, driven by technological and computational advancements (Song and Wu 2021). This evolution is crucial for the geosciences, where understanding Earth's inherently 3D structures and dynamic processes over time is essential. However, challenges in data management, interactivity, and collaboration persist, especially with the increasing volume and complexity of spatial data (Fitzpatrick and Hedley 2024). The motivation for this research is to aid in developing remote field data production systems that enhance in-field data processing, interpretation, and collaboration, addressing these challenges and providing valuable applications across various geospatial disciplines. This research aims to fill gaps in 3D geovisualization, ultimately improving decision-making and knowledge acquisition in geosciences and related fields.

1.1.1. Scope of this work

In this thesis, I present a review of the state of practice of geovisualization in the geosciences, an assessment of the data architecture and resource utilization of a custom vehicle, and a workflow to create an experiential data loop with the overarching goal to study the potential and feasibility of a remote field data production system.

The review of the state of practice provides an understanding of geosciences data acquisition, sensor mapping, geosciences modelling, and extended reality, while identifying key issues, limitations, and future developments in the industry. Highlighting these challenges allows for the problem to be framed and deficits to be addressed in the development of a cyclical data production process.

The assessment of the data architecture and resource utilization demonstrates field and lab capabilities through resource use including CPU, memory, power, and file size, as well as fidelity measured through point density. This compares and highlights the needs of a custom vehicle data collection system and its potential to operate in various environments. The evaluation of the architecture was conducted with the purpose to quantify and evaluate resource needs to develop the greater vision of a remote field data production system.

This thesis' exploration and development of a cyclical data ecosystem is completed with a workflow to bring raw data from the 3DMS LiDAR system, into a radical new field data visualization system (DRIVR). DRIVR fuses a 3DOF force-feedback driving simulator, game engine and virtual reality interface technologies – to deliver the ability to immersively drive through and experience 4D field data to support inspection and analysis of the data. DRIVR effectively implements the ability to connect field and lab, through the ability to engage in tele-present, tele-sensory geovisualization. The capabilities and implications of this are discussed.

Together, these pieces of research combine to deliver a multi-faceted, hands-on-implementation-based exploration of a vision for agile, emerging spatial data infrastructure, and experiential data science that links field and laboratory.

With this research, I hope to identify the feasibility of a remote field data production system and the capabilities of data to work between field and lab and establish a cyclical data generation loop culminating in an experiential data component with simulator and VR. This will be performed by:

- Identifying target limitations and growth areas at the intersection of geosciences and geovisualization.
- Exploring the potential for cyclical data production and user experience.

- Analyzing the needs and resource use of a custom vehicle-mounted LiDAR system and its feasibility within the context of remote field data production.

- Developing a custom workflow to bring data from a point cloud format to an immersive data experience.

1.1.2. Related research

The field of geovisualization has shown significant growth with advancements in technology and GIScience (Çöltekin et al. 2020; Nelson 2023; Fitzpatrick and Hedley 2024). The growing need to model earth systems in 3D has resulted in strong linkages between geovisualization and the geosciences. Advancements in geovisualization and GIScience have been mirrored by progress in information technology (Song and Wu 2021) and show strong links to information visualization. This all sets the stage for the development of a system that address growth areas in the sector, such as data management issues (Li et al. 2011) and interactivity and collaboration hurdles (Rydvanskiy and Hedley 2020; Havenith, Cerfontaine, and Mreyen 2019).

Increases in data volumes, currency and contextual understanding, and issues of tele-present and offline review of data pose issues in data management and processing. The technological needs of big data can be directly linked to data architecture (Yaseen and Obaid 2020). The NIST Big Data Public Working Group identified big data as "extensive datasets, primarily in the characteristics of volume, velocity and/or variety that require a scalable architecture for efficient storage, manipulation, and analysis" (Chang and Grady 2019). This definition fits the mass production of geovisualization data that is requiring new scalable architecture to efficiently store and manipulate it for effective decision-making in the geosciences field.

Yaseen and Obaid define the architecture as the "methods and mechanisms for collecting and storing data, securing it, processing it, and then converting it to into database structures and file systems" (Yaseen and Obaid 2020). By this definition, data architecture has potential in aiding the storing and processing of data collected for geovisualization purposes, and developing a more efficient system that addresses prevalent data management issues.

Geovisualization is directly linked to the developing field of XR. XR is a spectrum of technologies including virtual reality (VR), augmented reality (AR) and mixed reality (MR), creating immersive user experiences (Marr 2021). XR has shown rapid evolutions in its hardware, with the use of VR headsets and AR technologies becoming increasingly popular (Marr 2021). The rapid advancements in XR have led to new opportunities to use these technologies within the framework of geovisualization to view data more effectively and develop 3D spatial understanding.

The advancements in geovisualization and emerging XR interfaces, alongside the targeted growth areas in 3D geovisualization in the geosciences, helped develop a motivation for a remote field data production system. The data production cycle must include collection, in-field data interpretation and processing, and linking field and lab to improve collaboration and decision-making to meet current needs.

Developed with Jay Matsushiba, research assistant with the Spatial Interface Research Lab, the 3DMS is a homegrown, low-cost vehicle-mounted LiDAR system with basic mapping capabilities designed for the KXI Wildertec Mitacs Accelerate project. The system includes the hardware and workflow to produce point clouds, filling the data production portion of the iterative data loop. In the same vein, Jay Matsushiba has developed the Extended Reality Perceptual Support System (XRPSS) as a novel proof-of-concept for interactive visualization of the point cloud produced by the 3DMS to spatially query this environment. This work was initially motivated by the need to augment the spatial awareness of a driver in a wilderness navigation scenario, due to the inherent dangers of wilderness driving, but can extend beyond into the broader concept of a data production loop.

Through these related technological advances in 3D geovisualization, the progress in XR, and the need to support geovisualization data via data architecture, a framework from 3DMS collection, in-field processing, and data experiences backed by the analysis of its resources and feasibility were developed.

1.2. Research problem

The accelerated growth of 3D geovisualization is directly linked to technological advances. These advances are, in principle, allowing geoscience geovisualization the ability to become more capable of characterizing and communicating complex phenomena, but also to do it with agility in and between field environments, and through fundamentally new types of immersive information experiences. We therefore need to engineer and evaluate workflows and systems that support specific parts of, and this evolution of geovisual geoscience informatics as a whole.

Advances in techniques such as InSAR, Structure-from-Motion (SfM) photogrammetry, and LiDAR, among others are steadily increasing the quantity and dimensionality (3D, 4D) of data available to us. There are terabytes of data to use and explore that work to drive decision-making processes through data analysis. The growing desire for interactivity and collaboration in 3D geovisualization is linked to both the potential for improved communication, decision-making, and spatial understanding, and advances in XR. Developing more interactive data ecosystems can help foster an environment for collaboration and link field and lab environments more effectively. A key part of future 3D geovisualization in geoscience lies in improving its data management practices, due to large volumes of data produced by evolving sensing techniques (e.g. InSAR, LiDAR). While the visible parts of geovisualization systems often garner the most attention, the underlying data architecture, storage, processing and mobilization technologies are critical to realizing the potential for agile future geovisualization agility (field and lab), interactivity, and collaboration capabilities. Thus, we need to understand the "behind-the-scenes" capabilities of data collection processes and geovisualization interfaces to comprehend how to efficiently collect, process, and store applicable data in geovisualization scenarios.

The intersection of the fields of 3D geovisualization and data architecture, coupled with growing advancements in XR and data collection techniques suggest exciting possibilities for remote emerging and future field data production systems that possess the capability to collect and transfer data to other locations from in-field. These emerging and evolving trends go beyond just the hardware and technology in prospect. There is also needed to consider how the data produced can be mobilized and made accessible in the field and lab, and ideally, in a way that connects users in both working environments. It is for this reason, that this thesis implements, explores, and evaluates the idea of a cyclical data ecosystem to allow enhanced data mobilization, display, storage, and interactivity. Through three pieces of research, this thesis aims to support our understanding of these systems' data architecture to efficiently process, store, and understand the data and advancements in XR to improve collaboration and interactivity. Ultimately, the vision for a remote field data production system and the need to understand its potential capabilities, is an attempt to address the issues of larger data production and management and interactivity within 3D geovisualization in the geosciences, which is greatly supported by advancements in the fields of 3D geovisualization and data architecture, and technological advancements in XR allowing for new systems to be developed.

1.3. Research questions

The following research questions form the foundation for the thesis:

- What is the current state of practice of geovisualization in the geosciences?
- What are the limitations and key issues prevalent in geovisualization in the geosciences?
- Is a remote field data production system feasible?
- What are the resource needs of the 3DMS?
- To what extent does the 3DMS produce usable data?
- What are the potential benefits of a wilderness driving simulator?
- What is a potential workflow for an experiential data loop involving a simulated data experience?

1.4. Research objectives

The objectives of this research are to:

- Identify the current state of practice of geovisualization in the geosciences including key limitations, prevalent issues, and future potential.

- Report on the needs and feasibility of the 3DMS in the context of a remote field data production system by identifying resource utilization needs including CPU, memory, power, and file size, and understanding the fidelity of the data produced by the 3DMS using point density.

- Produce a workflow for an experiential data loop involving a simulated experience to gain the ability to simulate driving through data collected with the 3DMS and discuss decisions working towards an efficient workflow.

- Discuss the greater feasibility of a remote field data production system.

1.5. Thesis organization

This thesis is organized into five chapters. The three chapters proceeding the introduction are written as journal articles for submission to peer-reviewed journal. These chapters address the research questions and objectives outlined while working towards the feasibility of a remote field data production system.

Chapter 2 consists of a review of geovisualization in the geosciences to provide a greater state of practice, identify current limitations and issues in the industry and field to frame the problem context and develop concentrated efforts. Through an outline of the key issues, limitations, and future developments, a framing for the potential of a remote data production system is established by highlighting the rapid evolving sector, the existing limitations in data display and processing, and the future growth areas in efficient data display and interactivity.

Chapter 3 presents an introduction to a custom vehicle mounted LiDAR system. An assessment of the needs and feasibility is performed by analyzing the data architecture and resource use of the system. This includes an analysis on the CPU, memory, and power consumption, and file size reduction, in addition to an examination of the point cloud's fidelity using point density. Through the analysis of the resource and needs, a discussion on the system's limitations, potential benefits, and field and lab interoperability is established.

Chapter 4 outlines a continuation of the cyclical data feedback loop by presenting a workflow for simulated driving through collected data. The workflow details the creation of a ground mesh and non-ground class point cloud that are imported into Unity with the ability to navigate through the data in virtual reality and the Yaw2 simulator to establish an immersive data experience, detailing the decisions and future potential. This completes a cyclical data loop from collection to immersively experiencing the data.

The concluding chapter contains a discussion on the significance of research, limitations, and areas of future potential while commenting on the overarching framework of a remote field data production system.

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Chapter 2. Review of the state of geovisualization in the geosciences*

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2.1. Abstract

Geosciences modelling and 3D geovisualization is growing and evolving rapidly. Driven by commercial urgency and an increase in data from sensor-based sources, there is an abundance of opportunities to analyze geosciences data in 3D and 4D. Geosciences modelling is developing in GIS based systems, 3D modelling through both game engines and custom programs, and the use of extended reality to further interact with data. The key limitations that are currently prevalent in 3D geovisualization in the geosciences are GIS representations having difficulty displaying 3D data and undergoing translations to pseudo-3D, thus losing fidelity, financial and personnel capital, processing issues with the terabytes worth of data and limited computing, digital occlusion and spatial interpretation challenges with users, and matching and alignment of 3D points. The future of 3D geovisualization lies in its accelerated growth, data management solutions, further interactivity in applications, and more information regarding the benefits and best practices in the field.

2.2. Introduction

Mapping and modelling in the geosciences field have grown rapidly in the past 75 years (Mossa, Chen, and Wu 2019). The field has evolved from predominantly 2D cartography moving into 3D geovisualization (Kraak 2003). Geovisualizations are created using spatial tools and algorithms with spatial data (Papadopoulou et al. 2021); it is a visual tool for data exploration (Forsythe et al. 2021). This paper identifies limitations in the research and commercial applications of geovisualization while offering an evolving framing of geovisualization and interfaces and how they may grow into opportunities for geoscience to progress. The paper offers a road map vision of future opportunity for geovisualization in the context of the geosciences.

The Earth is not a 2D object - its structures and systems are geometrically three-dimensional, and four-dimensional when one includes change over time. These propositions may seem obvious, but they provide a context that led to the emergence of 'geovisualization' and subsequently, 'geovisual analytics' – fields that focused on developing multidimensional, interactive methods to support the analytical needs of 3- and 4-D spatial data analysis and visualization. (See (Robinson 2017) for an overview of this evolution).

The earliest definition of geovisualization comes from (MacEachren and Monmonier 1992) and is defined as "direct depiction of movement and change, multiple views of the same data, user interaction with maps, realism (through three dimensional stereo views and other techniques), false realism (through fractal generation of landscapes), and the mixing of maps with other graphics, text and sound".

As cartography and mapping evolved, the lines of definitions began to overlap and the boundaries of cartography blurred (Dykes, MacEachren, and Kraak 2005). MacEachren and Kraak noted that "at one level, all mapping can be considered a kind of visualization - in the sense of making visible" (Maceachren and Kraak 1997), aligning with the MacEachren and Monmonier statement in 1992 that "all map use involves both visualization and communication". As cartography evolved, so did geovisualization, as it is founded on cartography.

Propelled by the use of technology and increases of data, geovisualization found its foothold, drawing from the disciplines of cartography, scientific visualization, data analytics, and GIScience. The links between modern computing and visualization date back to the early 1990s (MacEachren and Monmonier 1992) and continue to become more evident through the early 2000s as experience was acquired from geovisual software and new instruments (Dykes, MacEachren, and Kraak 2005), and new advantages were gained through higher resolution data and faster computing (Mitasova et al. 2012). This has continued to grow as vast sets of data are acquired and computing continues to advance (Carbonell-Carrera and Hess-Medler 2019).

Influenced by technological advances, and increasing volumes of data, geovisualization, and its definition, has evolved throughout the years. Evolving from the definition given by (MacEachren and Monmonier 1992) geovisualization grew to be more about the process and the acquisition of knowledge, as opposed to the strict definition of information and graphics. (Dykes, MacEachren, and Kraak 2005) defines geovisualization as being about “people, maps, process, and the acquisition of information and knowledge” and can “lead to enlightenment, decision making”. The boundaries of cartography, and the nature of map use and visualizations broaden and welcome in a new era and definition of geovisualization as experience through technology and new volumes of data is gained (Dykes, MacEachren, and Kraak 2005).

The emergence of *visual analytics* (Wong and Thomas 2004; Keim et al. 2008; Thomas and Cook 2005) resonated with the field of geovisualization, and its scope from the early 2000s onwards. In the foundational volume on visual analytics (VA) Thomas and Cook envisioned VA as “the science of analytical reasoning facilitated by interactive visual interfaces.” (2005).

Much of what VA embodied and strived for was familiar to the geovisualization community, but it helped to legitimize and integrate a set of burgeoning subfields of geovisualization research that were on the rise (such as immersive interfaces, and new directions in interface-based spatial cognition). It made total sense that geovisualization scholars initiated *geovisual analytics (geoVA)* to make a significant and distinct contribution to this movement (Andrienko and Andrienko 2007).

The need for visualization to extend beyond traditional methods and to combine with computational analysis, and other computer based operations is noted in (Andrienko and Andrienko 2007). Visualization is shown to play an increasingly important role, as it allows for background knowledge of the human analyst to be used (Andrienko and Andrienko 2007). Reaching beyond just geovisualization, and into scientific visualizations, this importance of visualization is shown to aid in analysis and communication (Mitasova et al. 2012). These improvements continue into present day, where it is shown that geovisualization can improve spatial thinking and decision making (Carbonell-Carrera and Hess-Medler 2019).

As boundaries are pushed and technology grows, the volumes of data increase and geovisualization has evolved to become a cornerstone to decision making and spatial thinking. Drawing from many disciplines, including cartography, it has grown beyond its roots of a “direct depiction of movement of change” and the “mixing of maps with other graphics” (MacEachren and Monmonier 1992) to include the people, processes and decision making aspects (Dykes, MacEachren, and Kraak 2005), and become founded on the evolution of computation and data (Andrienko and Andrienko 2007; Mitasova et al. 2012).

The 30-plus year evolution of geovisualization has always been driven by a need for spatially analytical visualizations that support ideation, analysis, interpretation and communication, informed by both deep roots in analytical cartography, and spatial analysis with mainstream GIS. But what geovisualization offers now, versus 18 years ago, let alone at its inception 30 years ago, far exceeds the scope of its formative context. Advances in data acquisition/generation technologies have transformed our ability to record and reconstruct geographic spaces and phenomena. More recently, the latest wave of spatial interface technologies (virtual reality, augmented reality, mixed reality, extended reality), have delivered far more mature and durable platforms on which to iterate and develop meaningful geovisual information experiences.

As illustrated above, geovisualization has become far more than “simply a synthesis of the long-developed visual communication of cartography with current digital analytical technologies, principally GIS” (Smith 2022). The preceding snapshot of the scope, context and evolution of geovisualization are not intended as an exhaustive review. Rather, our aim is to illustrate how contemporary geovisualization, and the many facets of it, are the result of an ongoing, dynamic evolution. And that the scope and definition of geovisualization are in constant flux. This quote is not intended to criticise the interest, but to offer an even deeper framing of geovisualization, that has utility for Earth sciences.

Advances in the capabilities, integration and application of enabling technologies have in turn led to an expansion in analytical methods. Perhaps one of the most exciting parts of this evolving geovisualization ‘landscape’, has been the way in which new opportunities with visualization technologies and methods, has led to exciting new vectors in spatial information design, spatial interface technology design, interaction design and information experience design applied to spatial phenomena (Lonergan and Hedley 2014; Rydvanskiy and Hedley 2020; Lochhead and Hedley 2021; Fenech et al. 2017). These have all led to a new expanding frontier of variously immersive and interactive geovisualizations (Çöltekin et al. 2019). These developments have in turn elevated interest and research into the relationship between users and spatial phenomena - mediated by their perceptual experience with spatial data in new spaces of analytical visualization (Lochhead et al. 2022).

Geovisualization offers methods through which geoscientific research and communication may be enhanced – through their ability to deliver rigorous, analytical multidimensional visualizations of geoscience data and phenomena at any spatial or temporal scale. While legacy planar mapping methods may suit some applications, 3D/4D geovisualization approaches have considerable value for fields such as geological mapping, rock fall mechanics, and flood plain visualization – where an ability to analyze structure and dynamics in three and four dimensions is a core need.

In the context of this paper, the geosciences are framed as a research endeavour where physical Earth systems are being studied. It is important to note that these definitions and disciplines overlap frequently with geographical research domains, and in real life situations such as in riverbed morphology or natural hazard studies. This paper explores geovisualization in the geosciences in the context of characterizing and studying the Earth and Earth systems. As the data with which we characterize 3 and 4D has become more sophisticated, so too have the opportunities to utilize these data not just in visualizations but in analytical simulations (and that can be experienced using a range of interfaces). Exploratory work of this type is increasingly being conducted by practitioners at the overlapping borders of the geosciences and geography.

Geovisualization is critically valuable to geoscience modelling, is necessary for analysis and communication of data, encompasses a broad range of formats and visual representations, and goes beyond data representation into the exploration of data through “interactive and dynamic interfaces” (Marmo, Cartwright, and Yuille 2010). Geovisualizations are used to enhance visual thinking about geospatial relationships (Kraak 2003). Geovisualization can reach beyond the formal definitions such as those listed above from Marmo, Cartwright and Yuille and Kraak. At its heart it is the visualization of geospatial data and works to enable simulation and exploration of said data. It has many defining characteristics and in the context of this paper, geovisualization as the general simulation and exploration of geospatial data to enhance thinking will be explored. It enables and develops spatial thinking which can furthermore benefit the analysis of complex geoscience situations such as rockslides, flood mitigation, and contamination migration (Carbonell-Carrera and Hess-Medler 2019). Unlike generic use of spatial analytical software to output a standard visualizations of inputted data, 3D (and 4D) geovisualizations can be intentionally designed and tuned to the specific characteristics of a geoscience phenomenon, to the needs of users across the whole scientific process. Geovisualization outputs (and the information science behind their implementation) therefore, powerfully support the communication of data, geovisual analysis exchange of data and information between stakeholder groups including public officials, citizens, and experts in the field (Jacquinod and Bonaccorsi 2019).

Traditionally, geoscience data were represented in the form of 2D maps, but has been evolving to different representations. Data collected for pseudo 3D is being represented in the form of digital elevation models (DEM), hillshades, slope maps, triangular irregular networks (TIN), among others. However, 3D data is now being represented with all three coordinates (x, y, z) in the form of point clouds, generally collected using Light Detection and Ranging (LiDAR) (Sarakinou et al. 2016).

The evolution of 3D/4D spatial data acquisition technologies (multibeam, LiDAR, MVS-SfM photogrammetry) has created immense opportunities for geoscientists. As a result, 4D spatial reality capture, data production and geovisualization (though not always labelled ‘geovisualization’) have become key pieces of geoscience characterization, analysis and communication.

Contemporary sensors and technologies offer methods that have the capability to record and reconstruct the 3D structure (and 4D change/dynamics) of geoscience phenomena with greater representational fidelity than the inferential dimensionality of pseudo 3D, and abstracted representations of historical 2D planar methods (that were largely inherited from cartography).

2D and pseudo 3D models have several shortcomings in the geosciences. Pseudo 3D is less effective in communicating complex terrain information than 3D

(Forsythe et al. 2021), a shortcoming that occurs when the data is transformed. 3D features undergo distortion through transformation, which can affect accuracy and analysis of the results (Ahmed, Mahmud, and Tuya 2021). Difficulties exist when presenting complex information using 2D methods (Juřík et al. 2020). Additionally, historic 2D data, both in maps and databases, can lack precision and accuracy. Previous cartographic models for geoscience applications can lack precision and the ability to communicate and analyze complex information; this has given rise to the popularity of 3D geovisualization.

Note that the authors recognize that the performance of contemporary methods over traditional ones, is not only the result of technology. It is also a function of the quality of information design, execution of the methods, as well as understanding the needs and capabilities of end users. These and other considerations must form part of a commensurate 3D/4D spatial information science that informs the integration and use of cutting-edge geovisual technology and methods in the geosciences.

The paper reviews the methods used to select and analyze the papers, provides an overview of the current state of practice and applications, reviews the limitations and key issues in the current state of practice and then moves to future developments in the field, followed by conclusions.

2.3. Methods

The following methods were used to select papers relevant to the literature review regarding the current state of practice of geovisualization in the geosciences. The literature review strategy involved searching databases using keyword retrieval, content review and assessment of whether the paper met the grounds for inclusion.

The purpose of the approach used was to begin by selecting a wide range of papers at the intersection of geovisualization and the geosciences. Our aim was to capture a broad spectrum of papers, through which to be able to capture the evolution of geovisualization while identifying potential linked opportunities in the geosciences and limitations of practices in the field. A road map of past and present opportunity has been established by taking in evolving research, industry standards, best practices, and past evolution.

2.3.1. Databases

The databases we used are central to the fields of geosciences and emerging interfaces (and common in scientific disciplines). These databases were: Web of Science (WoS), Elsevier Science, GeoRef, GEOSCAN, and SpringerLink.

2.3.2. Keyword Retrieval

The search for literature papers involved used keywords from two lists (List I and List II) to identify intersections for relevant papers. List I was comprised of geovisualization related keywords and List II keywords was comprised on geoscience related keywords. The lists are shown in Table 1. The search results included combination of words from List I and List II using “and” to ensure both categories were included. This helped target potential papers in the selected database, which were then further vetted using the grounds for inclusion.

Table 1. Lists of search terms for article review.

List I (Geovisualization)	List II (Geosciences)
Geovisualization	Geosciences
Simulation	Mapping
Extended Reality	Natural Hazards
Game Engine	Geology
Modelling	Earth Sciences
Simulation	Geo
Virtual Reality	Geoengineering
Augmented Reality	Rock Mass
Mixed Reality	Geological
Emerging Interface	Survey
Interactive	Terrain
Visualization	Geotechnical
3D Models	Geohazard

The rationale for the search term selection was to attempt to encompass all potential geovisualization and geosciences papers by utilizing a broad range of search terms. A wide net of terms was intentionally cast to avoid disqualifying potential candidates prior to reading their abstracts. By using interlinked key words that are tangentially related to geovisualization and the geosciences, a variety of papers were selected to frame the evolution of geovisualization in the context of the geosciences.

2.3.3. Grounds for Inclusion

The grounds for inclusion are based upon five main rules. Firstly, the publication must be in the field of geosciences. Secondly, geovisualization or emerging interfaces must be a central theme to the paper to ensure it is relevant to the current state of practice for geovisualization. Geovisualization or synonyms had to be in the title and substantively in the abstract. Thirdly, it must fall in the time of 2003-Present, to be based on the current state of practice while also covering the emergence of geovisualization in the early to mid 2000s. Fourth, the publication must include the shortcomings and issues of the technique or emerging technology and potential future developments to target key issues in the field and upcoming progress. Finally, the publication must either have contributed to the emergence of the field of geovisualization or be representative of the current state of practice.

In total, 50 papers were selected for the review. This is out of a large central collection of 160 articles where at minimum, the abstract was read. The distribution of papers included, and total papers are shown in Figure 1 and Figure 2. Each paper in the List I corresponds to a paper in the List II figure as it must meet both search terms to be eligible for review. The total inclusion rate is 31.2% over 160 articles. This does not include articles that did not meet grounds for inclusion based on title. The references include all articles selected, in addition to supplementary literature to provide background in the field and definition of key terms.

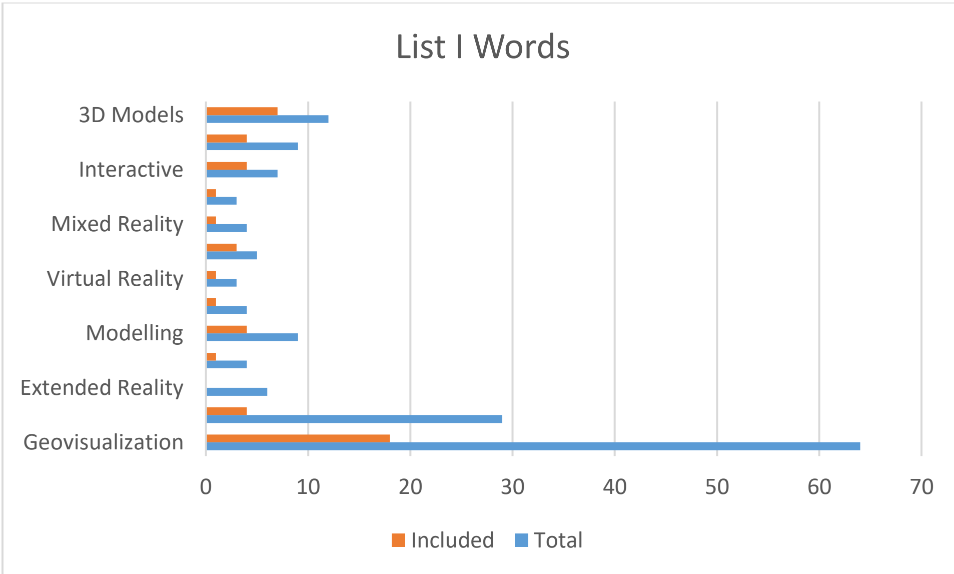

Figure 1. **List I articles that were read and included for the review.**

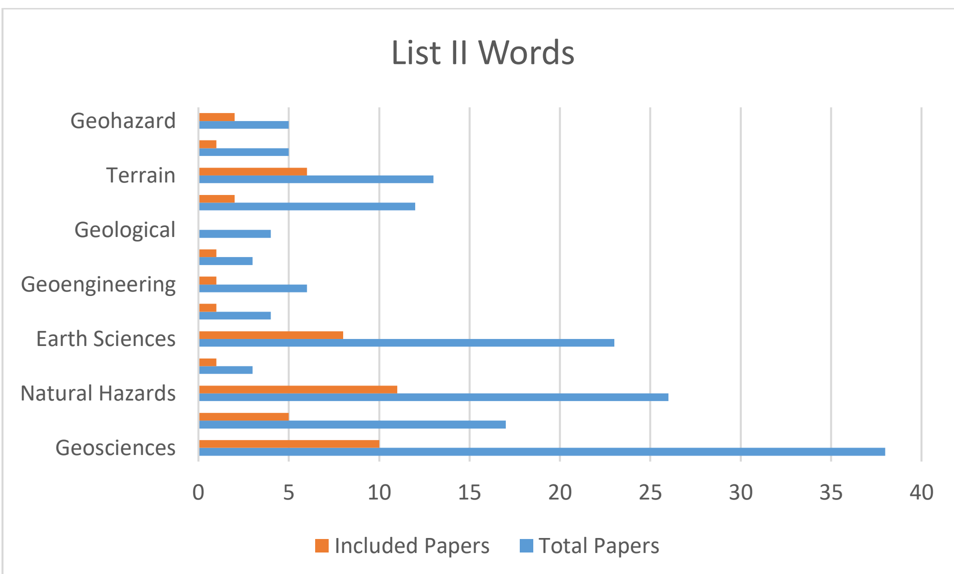

Figure 2. **List II articles that were read and included for the review.**

2.3.4. Processing of Literature

The literature was filtered and selected, read, and processed, then the relevant information was extracted. The cited papers were then cross-referenced and synthesized to identify the current state of practice, limitations, and key issues, as well as future developments in the field.

Thematic coding was used to identify prevalent themes in the qualified literature. The main priority was to find patterns in the current state of practice and link the themes through themes of limitations, key issues, and future development. The main concepts focussed on were data acquisition, sensor mapping, geoscience modelling, and extended reality all through the lens of geovisualization and geosciences. These concepts were then linked and analyzed while highlighting limitations, issues, and opportunities in development.

The majority of themes were identified prior to thematic coding, by selecting key concepts at the intersection of geovisualization and the geosciences. Emerging themes that developed during the processing of literature were added to the review. The papers were classed into theme-based subsections and synthesized within each theme. The applicable themes to geovisualization and the geosciences were then cross-referenced to demonstrate their interconnectedness and generate an overall evaluation.

2.4. Results

2.4.1. Geoscience Data Acquisition

The geosciences acquire data from a number of sources including photogrammetry and LiDAR (Light Detection And Ranging) to analyze the morphological and geological landscapes (Westoby et al. 2020; Romeo et al. 2021; Guerin et al. 2020).

Geovisualization and modelling has come a considerable way in the past 70 years, particularly since GIS took hold in the 1990s and SAR monitoring gained popularity in the past two decades (Kraak 2003). In direct linkages, geological modelling has followed this evolution to become more advanced. The advances in geosciences and geological modelling are greatly spurred by the evolvement of LiDAR, photogrammetry, and other sensing techniques, generating increased volumes of data to analyze (Havenith, Cerfontaine, and Mreyen 2019).

These sensors advance the field at large and provide new opportunities to manipulate and analyze data in 3D and 4D environments (Havenith, Cerfontaine, and Mreyen 2019). Geomodelling is frequently being used to understand and interpret geological hazards such as rockfalls, floods, and earthquakes. The majority of these models use data derived from a combination of SAR measurements and field work, then rely on numerical modelling and qualitative assessments to determine hazard risk (Yao et al. 2021; Francioni et al. 2018; Jordan, Cigna, and Bateson 2017; García et al. 2019). Though these solutions exist there is a need for more dynamic interpretation methods. The capabilities of GIS and numerical modelling are limited in both the temporal realm and 3D space (Havenith, Cerfontaine, and Mreyen 2019). GIS predominantly uses pseudo-3D modelling as opposed to real 3D and therefore, cannot capture the complexities of real 3D space and data, in instances such as flood mapping where the transformation of 3D data to pseudo-3D can affect the flow patterns and results. Similarly, numerical modelling is but a snapshot in time and fails to capture long term progression or time-lapse simulations the way a physics game engine can simulate. GIS and numerical modelling pose limitations when working with real 3D space and time lapsed activities such as rock falls or tsunamis.

2.4.2. Sensor Mapping and Integration

Autonomous vehicles have been adopting LiDAR to sense their surroundings in urban environments (Wang et al. 2019). However, sensor technology can also be used to map remote areas (such as by using a specialized off-road vehicle) and gather data to be used in geomorphological studies.

Studies are being conducted using Mobile LiDAR Sensors (MLS) that are ground-based, airborne, and water-based (e.g., boats). Several studies involve the mounting of MLS on boats to acquire topographic data for fluvial research, creating a spatially dense point cloud by integrating navigational and data acquisition sensors (Alho et al. 2009). MLS on boats can reach accuracies of 1-4 cm (Vaaja et al. 2013). MLS requires efficient and automatic processing, which can be done through noise point filtering, and automatic identification and point classification (Vaaja et al. 2013). Boat based LiDAR can also monitor coastal sites where airborne LiDAR does not offer adequate coverage. The near horizontal view of the laser allows for high coverage and accuracy of steep topographical surfaces (Kaminsky et al. 2014). An MLS has also been employed to map railways, as a specialized mobile mapping tool that also functions for general surveying.

Mounting sensors to vehicles on rail networks has proven to be a powerful way to generate datasets along a fixed, and repeatable, path. The RailMapper managed to execute its mapping with a high level of accuracy and a precise location identification system using a coupled Global Navigation Satellite System (GNSS) – Inertial Measurement Unit (IMU) system (Kremer and Grimm 2012).

MLS is also being used in ground-based systems to evaluate slope mass rating and monitor rockfalls. Existing approaches involve the combination of multiple remote sensing methods, including LiDAR and photogrammetry, to scan slopes. While Terrestrial Lidar Sensors (TLS) and Airborne Lidar Sensors (ALS) are increasingly being used, minimal real time processing has been conducted, leading to gaps in the use of MLS and ALS for hazard monitoring. However, MLS is increasingly being used to monitor slopes and reach inaccessible areas through ground based exploration, to support development of a rockfall monitoring system (Romeo et al. 2021). Ground based systems are also being used to map forests (Pierzchała, Giguère, and Astrup 2018; Mokroš et al. 2021; Meadows et al. 2019). TLS is time-consuming, labour intensive, and computationally demanding when developing a forest inventory but the use of MLS in combination with SLAM is being explored to measure key variables, such as number and size of trees, and while immature, poses a strong future (Pierzchała, Giguère, and Astrup 2018).

MLS is providing better opportunities for inaccessible areas in comparison to ALS and TLS by allowing movement not tethered to a static object or only gaining an airborne angle. TLS allows the collection of data at a higher resolution but poses spatial limitations, while ALS can cover a wide area but does not have the same high point density as TLS. MLS combines these strengths, measuring objects with an accuracy of a few cm to tens of meters and presenting the ability to cover large spaces (Alho et al. 2009). In addition, ALS has poor coverage on vertical surfaces, while MLS can cover high relief topography with greater ease (Kaminsky et al. 2014). While ALS is the most widely used method, and has good visibility, it also comes with a high price tag, MLS provides similar potential range capabilities with a lower cost attached (Kremer and Grimm 2012). TLS can be time consuming and labour intensive when gathering a high point density, while MLS is immature and has less studies, it can maximize the density to the same level as a TLS survey (Pierzchała, Giguère, and Astrup 2018). MLS has been developing rapidly, and while it has several issues with regards to its extensive processing and analysis due to high volumes of data and noise, as well as its object recognition, it provides promising opportunities for monitoring in fluvial and geomorphological environments (Wang et al. 2019; Romeo et al. 2021; Kaminsky et al. 2014; Vaaja et al. 2013).

In order to successfully integrate sensors with vehicles for effective mapping and modelling capabilities, the analytical data visualization must be agile, and be able to connect to different programs and operate in a variety of scenarios. Existing research demonstrates that interconnected visualization infrastructure can enable new forms of geovisualization analysis. Immersive data exploration on Mars (Lochhead and Hedley 2021), coastal environment simulations (Lonergan and Hedley 2015; Lonergan, Hedley, and Clague 2015), and mixed reality flood simulations (Rydvanskiy and Hedley 2020) present the diversity of scenarios where emerging geovisualization technology can aid in understanding. Sensors and data can prove key to the operator's situational awareness in vehicle based sensing, as well as benefitting data collection and interpretation, as shown in the Mars rover project (Helmick, Angelova, and Matthies 2009). Integration is essential to successful operation and providing elevated geovisual analysis methods.

2.4.3. Geoscience Modelling

2.4.3.1 GIS-Based

GIS-based software such as ArcGIS and QGIS can be used to create both 2D and 3D visualizations. GIS can take in multiple data types including point clouds collected from LiDAR, historical maps, shapefiles, among others. The simulations can be interactive or static and have a variety of applications. GIS-based 3D visualizations have been used for mapping alluvial sites, modelling elevation and topography, measuring landslide vulnerability, and mapping water depth (Masse and Christophe 2015; Mossa, Chen, and Wu 2019; Ahmed, Mahmud, and Tuya 2021; Heitzler et al. 2017a; Wahyudi, Ramdani, and Bachtiar 2020). These techniques using GIS have demonstrated that 3D visualizations can provide new insight alongside their 2D counterparts (Mossa, Chen, and Wu 2019), can provide additional geographic data, and model virtual representations of real events (Wahyudi, Ramdani, and Bachtiar 2020).

2.4.3.2 3D Modelling Software

3D modelling software is being used more frequently, moving beyond the realm of GIS. It takes in point cloud or image data through methods such as LiDAR and photogrammetry and generally produces interactive visualizations. There are many different types of 3D modelling software from game engines such as Unity, applications such as AutoDesk or SketchUp, FARV3DPT, Spaceyes 3D, and Agisoft Metashape. These tools provide a wide range of options to explore three-dimensional data.

A wider range of applications, particularly those with a temporal component, have been used in 3D modelling software, as opposed to GIS. Modelling software has been used for active events and simulations such as landslides, flooding mitigation, and rockfalls (Jacquinod and Bonaccorsi 2019; Forsythe et al. 2021; Nordvik et al. 2009; G. Zhang et al. 2020). It has also been used in static instances to create more in-depth maps and 3D recreations of coastlines, bathymetry, and terrain (Papadopoulou et al. 2021; de Magalhaes and Mourao Moura 2020; Papakonstantinou et al. 2018; Sarakinou et al. 2016).

There are numerous benefits to using 3D modelling software over existing GIS techniques. These include the use of a physics engine in game engines to model collisions and liquid behaviour (Sala, Hutchinson, and Harrap 2019). In addition, they utilize real 3D over the use of pseudo 3D which can be beneficial in understanding complex shapes and generating spatial awareness (Juřík et al. 2020; Wahyudi, Ramdani, and Bachtiar 2020). Both GIS-based and 3D-model software are viable options for generating geoscience models, and in combination they can be used even more powerfully.

2.4.4. Extended Reality

The current state of practice in extended reality geoscience modelling has been advancing rapidly. Extended reality aids in the effective communication of complex three-dimensional data. Geological data is complex and layered and loses fidelity and becomes more difficult to understand when communicated in 2D. Extended reality helps communicate 3D information naturally, in an efficient way, to experts and laypeople alike (Janeras et al. 2022).

Virtual mapping and monitoring in conjunction with extended reality have been used in several studies. For instance, the RIMS system, Real-time Interactive Mapping Software, generates 3D models from DEM and texture data and allows measurements and geological reconstructions in an interactive 3D environment (Bernardin et al. 2006) and has been used to model the region surrounding the epicentre of the 2010 Haiti earthquake for practical fault analysis (Cowgill et al. 2012). Augmented reality has been used to model fluids in real time over the Fraser River watershed (Rydvanskiy and Hedley 2020) and developing mobile augmented reality system for on site analysis of the Snowy River flood plains (Haynes, Hehl-Lange, and Lange 2018). Augmented reality has also been used to model rock slopes and fuse geoinformation virtually into the slope environment, allowing identification of structural planes and potential rockfall hazard zones (Y. Zhang et al. 2019). Despite having the ability to map rock slopes, the majority of studies do not integrate a dynamic component, instead overlaying static visualizations onto the area.

Extended reality has also been used to communicate data for teaching and learning purposes. XR offers the ability to view remote and inaccessible locations such as volcanic sites, glaciers, and underground caverns or mines for teaching purposes (Janeras et al. 2022). For instance, at the University of Georgia they have developed the 3DIG, 3D Immersion and Geovisualization, to be used for Earth science teaching and learning. It uses a combination of image acquisition, VR, MR, and 2D panels. The 3DIG effectively communicated Earth science information to students and helped enrich their understanding of complex geological environments (Bernardes et al. 2018). In another instance, the Montserrat massif was studied through complex 3D models visualized using the Microsoft HoloLens 2 and Clino's software (Janeras et al. 2022). The system effectively and naturally communicated complex 3D information to experts in the consulting field (Janeras et al. 2022).

XR offers a rich opportunity to facilitate the understanding of multi-faceted 3D environments. The world of geosciences is 3D, often multi-layered, with many complexities. XR provides the ability to communicate this information for mapping and monitoring, teaching and learning, and general understanding.

2.5. Discussion

2.5.1. Limitations and Key Issues in the Current State of Practice

2.5.1.1 GIS Representation

Many advancements have been occurring in GIS representation including the emergence of cloud computing, the rise of big data analytics, open standards and interoperability, and the emergence of mobile and web GIS. Though advancements have been taking place, there are still many challenges plaguing the field. GIS has difficulties displaying 3D data beyond current applications that use DEMs, and both numerical modelling and GIS has issues displaying temporal changes (Havenith, Cerfontaine, and Mreyen 2019). Though in recent years, applications such as ESRI's ArcGIS Pro have been adding LiDAR integration and features (Price 2018).

When data is converted from 3D to the 2.5D (pseudo-3D) that is prevalent in GIS, representations become distorted (Ahmed, Mahmud, and Tuya 2021). The transition from 3D to 2.5D can cause a loss of detail and the 2D projections can add increased mental load as the user attempts to interpret the information from a flat screen (de Magalhaes and Mourao Moura 2020; G. Zhang et al. 2020). The increased mental workload coupled with the loss of detail can reduce interaction and limit the communicability of the data.

GIS can also rely on 2D visualizations, which can mask features. 2D GIS features can become indistinguishable; sills and steep slopes in bathymetry, for instance, can be difficult to interpret (Forsythe et al. 2021).

On the whole, information produced and displayed in 2.5D must undergo transformations which can alter its fidelity and accuracy, in comparison to 3D data, and thus lacks effectiveness in comparison (Juřík et al. 2020). Real 3D visualizations demonstrate the capability to increase spatial thinking and interpretation skills in comparison to 2.5D or 2D visualizations that GIS displays (Wahyudi, Ramdani, and Bachtiar 2020; Juřík et al. 2020).

GIS poses limitations when displaying 3D data, particularly its distortion when converting to 2.5D, and reliance on the 2D or 2.5D data presentations. This leads to less significant data display, in terms of accuracy, which ultimately affects decision making, and lacks full interpretation and interactivity abilities that are capable in real 3D visualizations.

2.5.1.2 Knowledge and Financial Capital

Virtual reality is rarely used in the geosciences due to both its high cost and the required computing knowledge to correctly apply the emerging interfaces to geoscience applications.

Financial capital can be expended through imagery techniques or personnel. Imagery, including LiDAR, UAV, and MLS can be costly, particularly if data must be collected on an as-needed basis (Ahmed, Mahmud, and Tuya 2021). It is also difficult to acquire high resolution data that is applicable to rural landscapes that are not accessible by roads; this can make accurate modelling a challenge (Francioni et al. 2018).

The lack of data sharing in the industry and academia has been raised, which may cause additional costs when developing systems to exchange terabytes of 3D data. Personnel and risks gathering data, such as traversing an area with natural hazards or poor weather conditions, can also drive up costs (Rydvanskiy and Hedley 2020). There is a knowledge capital required via personnel, as 3D tasks generally take longer to solve (Juřík et al. 2020) and the spatial thinking skills must be learned in order to effectively analyze and interpret 3D data.

2.5.1.3 Processing Issues

When high resolution data are acquired, processing speeds are slower and real time processing is difficult but may be able to be completed with effective cloud computing (Havenith, Cerfontaine, and Mreyen 2019). Real time processing could aid in efficiency when identifying issues such as runoff and unstable slopes, however, the large volumes of data such as those in the intricacies of a rock mass, can lead to longer processing times.

3D data has additional complexity which may lead to issues in rendering efficiency, particularly if the data is of a finer resolution. In addition, Cartesian coordinates are not transformed automatically when input into a 3D engine (G. Zhang et al. 2020) which can lead to a longer processing time while the coordinate system is converted. The multi-dimensional data requires an effective data management system moving forward (Núñez-Andrés, Lantada Zarzosa, and Martínez-Llario 2022).

Processing times can also be longer due to the large data pool. Data reaches up to terabyte levels quickly when collecting in three dimensions and the computing power can be a limitation in processing. When collecting geosciences data for geovisualizations it often contains high complexity and large-scale areas to gain a full understanding. For example, when modelling a large outcrop formation, surrounding data covering many square kilometers is needed to establish a full picture. Past trends have shown that computing and processing capabilities are consistently behind the increase of data volume and complexity (Li et al. 2011). A consistent limitation has been processing time and computing power as data grows in this era of geovisualization. (DISCUSS UNREA:L)

2.5.1.4 Digital Occlusion and Spatial Interpretation

In the realm of augmented reality, digital occlusion is an issue that plagues many simulations and users can experience motion sickness or experience data interpretation issues (V Juřík et al. 2016; Lonergan and Hedley 2014). The synchronization and rendering is a key piece, particularly as users may experience motion sickness due to frame rate or unsynchronized interaction (Havenith, Cerfontaine, and Mreyen 2019). Occlusion has been shown to be an issue when modelling digital earth (G. Zhang et al. 2020). Digital earth has been used to model earth systems and when utilizing digital earth to perform flood visualizations, occlusion was a prevalent issue. When the viewpoint moves and the flood object is occluded, the flood may not be rendered and understood correctly (G. Zhang et al. 2020).

Users are not only subject to occlusion in simulation but also need to apply spatial thinking skills to interpret visualizations. 3D geovisualizations cannot be rapidly understood without explanation or previous spatial thinking skills (Jacquinod and Bonaccorsi 2019). When viewing the Earth in a VR setting, as many as one in ten users experienced motion sickness (Havenith, Cerfontaine, and Mreyen 2019). 3D geovisualizations and communicability of information therefore relies heavily on the user themselves; including their spatial thinking skills, which can be heavily impacted by issues with motion sickness, and reaction to frame rate or occlusion.

2.5.1.5 Matching and Alignment

Another predominant issue in AR is tracking, registration, and rendering; specifically, linking 1:1 relations in real time between the virtual environment and real world (Lonergan and Hedley 2014; Y. Zhang et al. 2019). Despite being a challenge, it is being solved using edge tracking and camera posing and has the potential to be overcome in AR environments.

The accuracy in matching points to their true location can depend on the techniques used and the surveyor's skill leaving room for uncertainty and errors, which can lead to misaligned data. This is noted when modelling 3D landforms to enhance spatial thinking (Carbonell-Carrera and Hess-Medler 2019). Matching issues can also occur during the transformation in the Cartesian alignment of space (Rydvanskiy and Hedley 2020). When modelling floods, transformation issues with the Cartesian alignment can affect the flood paths and ultimately, the result (Rydvanskiy and Hedley 2020). This demonstrates the need for proper matching and alignment in geoscience applications such as flood visualization. Object tracking methods and recognition, including point matching, is an issue that persists (Jian et al. 2017). Furthermore, misalignment leads to errors and uncertainties in data location that can cause interpretation issues and incorrect conclusions drawn from data.

2.5.1.6 Other Prevalent Issues

There are other prevalent issues that exist with specific data acquisition techniques. Each data collection technique has its advantages and disadvantages; for instance, LiDAR cannot reach underwater (Mossa, Chen, and Wu 2019) while high resolution InSAR data can be difficult to acquire. For instance, LiDAR DSM and SfM DSM have similar results in bare plots but SfM is inaccurate in forested areas as the signal cannot penetrate the vegetation (Hua, Zhou, and Yang 2021). Data resolution is another prevalent issue where surficial data is dense but subsurface or underwater data is lacking, leading to misinterpretations (Nordvik et al. 2009; Mossa, Chen, and Wu 2019). The significance of resolution lies in its ability to provide finer details which can aid in effective decision making when using the data.

2.5.2. Future Developments

The future of 3D geovisualization still has many unknowns but is moving towards increasing interactivity, studies exploring its uses, and data management.

Interactivity and immersion are becoming more popular, particularly in the field of extended reality. Immersive navigation has been shown, as of late, to increase recognition and overall spatial awareness, and increase performance when interpreting complex terrain (Ahmed, Mahmud, and Tuya 2021; Nordvik et al. 2009). Interaction and collaboration are current obstacles as it is difficult to create real time, collaborative interfaces, however, emerging interfaces are offering better options to improve the interactivity of 'geovisualized' data (Rydvanskiy and Hedley 2020; Havenith, Cerfontaine, and Mreyen 2019).

New methods are also being developed to manage the increasingly large amounts of data. As terabytes of data are being produced through photogrammetry and LiDAR, among other recording techniques, data management becomes more integral. Computing and processing continually lag behind the development of data collection methods, leaving a gap between the data management and processing and the collection itself (Li et al. 2011). The development of algorithms to reduce data size is a strong avenue for future development (Heitzler et al. 2017b).

There are still many unknowns in the use of 3D and its effectiveness in increasing decision making in geosciences applications. Results have been contradictory, some showing that 3D methods do not necessarily communicate risk area more effectively than 2D solutions (Wahyudi, Ramdani, and Bachtiar 2020) and that its use may simply be a novelty. Lab studies do not reflect usability in the real world, and its uses remain ambiguous, not yet being analyzed critically (Havenith, Cerfontaine, and Mreyen 2019; V Juřík et al. 2016). The benefits of 3D visualizations are not yet clear in geoscience applications, and the lack of evidence for efficiency could negatively impact long-term growth of 3D geovisualization techniques and applications (Rydvanskiy and Hedley 2020; Nordvik et al. 2009).

Driven by commercial urgency and the growth of computing technology, 3D geovisualization and its applications are rapidly evolving. Future developments will have a strong focus on interactivity, data management, and determining the benefits and best practices for use of 3D geovisualization.

2.6. Conclusions

Geosciences modelling has made great strides, particularly in the past few decades, being driven by large increases in data which are providing new opportunities to analyze data in 3D and 4D. The geosciences have been acquiring data from an increasing number of sources, and as more data becomes available through methods such as LiDAR, photogrammetry, and InSAR, there are more opportunities to utilize the data in 3D and 4D settings. Geoscience modelling is using said data in GIS based programs and experimenting with their newer pseudo-3D interfaces, in 3D modelling in game engines and custom-built programs, and in extended reality interfaces with increasing interactivity.

Though research and commercial use in the field of geovisualization is increasing, there are several key limitations that remain. In GIS representations there is a difficulty displaying 3D data and it is frequently translated to pseudo-3D, which can mask features and cause distortion when translating points. There is also financial, and personnel capital being used due to the novelty of 3D geovisualization and the cost of gathering data, which oftentimes cannot be gathered on demand. Processing issues remain prevalent as computing power, related to CPU and GPU use, is lagging behind data volumes leading to limited speeds when processing the large data pool. There are additional issues with newer interfaces and users such as digital occlusion and spatial interpretation of the user potentially causing motion sickness and limiting understanding. Matching and alignment issues with 3D points are another limitation. On the whole, the large data pool and translation of 3D data is causing a barrier but is being explored in both research and commercial sectors.

The development of 3D geovisualization is evolving rapidly, with a focus on interactivity, data management, and identifying the benefits and best practices. Both industry and academia are attempting to overcome key limitations while interfaces expand, and interactivity becomes more prevalent. The future of 3D geovisualization is growing quickly and moving to tackle more geoscientifically complex applications and address limitations.

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Chapter 3. Assessing the data processing architecture and resource utilization of a custom vehicle-mounted LiDAR system

3.1. Abstract

This paper reports on the data processing architecture and resource utilization components of a research project that developed the 3D Mapping System (3DMS), a homegrown vehicle-mounted laser scanning system, where the goal was to develop a functional, low-cost, agile LiDAR system. The data processing architecture was analyzed by documenting the CPU, memory, and power usage. The file size and data quality (based on point density) were also recorded. The limitations and feasibility of the 3DMS in field situations was assessed by analyzing the data processing capabilities, resource use, and data quality.

3.2. Introduction

Spatial data capture has evolved over the past decade through the adoption and continued evolution of several key technologies. These include LiDAR (light detection and ranging) which has been constantly evolving since early applications in mapping (Zwally, Bindschadler, and Thomas 1981; Gardner 1982) and multi-view stereo (MVS) photogrammetry, such as Structure from Motion (SfM) (Westoby et al. 2012).

Despite being an approximately 50-year-old technology, LiDAR continues to develop, the technology becoming more mature and affordable (Jin and Mountrakis 2022). LiDAR without the use of GPS (Global Positioning System) and INS (Inertial Navigation System) is limited in its use due to lack of referencing. Calibration of the sensor is key, as the localization error rapidly increases with time and the geometry and placement of objects can be negatively impacted by the misregistration or lack of calibration of the LiDAR system (Nie et al. 2023). Innovations continue in core laser, sensor, and measurement technologies, miniaturization of sensor systems, and data processing algorithms (Li et al. 2022).

Increasing compactness and customizability have led to active sectors of research and development that use LiDAR to sense geographic spaces in real-time, while moving and from a variety of platforms. One such area is the use of LiDAR systems on vehicles. Much of the vehicle-based LiDAR-based work focuses on driver assistance systems in retail-sector vehicles (collision anticipation; proximity warnings), autonomous vehicle systems, and vehicle-mounted data acquisition platforms (Abdelkader, Elgazzar, and Khamis 2021; Royo and Ballesta-Garcia 2019; Yeong et al. 2021).

At the same time that LiDAR has led to many new scanning and surveying products in industry, increasing availability of low-cost sensors, hardware, and open-source robotics software, has enabled researchers to build 'homegrown' LiDAR systems that they imagine, for new application contexts they are exploring.

Emerging vehicle-based and mobile field-based LiDAR systems are allowing researchers to explore new modes of data acquisition and protocols for field operations and field research. These evolving capabilities have the potential to transform the relationships between remote field sites and sedentary research facilities:

- When and where we are able to generate 3D data.
- Where we process data.
- The ways in which we move data.
- The speed with which we move data.
- The ways we get to interact with data both in and out of remote field environments.

We have documented and reported the specific design and development of a 'homegrown' vehicle-based LiDAR system (3DMS) in detail in Matsushiba and Hedley, 2024 (forthcoming). This (companion) paper underscores the importance of not just implementing novel systems but also being able to assess and quantify data architecture performance and resource utilization of LiDAR prototypes. While perhaps less 'exciting' than the design and prototyping of LiDAR systems themselves, data architecture and resource utilization performance are critical to demonstrate the new field capabilities. Through this kind of work we have the potential to utilize these new LiDAR systems to alter the ways we link field and laboratory through data.

3.3. Evaluating the Data Processing Architecture of Applied Prototypes

To understand the potential of LiDAR data generation in each new prototype application context, we must also understand the resource utilization and data processing architecture to properly assess the system. Resource utilization and data processing architecture are of key importance when collecting, processing, and using data. There is an increasing need for data acquisition, storage, processing, and transfer, especially when collecting vehicle-based data (Alexakis et al. 2023).

The data processing architecture is classified as the workflow that converts the data to a spatial data format and performs cleaning operations, then saves the file in its stored format. The data processing architecture directly impacts the allocation of properties such as power, memory, and CPU (Central Processing Unit) which in turn has impacts on resource distribution. In this paper, the CPU is the classed as the percentage capacity of the central processing unit being utilize, the memory is the capacity of the RAM (random access memory) being allocated to the data processing architecture or data collection processes, and the power is the draw of power the system is utilizing in kWh. The quality of the data produced, and its subsequent upload and transfer speed affects the potential use cases of the data.

Establishing effective data processing architecture can properly allocate the required resources for the project, and make data usable quicker, and more efficiently through reduced use of CPU and memory. Resource utilization, specifically how much power is required and how it is distributed, as well as how much of the unit's CPU and memory are used can greatly affect the data collection process. When the processing of the data is streamlined and a proper data architecture pipeline is developed, the time and subsequently the financial capital can decrease and maximize the available resources (Agliardi et al. 2018). Achieving these goals of effective data architecture can be accomplished by batch processing the data, automating stages of the process, compaction of files, and other data architecture streamlining (Jin, Paik, and Biadgie 2020; Agliardi et al. 2018).

The data quality can be impacted by the data architecture. Point cloud quality has a direct impact on the accuracy and completeness of models (Zhu et al. 2023). With efficient streamlining and automation of the data processing, the data quality can be improved by maintaining fidelity but increasing speed, and lowering file size. However, if the architecture is unable to adapt and limits the range of processing capabilities, it could eliminate key data points or incorrectly process the data, utilizing valuable time and resources. Data quality can be measured in several ways, including point density, qualitative feature identification, point error, and registration quality (Zhu et al. 2023; Mian et al. 2014).

Data architecture also has an impact on the speed at which data can be both processed and transferred. Remote locations, especially in Canada, can pose data transfer difficulties due to its large geographic size, and dispersion of population outside of main centres which makes internet connectivity and accessibility vary widely throughout the country (Soanes-White 2022). The upload/download speed can be measured in Mbps and divided into both cellular and fixed categories. A higher data processing speed, and transfer speed results in the data being shared quicker, which leads to decisions being made with more ease. Particularly when in-field decisions need to be made.

Data architecture optimization has been well-studied (Aleti et al. 2013), this paper will be directly linked to the 3DMS, a homegrown vehicle-mounted LiDAR system, and will systematically assess its performance through resource use. The goal of the 3DMS was to develop a low-cost, efficient LiDAR system with basic mapping functionality including a point cloud density ≥ 0.5 points per cubic meter at the Ouster OS0 range of 35 m or less, the ability to generate a base ground mesh, and the ability to create basic 3D models for applications such as forest inventory, dam and flood modelling, and multi-purpose 3D data modelling. In this context, the data collected from the 3DMS is moved through the process of data preparation, data validation, and data analytics to gather information about the feasibility of the applied data architecture. The goal was to ensure that in-field data preparation was equivalent to, or close to equivalent to, post-processing in the lab. The user can experience the data collection process and visualization from the front end. This paper reports on the resource utilization, including CPU, memory, and power, during the data collection and processing components of the system and the fidelity of the data produced. The comparison between field and lab procedures and the capability of the system are analyzed to highlight the needs of the 3DMS and its efficiency, flexibility, and potential.

3.4. Overview of 3DMS and Data Architecture

Our exploration of data architecture and resource utilization focuses on the 3D Mapping System (3DMS), a low-cost mobile LiDAR system with basic mapping capabilities our team developed to generate point clouds for use case applications in forestry, mining, and geosciences. Driven by commercial urgency and an influx of data collection systems, the goal was to develop a more efficient workflow that bridges field and lab capabilities by building an agile geovisual LiDAR mapping system.

Figure 3. 3DMS: a vehicle-mounted mobile data acquisition system, combining LiDAR, Stereo camera imaging and GPS.

The 3DMS, as shown above in Figure 3, uses a combination of mobile LiDAR sensor, stereo camera, and GPS. The mobile LiDAR used is the Ouster OS0 with a 90° field of view, 32 channels of resolution, and a range of 35 m at 10% (Ouster 2024a). The stereo camera used is the Zed2 stereo camera (Stereolabs 2022). This data collection was performed on a typical research laptop used for these types of sensors and data in field environments (an ASUS G513Q laptop) ("2021 ROG Strix G15 G513 | Gaming Laptops｜ROG - Republic of Gamers｜ROG Malaysia" 2024).

The system components are not only hardware but involves the workflow behind the hardware that is purpose-built to support and produce point clouds; taking the data from its raw format and bringing it into a processed form for applied use cases (Matsushiba et al. 2024, forthcoming). The raw data intake is performed by collecting

LiDAR data in *rosbag* format and raw stereo camera and GPS data. Robot Operating System (ROS) is used as the intermediary and the nervous system of the workflow to connect the hardware to produce a point cloud (Open Robotics 2024a). The data is then processed through a Simultaneous Localization And Mapping (SLAM) algorithm, which was performed using the Ouster Web SLAM algorithm (Ouster 2024b). Then, using ROS and the produced files, the data can be shared and linked to other software applicable for use cases such as CloudCompare, Blender, and Matlab, and can move into additional packages in an applicable format for increased potential.

The system was implemented in a combination of rural and urban settings and was run as a mobile mapping system with visualization of the surroundings on the laptop within the vehicle. It presented the ability to collect and visualize data in real-time in forested, city, indoor, and rural environments both while stationary and while moving at sub 40 km/h speeds.

The 3DMS works to support a greater vision and acts as a catalyst for a remote field data production system that has the capability to collect and transfer data to other locations within the field, to research facilities. Thus, supporting an agile field-driven data acquisition and access architecture. A visualization of how the data could be disseminated from the field beyond is shown in Figure 4 below.

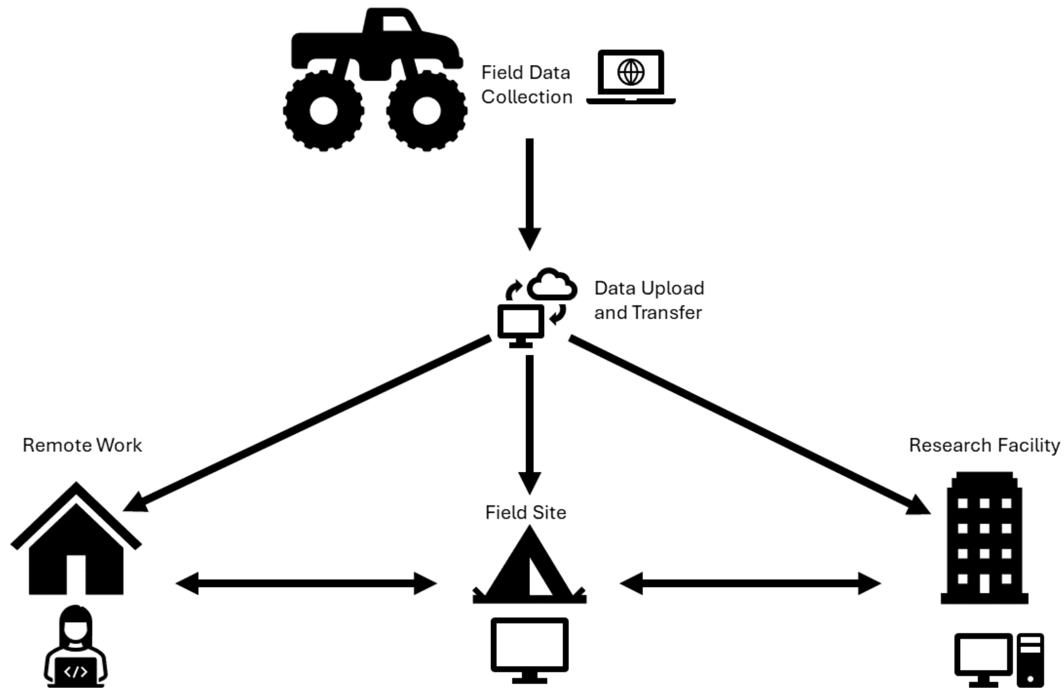


Figure 4. Vision for data dissemination in a remote field data production system.

In order to evaluate the potential for data dissemination between field sites, field collection areas, and research facility, at low cost and with agility, it is imperative to quantify and evaluate data architecture and resource utilization.

For a more detailed description and discussion of the design and development of 3DMS, in Matsushiba and Hedley, 2024 (forthcoming).

3.5. Methods

Our assessment of data architecture and resource utilization was applied to the sequence of events that occur during the operation of 3DMS to record data in the field. The laptop used was the ASUS G513Q laptop, which was selected to mimic a general research environment and provide baseline information regarding CPU, memory, and power draw in a typical field scenario. This workflow, pictured below in Figure 5, included generation of the initial LiDAR *rosbag* (ROS data storage method collecting ROS messages) file (Open Robotics 2024b), the calculation of point cloud density, file size reduction, and collection and processing of data surrounding resource utilization (CPU, memory, and power).

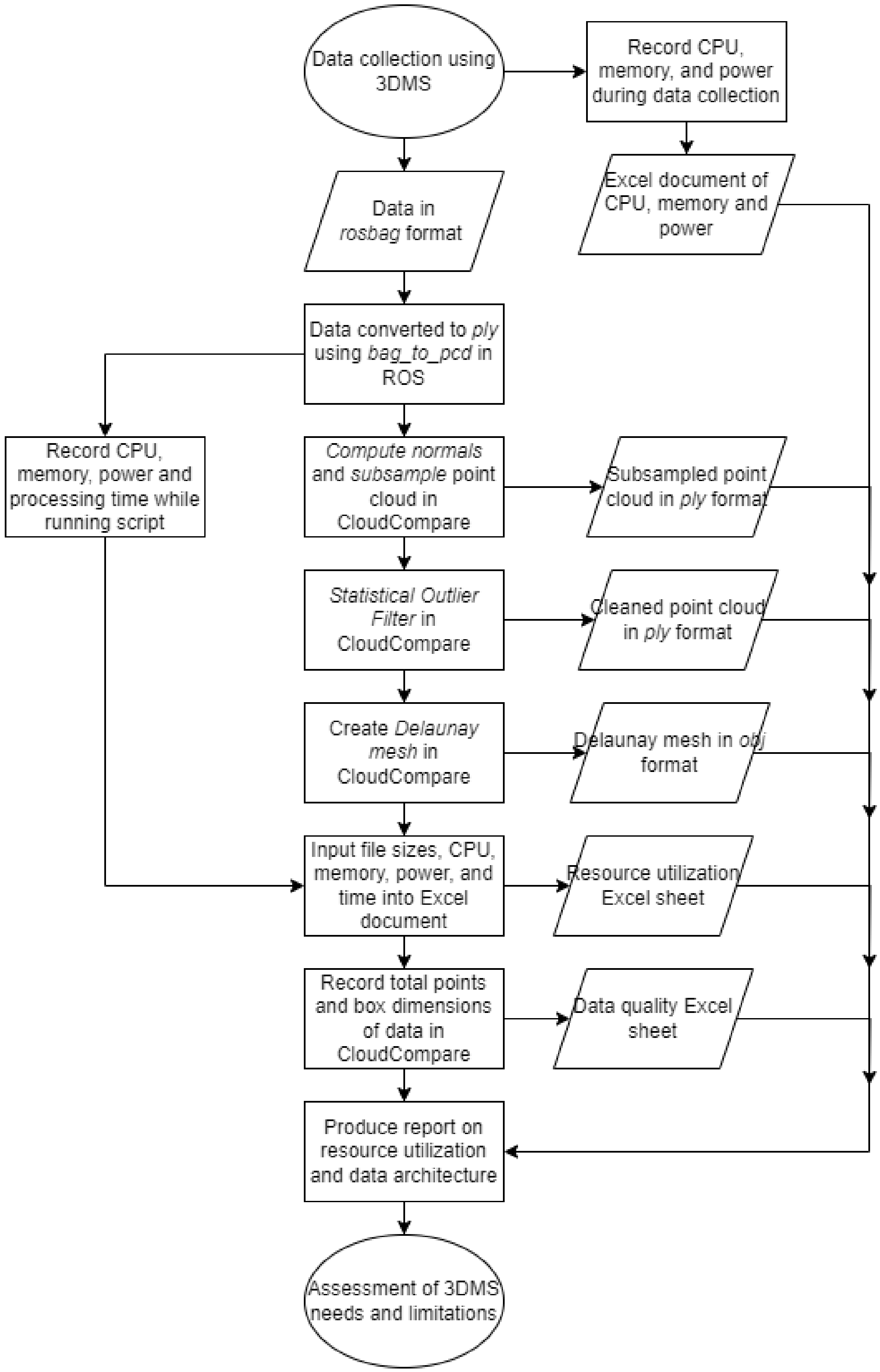


Figure 5. **Workflow diagram of the assessment of resource utilization and data architecture used as the overarching methodology.**

In correspondence with Figure 5; the data was prepared in stages from the initial raw *rosbag* file to the final uploaded data. The 3DMS collected data in the form of a *rosbag* file (contains a stream of ROS messages). The *rosbag* file was then converted to a *pcd* (file format storing 3D point cloud data) file using the *bag_to_pcd* node of ROS within the Point Cloud Library (PCL) ("Pcl_ros - ROS Wiki" 2024). The data is then prepared using a batch processing script, using unix commands, within CloudCompare which *computes the normal* of the cloud, *subsamples* the cloud with the spatial method and a minimal point distance of 0.1 and saves the subsampled cloud. Then, the *Statistical Outlier Removal* filter is applied using 10 points as the number used for mean distance estimation, and a standard deviation multiplier threshold of 1.0; this new cloud is then saved. The subsampled, and cleaned cloud then undergoes the *Delaunay mesh creation* with a maximum edge length of 0.2, and the mesh is saved. The data is saved as a point cloud file and a mesh file which are subsequently saved to the solid-state drive (SSD) and uploaded to the cloud.

For the purpose of this paper, additional functional properties were measured during each process including time to complete the process, memory consumption, CPU use, and power consumption. Time was measured by recording the time stamp at the start and end of the processing code and using arithmetic to determine the elapsed time in nanoseconds. Memory of the operating system was measured using the *free* command (checks memory RAM on the system) and CPU was measured using the *mpstat* (reports processor statistics) command. Three trials were performed for each dataset, and the average of the CPU and memory taken. This was performed to reduce variance in data, and ensure a clear picture was developed.

Memory and CPU use were recorded during both processing and recording of data. The CPU and memory use were recorded at intervals of every second using *mpstat* functions and saved in a txt file. Using the time stamp at the start and end of the process, as calculated using the system clock and basic arithmetic, the output of memory and CPU were then trimmed to match the time of the process to ensure logged data beyond the processing or running of the system was not logged, then input into a Microsoft Excel spreadsheet for data manipulation. The average and peak of the CPU percentage utilization and memory for each dataset were calculated using the Average and Large functions in Excel. The average CPU and memory consumption (in percentages) were identified, as was the peak workload in percent of memory and CPU.

Power consumption was measured using a RioRand model type RRAVDABCSALIUKNCVXZQ power meter that displays energy consumption and cost parameters. Power consumption was recorded in kWh while processing sample datasets using the command line, scanning, running a SLAM algorithm, and processing using the GUI. The total kWh and time were noted in an Excel spreadsheet, and the kWh/min were calculated and extrapolated for the power consumed in an hour and a working day (8 hours). The measurement of power draw was conducted in kWh to ensure it was easily convertible and could compare the draw to other power sources and estimate the total power draw for a working day.

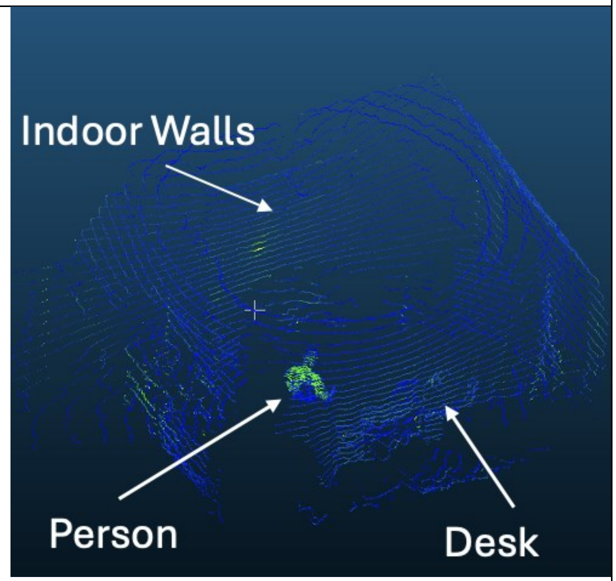
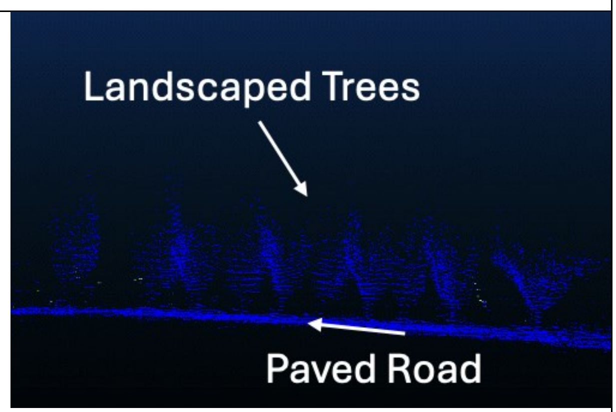
The file size calculations were identified via File Explorer and recorded in an Excel spreadsheet. The *rosbag* file size, and file size (in megabytes (MB)) of *ply* files, both pre- and post-processing, were recorded. The percentage of the file size that had been reduced was then calculated using arithmetic within the Excel spreadsheet.

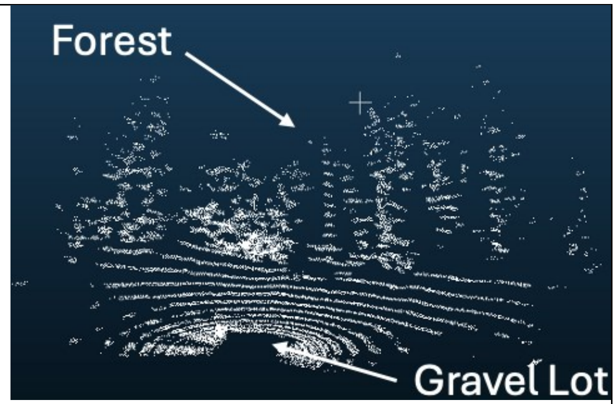
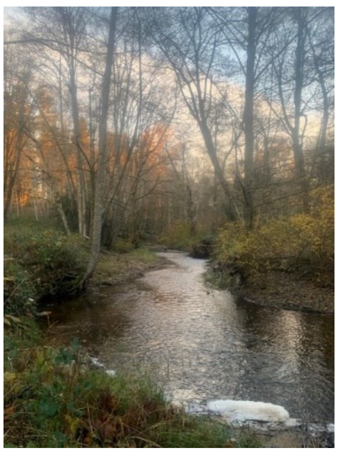
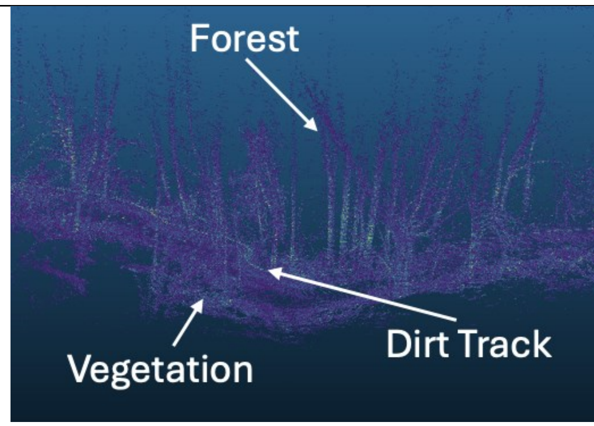
The calculation of point cloud density was performed using CloudCompare v2.13.1 and an Excel spreadsheet. The total points in both pre-and post-processed point clouds were recorded in the spreadsheet. The XY box dimensions of the point cloud were also recorded in square meters (to align with points/m^2 as used in USGS classification) (United States Geological Survey 2012). One unit in CloudCompare was found to be one meter when recording using the 3DMS workflow and was verified by using building plans of a room at Simon Fraser University and comparing the digital scans to the building measurements, finding a 1 m: 1 unit ratio. The point density was then calculated by dividing the points by the box size in square meters and the post-processed point density compared to USGS point density metrics.

Figure 6. Development and testing of 3DMS in lab spaces.

All these operations were run using ten key datasets. These ten datasets were selected to allow the development of a well-rounded understanding of the back-end resource utilization and efficiency of the data architecture put in place for the 3DMS – across a selection of possible geographic recording environments. They were selected for their variety including variance in file size (from 1.7 to 261 MB), spatial complexity of the dataset, differing applied use cases, indoor and outdoor datasets, and data collected while both stationary and moving. A sample of the representative point cloud environments used are shown below in Table 2. This variety helps establish a wide range of applicable data processing scenarios to best comprehend, quantify, and evaluate the resource utilization and outputs for the greater goal of developing a field-driven data acquisition and access architecture.

Table 2. Variety of environments in representative point cloud and real-world image.

Environment	Representative Point Cloud Image
Indoor – Robert C. Brown Hall Room 6121 	
Mixed Urban/Forest – Simon Fraser University Campus 	

<table>
<tr>
<td>Flat Rural – Cypress Mountain
</td>
<td>
</td>
</tr>
<tr>
<td>Forested/Wilderness – Panther Paintball and Airsoft
</td>
<td>
</td>
</tr>
<tr>
<td>Urban Infrastructure – Burnaby Mountain
</td>
<td>
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</tr>
</table>

3.6. Results

3.6.1. Resource Utilization

Resource utilization includes the use of memory, CPU, and power throughout the processing and operational phases. The CPU and memory recorded during command line processing conducted via CloudCompare are shown in Table 3 below.

Table 3. CPU and memory through the processing phase.

Dataset	File Size	CPU (Average)	Memory (Average)	CPU (Peak)	Memory (Peak)
KXI Test 1	259.2	14.69458	9.917053	99.81	13.7128
KXI Test 2	261	11.54522	10.08012	74.45	13.88605
Cypress 10	9.4	2.3525	8.768105	3.54	8.871531
Cypress 15	5.2	2.37	8.741301	3.75	8.86704
Cypress 20	12.6	2.805	8.807768	4.55	8.997061
Burnaby Mountain	111.4	23.23389	9.072385	99.94	10.74222
Campus 1	107.9	7.57	11.36304	21.01	11.46067
Campus 2	11.5	15.48571	11.11736	54.09	11.75226
RCB 1	51	6.232683	15.36174	19.11	25.07753
RCB 2	680.3	2.703333	11.09579	3.8	11.1904
AVERAGE		8.899292	10.43247	38.405	12.45576
MEDIAN		6.901341	10.08012	20.06	11.32553

The average CPU used during processing is 8.89%, and the average memory used during processing is 10.43%. The respective medians during processing are 6.9% for CPU and 10.08% for memory. The average peaks are 38.41% for CPU and 12.45% for memory. The respective medians of peak CPU and memory are 20.06% and 11.32%. Memory usage does not exceed 26% at any point, and CPU reaches a peak of 99% in two datasets, KXI 1 and Burnaby Mountain. As a control, the CPU and memory are both at <1% “at rest” with no programs open. This was treated as a negligible amount of use for the purposes of this assessment.

An identical process was conducted running the processing through the CloudCompare GUI, utilizing the same commands but selected in the user interface, as opposed to using command-line operations. The process utilized 99% of CPU consistently and then would become overutilized and cause CloudCompare to shut down with datasets above a file size of 10 MB. The memory remained below 30% and was not a limitation. The ASUS G513Q did not have the computational power to process the dataset with the GUI for any dataset above 10 MB (Cypress 10 and 15 m datasets were the only ones able to be completed with the GUI).

The memory and CPU were also tracked while running the Ouster OS0 and RTABMap off the ASUS G513Q. No processing was performed while tracking this usage to understand the computational requirements of the system alone.

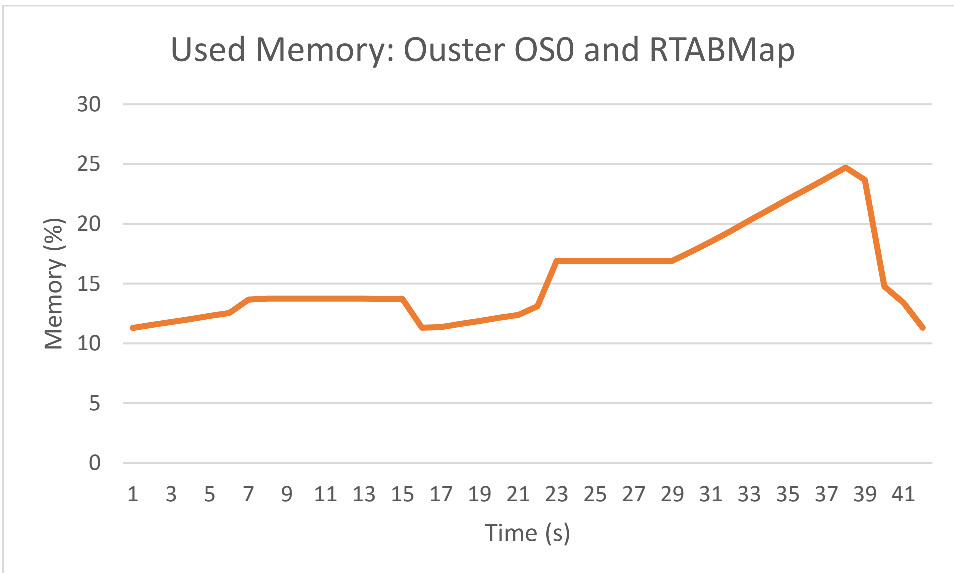

Figure 7. Used memory while running the Ouster OS0 and RTABMap simultaneously.

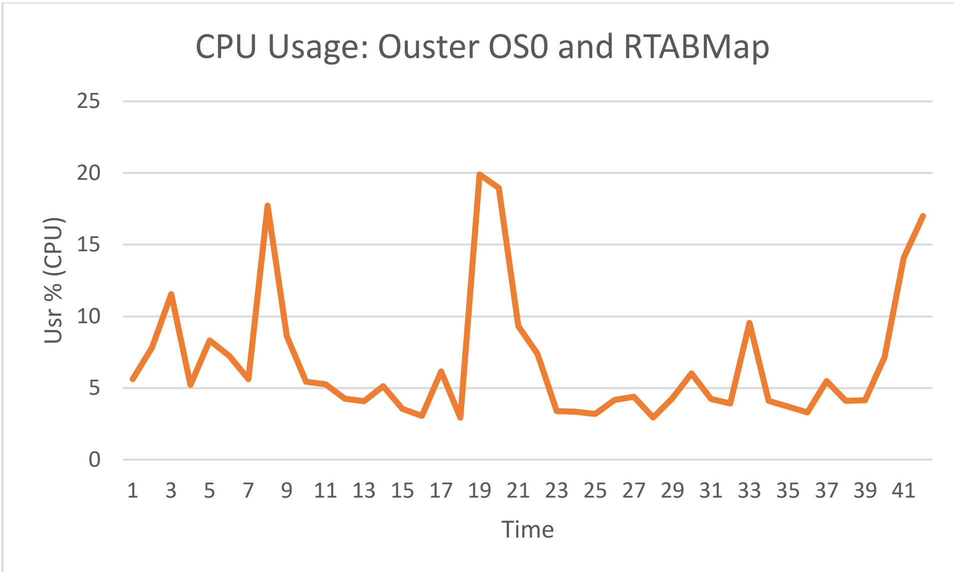

Figure 8. CPU usage while running the Ouster OS0 and RTABMap.

CPU and memory, while running the 3DMS off the ASUS G513Q, never surpass 25% of maximum computational power or memory storage. The peaks are at 25% for memory and 20% for CPU, maintaining moderately low values for the 3DMS.

Power consumption is dependent on which programs are running. The RioRand power meter displayed power consumption when running the following programs for an hour: the Ouster OS0 scanning, the ASUS G513Q running RTABMap while the Ouster is scanning, the ASUS G513Q running the command-line batch process, and the ASUS G513Q running processing with the GUI. Power consumption by minute and workday (8 hours) was then extrapolated from the measured power consumption.

Table 4. Power consumption of 3DMS components.

Device	Program	kWh/min	kWh/hr	kWh/Work Day (8 hrs)
Ouster OS0	Scan	0.073	4.38	35.04
ASUS G513Q	RTABMAP	0.004	0.24	1.92
ASUS G513Q	Command line Process	0.00064	0.0384	0.3072
ASUS G513Q	GUI Process	0.00085	0.051	0.408

The Ouster system uses the majority of the power supply at 4.38 kWh/hour followed by the running of RTABMap with the ASUS G513Q at 0.24 kWh/hour. The power draw was recorded while processing with both the command line code and the

GUI for CloudCompare, and the command line code used 75% (0.0384 kWh/hour) of the power required for the GUI process (0.051 kWh/hour). As measured with the RioRand power meter, an alternator can provide approximately 1.25 kWh while running. The Ouster OS0 should be supplemented with a stored power pack and allow the inverter to power the laptop. For a full working day of power, 40 kWh must be budgeted between using the inverter and a stored power pack.

3.6.2. File Size Reduction

When transferring data, file size can be a limiting factor. The data needs to be able to be stored and transferred to other machines for processing and additional use. When collecting data with the Ouster OS0, the initial raw *rosbag* file has a file size of approximately 1 GB/30 s of recording. The data should be reduced in size to be transferred and efficiently stored to maximize field storage and processing abilities.

The first step to reducing the data size is to convert it to a *ply* file by running the *rosbag* file by using *rosrun pcl_ros bag_to_pcd*. This greatly reduces file size by converting individual messages into a point cloud and eliminating unnecessary data. Condensing the messages into a spatial file format to best represent the 3D data, as opposed to storing individual messages collected from ROS.

Table 5. File size reduction from rosbag to ply conversion.

Dataset	***Rosbag*** **File**	***Ply*** **File**	Reduction %
KXI Test 1	21170	259.2	98.77562589
KXI Test 2	45220	261	99.42282176
Cypress 10	1289	9.4	99.27075252
Cypress 15	986	5.2	99.47261663
Cypress 20	1347	12.6	99.06458797
Bby Mtn 1	12430	111.4	99.10378117
Bby Mtn 2	13821	107.9	99.21930396
Campus	79000	11.5	99.98544304
Campus 2	139000	51	99.96330935
RCB 1	279054	680.3	99.75621206
RCB 2	503	1.7	99.66202783

Nine out of the ten studied datasets had a data file size reduction of at least 99% when converting from the initial rosbag file to the ply file. The average file reduction moving from a rosbag file to ply was 99.42%. Once this has been performed, the applicable file may be run through a SLAM algorithm such as RTABMap or Ouster's proprietary SLAM algorithm. The data is then processed using command line prompts, shown above in Data Preparation, which further reduces file size.

Table 6. File size reduction from processing point clouds.

Dataset	Original File Size (MB)	Subsampled (MB)	Clean (MB)	% File Reduction (Subsampled)	% File Reduction (Cleaned)
KXI Test 1	259.2	43.6	41.8	83.17901235	83.87345679
KXI Test 2	261	44.1	42.4	83.10344828	83.75478927
Cypress 10	9.4	0.1449	0.1431	98.45851064	98.47765957
Cypress 15	5.2	0.0503	0.0497	99.03269231	99.04423077
Cypress 20	12.6	0.0694	0.0682	99.44920635	99.45873016
Bby Mtn 1	111.4	31.3	30	71.90305206	73.07001795
Bby Mtn 2	107.9	31.3	30	70.99165894	72.19647822
Campus	11.5	6	5.9	47.82608696	48.69565217
Campus 2	51	11.5	11.2	77.45098039	78.03921569
RCB 1	680.3	4.8	4.4	99.29442893	99.35322652
RCB 2	1.7	0.1681	0.1498	90.11176471	91.18823529

The data size reduction post-processing varied from 48.69% to 99.35% and had an average file size reduction of 84.28% by removing statistical outliers and subsampling the point cloud. This demonstrates the potential to save file space. Files can be further reduced by compressing a folder into a zip for effective data transfer.

3.6.3. Data Processing Speed

Efficiency in data processing speed is an integral measuring tool when determining if in-field processing is feasible, and demonstrates the effectiveness of batch processing, and using command line features instead of the GUI. It also helps evaluate the time of processing in a scalable way when compared to file size.

Data processing speed is measured in nanoseconds by recording the time at the start and the end of the CloudCompare command line processing. Though a unique set of operations were performed, it helps define a general speed of data processing when compared to file size.

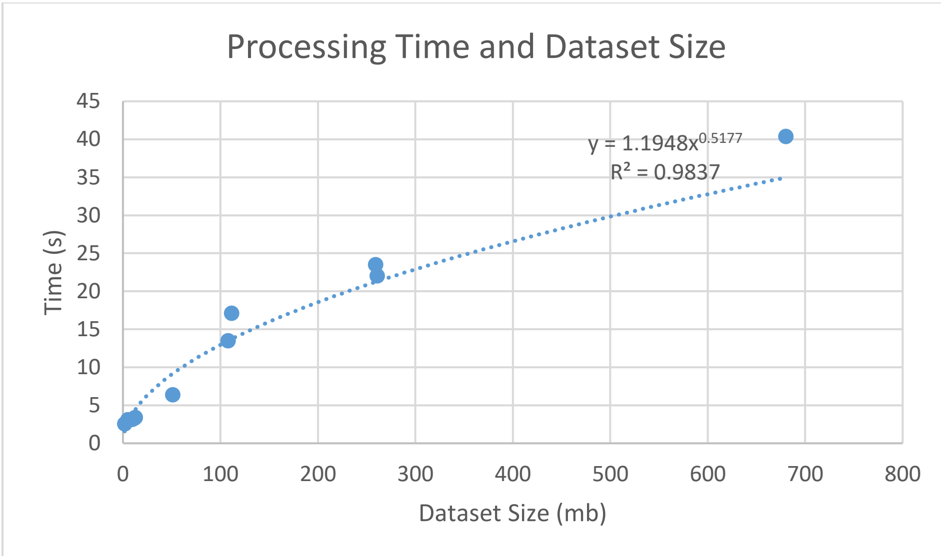

Figure 9. Processing time using command-line processing compared to the size of the dataset in megabytes.

The size of the original dataset (pre-processed) point cloud is measured in mb on the x-axis while the time to process is measured in seconds on the y-axis. The trendline of best fit was a power trendline which shows an R^2 value of 0.9837. The suitable equation that determines processing time based on file size is: $y = 1.1948x^{0.5177}$ where x is the dataset size in megabytes and y is time in seconds.

Operationally, the CPU is not overutilized, staying at 99% for <3s at all instances, and the memory is never above 15% capacity at any given time. The power draw is most greatly impacted by the use of the Ouster OS0 and should be supplemented with a power pack. The data size can be reduced by converting the *rosbag* to a spatial file format such as a *ply*. The data processing speed is scalable when compared to dataset size.

3.7. Data Validation and Point Cloud Density

The importance of the data lies in its ability to be utilized and its accuracy. The data must be usable to fulfill its purpose. The goal of the 3DMS is to generate a usable point cloud with moderate to high point cloud density; to be used in various models including the creation of a ground mesh for a driving simulator and has a point cloud density high enough to support the modelling for multi-purpose data sets, forest models, and other applications such as flood modelling or 3D models. This was used as a preliminary test to identify the current point density of the 3DMS in its sample datasets and is not an exhaustive analysis. Further research in greater detail is required to understand its data quality by limiting variables such as specific placement, vegetation state, and weather.

The United States Geological Survey (USGS) uses nominal pulse spacing (NPS) and nominal pulse density (NPD) to measure quality levels of data. As defined by the USGS, NPS is “the typical or average lateral distance between pulses in a lidar dataset, typically expressed in meters and most simply calculated as the square root of the average area per first return point” (United States Geological Survey 2012) and can be calculated from NPD using:

$$NPS = 1\sqrt{NPD}$$

NPD is the “typical or average number of pulses within a specified areal unit” (United States Geological Survey 2012). NPS is used in high-density, while NPS is generally used for lower-density datasets. The USGS quality levels (QL0 being of the highest quality, and QL3 being the lowest for LiDAR datasets) are defined below (United States Geological Survey 2012).

Table 7. Quality level as per aggregate nominal pulse spacing and aggregate nominal density according to the USGS.

Quality Level	Aggregate Nominal Pulse Spacing	Aggregate Nominal Density
QL0	≤0.35	≥8.0
QL1	≤0.35	≥8.0
QL2	≤0.71	≥2.0
QL3	≤1.41	≥0.5

Common point density brackets, as defined by Felix Rohrbach in the field of geomatics (Rohrbach 2015), are shown in the table below, and provide a more generalized, less rigorous version of point cloud density brackets.

Table 8. Point density applications according to Rohrbach. Assigned a letter for ease of identification.

Point Cloud Density (Pts/m^2)	Level	Application
0.5-1	E	Basic surface model Forest inventory

1-2	D	Flood modelling Dam and water inundation calculations
2-5	C	Multi-purpose data sets
5-10	B	Basic 3D models
10+	A	Detailed 3D city models

Point cloud density was calculated using the formula for NPD which is:

$$NPD = Points/Area$$

The point sets used were denoted as both pre-cleaned and post-cleaned points (cleaned having been subsampled and an SOR filter applied). The area was calculated using the X and Y box dimensions of CloudCompare to encompass the entire point cloud area. CloudCompare had a 1:1 scale of measured distance to real-world meters. The quality level and density level were assigned based on cleaned point cloud density to negate the noise.

Table 9. Point density quality of sample datasets.

Cloud	Point Density	Point Density (Clean)	Quality Level (Aggregate Nominal Density)	Point Cloud Density Level
KXI Test 1	161.5280214	41.63484347	QL0	A
KXI Test 2	147.6753532	38.37239605	QL0	A
Cypress 10	336.0141597	6.780966089	QL1	B
Cypress 15	264.8087915	3.327888804	QL1	C
Cypress 20	210.8328061	2.025313787	QL1	C
Burnaby Mountain	1.655696439	0.712892778	QL2	E
Campus 1	0.587147511	0.480650765	QL3	F
Campus 2	2.737380441	0.963591323	QL2	E
RCB 1	16012.82413	161.3454868	QL0	A
RCB 2	630.2227974	78.35472646	QL0	A

Out of 10 test datasets of varying environments, 40% were of the highest quality level (QL0) based on the USGS quality levels. 30% were of QL1, 20% of QL2, and only one dataset fell into the lowest quality category of QL3. Similarly, when using common point cloud density levels, 40% had the highest density (10+), as denoted by the letter A, 10% had the next highest density, 5-10, denoted by B, 20% had a density of 2-5, denoted by the letter C, and three datasets fell below a density of 1 pt/m^2.

3.8. Discussion

3.8.1. Comparison of Field and Lab

The goal was to be able to generate iterative cycles of remote data production using the 3DMS. To support agility and ease of data transfer/mobility, the understanding of how the data processing architecture is operating is fundamental. By understanding the use of CPU, memory, battery, and file size, it allows more scrutiny in determining if the same operations may be conducted in the field. As shown above, CPU and memory are never fully utilized while operating in command-line processes. The limiting factors in the field are the battery life of the machine performing the operations, and the file size.

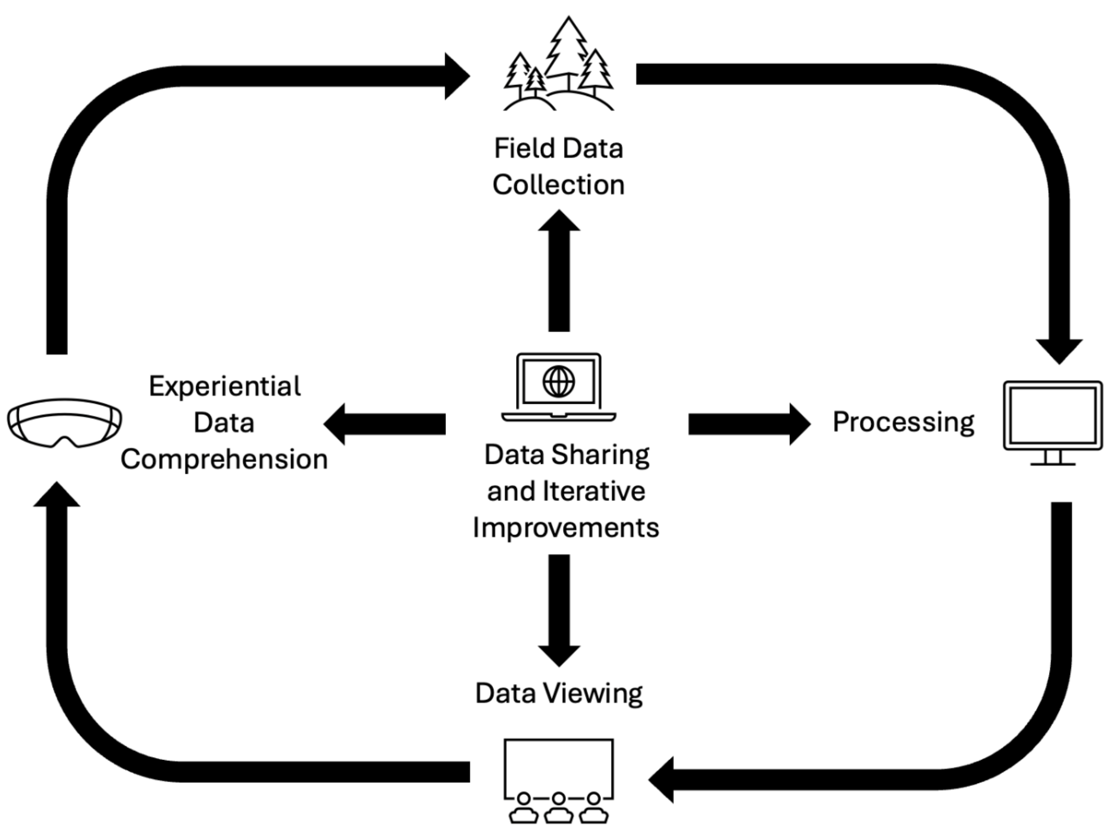

Figure 10. Cyclical data generation and interpretation.

File size is a limiting factor as the initial *rosbag* files produced by the 3DMS are amassing gigabyte levels of data from just minutes of recording. To perform effective data storage in the field and demonstrate the ability to transfer the data to the lab, the file size must be reduced. By reducing the file size, faster data transfer can be allowed when mobilizing the data and longer periods of field data collection can occur with less SSDs. Data can be mobilized in a variety of ways such as Sneakernet, Bluetooth, or Thunderbolt. These data mobilization strategies must be further explored. By converting to a *ply*, the file size is reduced by an average of 99.42%, greatly improving the file's ability to be transferred and utilized. Once undergoing processing, the file size is further reduced by an average of 84.28%. By greatly reducing the file size, these *ply* files can be easily transferred to machines out of the field, save storage space in the field, and allow more efficient file transfer. The most effective methods to reduce the large file size are converting from a *rosbag* file, created by ROS, to a *ply*, and then further reducing the points in the *ply* through processing.

The Ouster OS0 consumes the majority of battery in the field, followed by the lower amount consumed by the ASUS G513Q while running RTABMap, and then processing by either command line or GUI. The Ouster OS0 would not be running constantly in the field. However, data processing could be performed in interludes while using the inverter to charge power packs to supply the Ouster, thus extending battery life. The recommendations to extend in-field battery life and better the potential of field processing is to utilize command line processing over GUI to save battery life both in terms of power draw, and overall time used, and to charge the power packs to and from scan sites while processing data in a data collection cycle loop, as shown below in Figure 11.

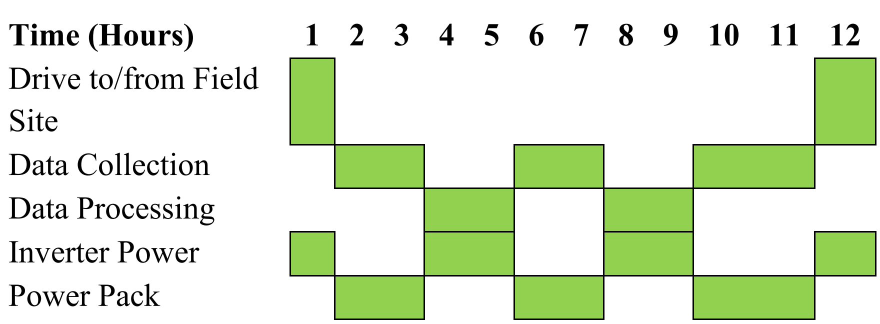

Figure 11. **Gantt chart demonstrating the potential cyclical nature of data collection and data processing while utilizing the inverter, and the power pack for field data collection.**

Field data acquisition and processing is possible and has high potential. The running of both RTABMap and command line processing can be run in the field without being limited by CPU or memory usage. Though the main limiting factors are file size and battery life, both can be appropriately addressed. File size can be reduced through compression and processing, while battery life can be extended by limiting the use of the GUI and utilizing an inverter and power pack. The potential for in-field processing is high, and the 3DMS demonstrates the ability to perform full-circle data collection.

3.8.2. Resource Use

Understanding the use of resources such as CPU, memory, and power are important to best comprehend the efficiency and performance, cost savings, scalability, hardware lifespan, and reliability of the 3DMS. By documenting resource use, the user can ensure that maximum computational power is not overutilized, and allows tasks to be completed promptly. Documenting the CPU and memory, in addition to file size, allows for scalability and determining the heavier workloads that can be performed using the system. Resource usage is also key in extending hardware lifespan and ensuring the system is stable. By avoiding excess use of CPU and memory, the computer and equipment will not overheat and decrease hardware lifespan. Overutilization of CPU or memory can also lead to system crashes, slowdowns, or failures.

Batch processing is integral to the processing pipeline as it streamlines the initial point cloud cleaning and processing, and reduces the CPU, memory, and power required. By utilizing batch processing, the GUI does not take up valuable computing power required for rendering the interface. In addition, time is saved by automating the process using the commandline as opposed to navigating the GUI to find individual operations, and the point cloud re-rendering for each update. Batch processing with the commandline saves the lag time between loading individual clouds, even if all operations are performed in command-line either individually or on one cloud in a single coded line. Processing using the GUI with CloudCompare leads to crashes due to overutilization of CPU, at 99% over a period of 5 minutes or more, and is thus not feasible in the field. Command line processing should be used to process data within the field.

Memory and CPU are not limiting factors when processing or recording data in the field. There is no risk of overutilization of CPU or memory when running the 3DMS, and it demonstrates the feasibility of operating the system on a mid-tier gaming laptop and performing field mapping capabilities with a SLAM algorithm. Processing can also be performed in the field without CPU or memory limitations. The CPU peaking at 99% is brief and lasts < 3 s when it occurs. Using command-line processing is effective and does not overexert the computational capabilities of the ASUS G513Q and would be equally effective on other mid-tier gaming laptops or higher.

3.8.3. Data Validation and Point Density

Data validation is ultimately very subjective. There is an inherent tradeoff between speed and cost with a dataset of higher quality. Higher point density also does not necessarily indicate a better dataset. Raw data can oftentimes have a high point density, and processing leads to a lower NPD and a higher NPS, but the data has been cleaned of noise and duplicate points. Every dataset is a balance between cost/speed and point density. A dataset can always be of a higher point density – but at what cost, both financially and in terms of speed? Even feature classification can be flawed as it possesses bias depending on who the classifier is, what techniques they are using, and what their background is.

The purpose of the 3DMS is to provide a low-cost alternative that generates usable point clouds for multi-purpose modelling. Its point densities are being compared to recognized industry standards including the USGS LiDAR quality levels and common point densities used in geomatics.

When comparing the point density of the 3DMS to applicable USGS metrics, 40% of datasets (post-processing) fall into the highest quality level of QL0. Followed by 30% in QL1, 20% in QL2, and 10% in QL3. With the majority of data reaching a high level of quality in accordance with point density, it demonstrates the applicability of the 3DMS to settings mapped by the USGS such as bare earth areas, forested land, crops, urban areas, and brush lands (United States Geological Survey 2012). At minimum, all datasets show the ability to record bare earth and forest inventories with a single pass, which can in turn be utilized to create a ground-based mesh to navigate.

When using basic point density metrics, as defined by Rohrbach in 2015, 40% of datasets are of high enough quality to be utilized for detailed 3D maps, 10% for basic models, 20% (the stationary datasets) for dam or flood modelling, and all but one dataset has the capability to develop a forest inventory and create a basic surface map. Given the context of the 3DMS is to create a low-cost, efficient laser scanning system that can perform base functions such as recording points to create a surface mesh and map surrounding forested areas; it is shown to perform its functions based on point cloud density.

The lowest speed recordings, the KXI test in the truck moving <10 km/h and the RCB tests run on foot, have the highest point density. The fastest speeds, run by the campus tests when driving 40 km/h or greater show the lowest point density and the high impact that speed has on the final point cloud. The quality of point density can also be improved with additional passes through the area or lower speed passes to improve coverage. The initial pass point density, post-processing, is acceptable in developing at the least a ground mesh, and a forest inventory. Provided a speed of less than 40 km/h is run while recording, a usable point cloud is produced and the 3DMS fulfills its core purpose with flexibility to improve the density and develop more complex applications with additional passes or slower speeds.

3.8.4. Future Potential

The future potential of the 3DMS for creating a loop of field data generation and processing that is transferable to the lab is very high. The system allows for the collection and processing of data in the field using the Ouster OS0 and the ROS pipeline for ease of transfer to the lab via file reduction and storage on an SSD. The system allows for remote field mapping for continuous workdays with limited power access. There is high potential for use in mapping within industries such as mining, forestry, and civil engineering.

3.9. Conclusions

The visual and graphical outputs of LiDAR systems (such as screenshots or videos of 3D point clouds) are often the most common outputs we see of new LiDAR work, systematic assessment of the underpinning hardware and systems performance needs to be verified so that we know the system is feasible for further development and deployment (in field situations in this case). Given that our LiDAR system, 3DMS) is largely open-source, this paper has reported on the commensurate system hardware performance, so that others developing agile, open-source systems of their own, may use our work as guidance and for comparison.

The 3DMS was created to develop a functional, low-cost LiDAR mapping system. The system has met its initial goals of in-field data recording and processing, ease of data transfer, and the generation of a suitable point density when creating clouds.

The CPU and memory on a midtier gaming laptop are suitable for recording data, with memory and CPU functions at or below 25%. Similarly, processing is not limited by the CPU and memory and thus can be performed in-field without overutilization. The speed when generating point clouds during processing is reasonable and appropriate for in-field applications.

The limiting factors of power and file size can be addressed to increase the potential for field data generation and processing. The power supply can be extended by rotating recording and processing while charging a power pack between recording phases and storing additional power supplies within the vehicle. File size can be reduced by converting the *rosbag* to a *ply* file and processing it to remove noise points, which allows for better storage and transfer potential.

The system generates acceptable point cloud density and can reach the top standards of the USGS. The point clouds collected possess the ability to extract points and create a ground mesh to replicate in-field navigation, and have the point density to create forest inventories, flood, and dam modelling and mapping, and basic 3D models.

The 3DMS has demonstrated a strong potential as a solution for a low-cost in-field LiDAR mapping system that can create a loop of data collection, processing, transfer between lab and field environments, and inspection. The system we developed possesses feasibility for operating in the field and is not limited by resource usage or file size, and can generate point clouds of a mid to high-quality point density.

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Chapter 4. Completing data cycles with virtual vehicles: Driving through data using tele-sensory geovisualizations

4.1. Abstract

This paper introduces DRIVR, a novel tele-sensory geovisualization interface revolutionizing spatial data interaction. DRIVR enables users to not just visualize but also physically immerse themselves in landscapes, bridging the gap between field and lab environments. By integrating immersive technologies like VR, the workflow facilitates data exploration from remote field locations to an immersive experience in the lab. The paper details the development and implementation of DRIVR, focusing on transforming raw point cloud data into immersive VR experiences. Through a comprehensive approach, including adapting a 3DOF simulator and a game engine, users can navigate through datasets, experiencing spatial relationships in real-time. DRIVR offers a unique approach to data exploration with potential applications in wilderness driving and 3D spatial understanding.

4.2. Introduction

4.2.1. Overview

This paper introduces DRIVR – a 'tele-sensory geovisualization' interface that allows users to not just view data, but to drive through it immersively and physically feel the morphology of the landscape while doing so. Through this work, this research also demonstrates how we are turning traditionally linear workflows between field and non-field data use spaces, into interconnected data loops. This in turn offers new possibilities for how geovisual data use occurs in-field and in-lab, and how new forms of experiential interconnectedness might support new capabilities for situational awareness, and use.

4.2.2. Background

Data collection capabilities have greatly increased in the past decade as sensing technologies such as LiDAR, photogrammetry, and InSAR have improved (Fitzpatrick and Hedley 2024). With the rise of data being collected, harnessing said data is becoming increasingly crucial. By establishing an iterative data collection ecosystem, the relationship between field and lab can be lessened, closing the gap between remote spaces and lab research.

One area of particularly active development of sensors and data production are human vehicle operations in unprepared field environments (Herman and Ismail 2021; Sapkal et al. 2023), and 3D/4D data production in field environments (Jurado et al. 2022; Di Stefano et al. 2021). These each have significant value in professional driving operations and safety, industrial and academic research.

Wilderness driving is a particularly hazardous vocation, and safe navigation can be impacted by changing weather, lack of resource access, and complex landscapes. Humans have individual peculiarities in wayfinding behaviours that differ based on spatial skills, and human traits (Brunyé et al. 2015). Individual wayfinding performances can vary based on experience, knowledge, visuospatial attention, and gender (Malinowski and Gillespie 2001). Training is integral to safe passage, and by placing less experienced drivers in immersive environments, their confidence, spatial skills, and route selection abilities will improve. Collecting data in the field, particularly in remote locations, can pose risks. Having the ability to review and simulate situations out of the field can limit said risk. Data collection and mapping in wilderness locations can pose hazards such as unmaintained roads, navigational challenges, changing weather conditions, and lack of access to resources in remote locations such as cell service and GPS signal. Data collection can be challenging in areas of complex morphology (Coppa et al. 2014) and sites that have accessibility challenges due to cost or logistical reasons (Harknett et al. 2022).

4.2.3. Problem context

In off-road vehicle activities, vehicle operator situational awareness is certainly informed by the ability to view geographic spaces in all directions. 4D spatial data can allow data users to view the structure of space (up to the limits of sensors and data fidelity) (Clement et al. 2022). The goal of the system is to implement the ability to drive through collected data at a later time under similar conditions for improved spatial understanding. There is an increasing number of driving simulators, but many focus on photorealistic environments and training simulation, over spatial data analysis (Wynne et al. 2019; Xue et al. 2023).

Building systems architecture and workflows that allow agile and timely data acquisition, mobilization, processing, analytical inspection, and communication - may enhance situational awareness, hazard identification, risk mitigation, more sophisticated comprehension of phenomena being recorded, and opportunities to record new data while still in-field.

However, the processes for data production, delivery, analysis, and communication involved in these activities have for the most part been largely linear to date. Turning 'linear' data production and data use workflows that perpetuate spatial and temporal disconnects between lab and field into iterative, cyclical data (production and use) 'loops' has the potential to simultaneously interconnect field space, lab space, and users in all locations, this may support greater agility and interoperability.

Expressing three-dimensional landscapes and objects in them, as 2D maps, abstracts from 3D/4D reality, degrades their representation, and our ability to understand phenomena in them (Rydvanskiy and Hedley 2021). Research in 3D and 4D geovisualization (and related fields) have made advances over several decades to implement compelling reconstructions and simulations of complex phenomena (Rydvanskiy and Hedley 2021; Lochhead and Hedley 2019; Lochhead and Hedley 2021).

However, even the most sophisticated geovisual simulation is impeded by its presentation on a 2D computer display. For humans to fully perceive and comprehend geographic spaces and phenomena as they exist in reality, we must dissolve dimensional abstractions of both visualization and interface (Lochhead et al. 2022). As human-computer interface technology has matured, virtual reality (VR), head-mounted displays (HMDs), extended reality (XR) including augmented reality (AR) and mixed reality (MR) devices, have allowed us to change the way in which we experience spatial data visualizations. XR is an umbrella term covering AR, which overlays the physical world with virtual components, MR, which merges the physical world with virtual components that can be interacted with, and VR, which is a simulated experience (Marr 2021). Instead of looking at the perspective rendering of a 3D/4D geovisualization on a

2D display device (screen), we can step into a virtual space with the same 3- or 4-dimensional characteristics of data and the reality that was recorded. It is for this reason, that a community of geovisual researchers increasingly use and explore VR, AR, and MR interfaces to deliver varying degrees of immersion and interactivity with spatial data (Lonergan and Hedley 2014; Lochhead and Hedley 2019; Çöltekin et al 2020; Rydvanskiy and Hedley 2021).

In remote field and research operations, the ability to view and review that have been previously collected, is key to developing an understanding of the environment. Being able to do it from an immersive perspective, rather than a viewing a perspective rendering of it, may enhance this ability further.

By taking field data, processing it in lab or field, and having the capabilities to experience and be tele-present in the environment, one might argue that emerging types of situational awareness (and operational capability) might be developed by interconnecting data users across both in-field and non-field environments. Reviewing field data in the lab through extended reality (XR) including virtual reality (VR), mixed reality (MR), and augmented reality (AR) may have potential benefits which could limit risk, potentially iterate data cycles and simulations, could improve cost-effectiveness and accessibility, and may possess training capabilities. This paper utilizes virtual reality in the lab to aid in a driving simulation.

In ways that perhaps exceed typical uses of mainstream GIS, practitioners at the frontiers of spatial reality capture, digital twinning, and immersive information experiences continue to explore and develop new ways to view, manipulate, and experience spatial data. Rather, these efforts are effectively exploring the potential for new combinations of sensors, data production and mobilization, and experiences made possible through emerging interface technology. Combinations of these evolving components offer new ways for us to connect field and lab spaces, and the phenomena we seek to characterize and communicate. While new sensors and interface technologies offer game-changing potential in reality capture and user experience respectively, it is the potential to elevate our understanding of spatial phenomena through transformative ways to record and observe them.

XR may extend an ability to prototype and create feedback loops of beneficial information, including climate modelling that can help map the future of the planet (Huang et al. 2021). The customizability, scalability, and iterative feedback loops can help test hypotheses, and comprehend data in a risk-free environment.

Many if not most geovisual XR research uses 3D or 4D data visualization, using VR headsets, and AR-enabled devices. For instance, there has been work to visualize and create an immersive visit experience of Naples city monuments using VR headsets (Gabellone 2023), the use of VR to prepare social work students for professional practice by interacting with, and viewing client reactions (Lie et al. 2024), and utilizing VR headsets to visualize and map fault traces on outcrop models (Seers et al. 2022). Instances of AR use include the monitoring of geoconservation efforts through mapping petrified tree trunks with an augmented map (Papadopoulou et al. 2020) and teaching students the foundations of landscape architecture through augmented mapping (Kerr and Lawson 2020). However, what typical geovisualization research examples do not do so well, are to record and communicate the physical relationships between humans, vehicles, and geographic spaces. Very little to date has gone further into multi-sensory information experiences (Hultén 2011; Luan et al. 2024; Laukkanen et al. 2022).

Limiting our reconstructions of geographic spaces to only visual ones is to ignore critical sensory information that can improve user perception and comprehension of landscape morphology and its relationship with vehicle and humans (and which could significantly enhance human ability to detect and avoid hazards and identify paths of safe passage).

4.2.4. Objectives

It is for this reason that we developed a vision for not just being able to create the systems to generate geovisualization of remote field environments from sensor data, but to also be able to physically experience the data through other senses.

Simply viewing perspective renderings of 4D data is not the same as being surrounded by a virtual reconstruction of reality based on data, at 1:1 scale. But it is also true that only viewing or moving around virtual reconstructions of data-driven environments limits our interpretation to visual inference. This is an intentional stepping stone towards a larger vision for experiential GIScience.

At the foundation of this vision, is to provide users across this interconnected data ‘ecosystem’, with the ability to experience phenomena in remote field locations, in the same dimensionality as they exist in. XR offers a range of opportunities to visualize data, then subsequently explore, experience, and interact with the results once the data has been collected (Çöltekin et al. 2020).

The ability to review and experience data in from field to XR can virtually immerse the participant and recreate the environment asynchronously. The iterative data cycle ecosystem and feedback can improve situational awareness and training while offering a low-risk environment to test hypotheses, extract useful information, and explore results. XR can offer training environments that are immersive, engaging, and educational (Innocente et al. 2023). XR facilitates understanding and communication and improves 3D understanding (Janeras et al. 2022; Harknett et al. 2022).

By adopting cyclical data collection processes and immersive experiences could be beneficial, particularly for training purposes. It may help improve understanding, safety, and feedback through repeated interactions with the data in immersive environments. In response to these challenges, this paper reports on the design and implementation of DRIVR – as tele-sensory geovisualization interface system.

The catalyst for this work was completion of a preceding research project with partners in industry, where we developed 3DMS, an agile low-cost vehicle-mounted LiDAR system to quickly generate and visualize 3D datasets of unprepared off-road landscapes (see Matsushiba and Hedley, forthcoming). Given our team’s background in developing spatial interface-based geovisualization prototypes, we felt there was an opportunity to explore the potential for mobilizing this new data generation capability, by developing new ways to experience them, and by doing so, interconnect all members of data acquisition/visualization/interpretation teams between field and lab space.

The 3DMS (3D Mapping System), a vehicle-mounted LiDAR system, uses a combination of mobile LiDAR sensor, stereo camera, and GPS; utilizing the Ouster OS0, and the Zed2 stereo camera (Ouster 2024; Stereolabs 2022). The system was developed using a midtier gaming laptop (an ASUS G513Q laptop) (“2021 ROG Strix

G15 G513 | Gaming Laptops｜ROG - Republic of Gamers｜ROG Malaysia” 2024). The software components use Robot Operating System (ROS) as an intermediary to connect the hardware and produce a point cloud (Open Robotics 2024) to produce spatial data that can be moved into additional packages for further processing.

Therefore, in this paper, we report on workflow that allowed us to link point cloud data from the 3DMS (Matsushiba et al. 2024, forthcoming), to generate an immersive virtual reality data visualization environment using VR, that could also be experienced physically through integration with a 3DOF simulator system. DRIVR delivers a new capability – not only to deliver an immersive experience driving based on directly recorded field data – but also completing a data generation and immersive experience cycles, as discussed above.

The paper explores the capabilities of the simulation, reflects on the potential benefits of exploring data through this method, and key decisions made to develop an efficient, and effective workflow. We offer perspective on the implications of this approach for future development and application.

4.3. Methods: Adapting a 3DOF simulator for use as a tele-present data exploration tool

4.3.1. Data Workflow

LiDAR point cloud data output from the 3DMS vehicle-mounted data acquisition system is exported as a *.las file. The data workflow begins with a cleaned point cloud exported from CloudCompare as a las file. Working in ArcGIS Pro (v. 3.2), the cleaned las file point cloud was brought in using the 3D Analyst extension. Within the 3D Analyst package, the “Classify LAS Ground” tool was applied to the point cloud. First, a conservative classification was performed to develop a tighter restriction on ground classification and allow differentiation of ground from low-lying shrub. Following the conservative classification, an aggressive classification was performed reusing the existing ground. This allows recognition of ground areas with higher relief. This step is not performed in urban and flat rural datasets to avoid misclassification of tall objects such as utility towers or lamp posts. Once completed, the classified las file was saved.

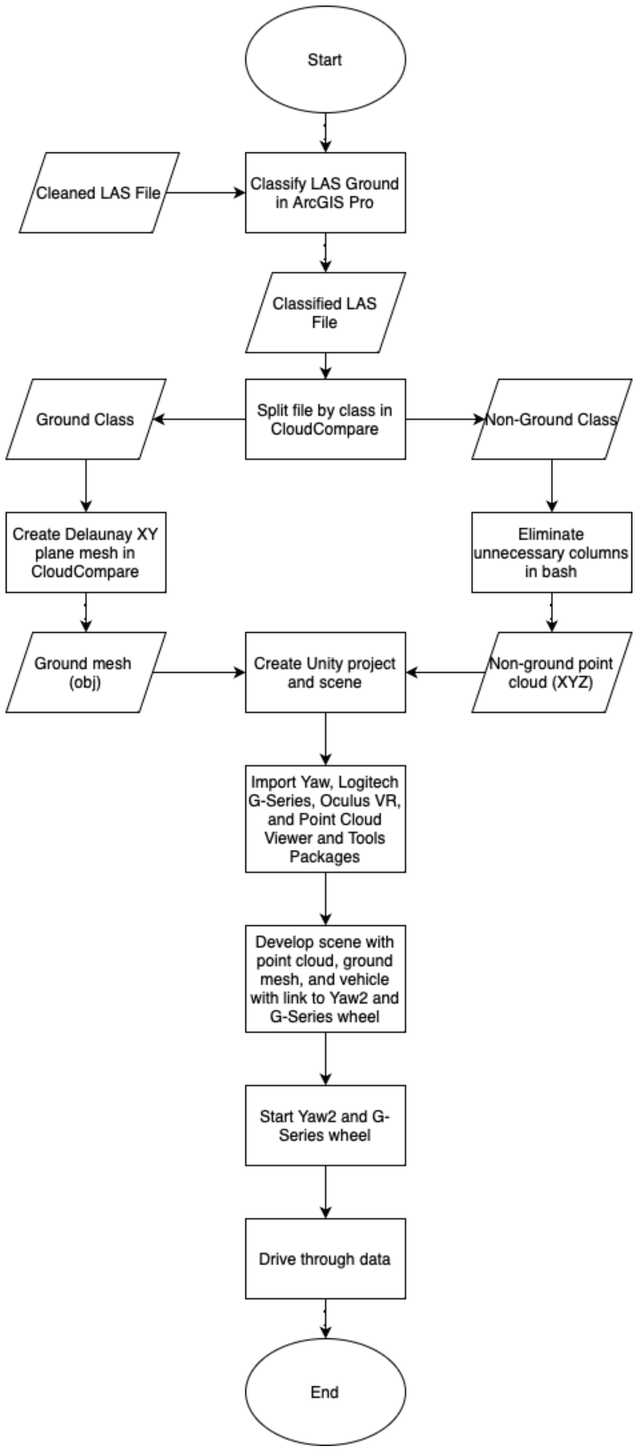

Figure 12. **Workflow for the development of an immersive data experience including collected point cloud data, the Yaw2 simulator, Logitech G-Series wheel and pedals, and Oculus Quest 2.**

Within CloudCompare, the classified las file was imported. First, the cloud was filtered to the non-ground class and saved as an *xyz* file. Then, the cloud was filtered to the ground class only. A mesh was created using the Delaunay 2.5D xy plane tool. The ground mesh was then saved as an *obj* file. The *xyz* non-ground class then had the non-applicable columns (colour, normals) removed using the *cut* operation in bash to delete unnecessary columns. It was saved as a new *xyz* file.

In a Unity project (using Unity version 2022.3.23f1), the ground mesh was imported as an asset. The Point Cloud Viewer and Tools, Yaw2 Software Development Kit (SDK), and Logitech G-Series SDK packages were imported into the project (mgear 2024; Logitech 2024; Yaw 2024). Within the scene, the Runtime Viewer script of raw point cloud files, taken from the Point Cloud Viewer and Tools package, was added to an empty GameObject and routed to the *xyz* file of the non-ground class. The material selected was the VR compatible material within Point Cloud Viewer and Tools, *PointCloud_DX11_FixedColorOpaque-VR.mat*. The ground mesh was added to the scene as an asset. The mesh and point cloud were then aligned based on the selection of reference points in CloudCompare where the obj mesh and point cloud align, then transforming these game objects to match the reference points within Unity.

To enable VR, VR support was activated in Unity in Player Settings. The VR device being used can be selected using the Unity VR SDK. In this case the OpenXR was enabled to allow use of the Oculus Quest 2 VR headset. The XR Origin (XR Rig) was added to the car and the camera at the vehicle's height selected to ensure the vehicle's view was tracked and mapped to the Oculus Quest 2. The Logitech G-Series steering wheel script was added to the vehicle. Logitech G-Series software and G-Hub downloaded, to connect the steering wheel and pedals to the laptop.

The Yaw2 car, camera, and YawController were imported as assets from the Yaw2 SDK package. Then simple velocity and orientation scripts were added to the car asset. The car was transformed to the appropriate size of the point cloud using reference points. The IP of the machine and the YawController were matched to ensure connection to the appropriate simulator. The position of the car was then transformed to lie on the ground mesh.

4.3.2. Hardware Integration and Configuration

The hardware setup involves a Yaw2 simulator, Oculus Quest 2 VR headset, and a Logitech G-Series steering wheel and pedals which are all connected to an ASUS G513Q laptop.

The Yaw2 simulator (see Figure 13), is a 3DOF motion simulator, with 360° yaw movement capability, 40° roll movement capability, and 70° pitch movement range (https://www.yawvr.com/). The Yaw2 is typically used to support 3DOF simulations such as driving and flight simulators. We are not aware of its use previously, for immersive experiential spatial data visualization. The Yaw2 is connected via Bluetooth, the Logitech G-Series steering wheel and pedals are connected via USB cable to the ASUS G513Q laptop, and the Quest2 is connected via USB-2 cable.

Figure 13. The Logitech G-Series wheel and pedals are connected to the Yaw2, which is in turn connected via USB to the laptop to the left of the image.

To initiate the data viewing experience, the Logitech G-Series is connected via cable, the Oculus Quest 2 linked, and the Yaw2 is started in the Yaw VR UI on the laptop. Through the headset, our immersive simulation environments can be entered, via activating Unity executables. The user (wearing the Quest 2 headset) finds themself in the driver's seat of a virtual vehicle with seat, steering wheel and pedals corresponding to the real-world simulator system and controls. Users are then able to freely drive around inside the dataset, controlling speed and direction with the wheel and pedals.

This system – we call it *DRIVR* – enables users not just to view and explore raw data from the remote LiDAR acquisition system, but to do this immersively and experientially. Users gain dynamic geovisual experiences from within the data-generated 3D scene. But these experiences are made more visceral by the engagement of vestibular (balance) and tactile and whole-body force-feedback when the virtual vehicle (and therefore the simulator seat) tilts while navigating virtual terrain with different slopes and aspects; and by the granularity of simulator movement and vibration, as the virtual vehicle and software-based simulation model translates LiDAR-data-derived landscape morphology into physical movement that can be felt by the user/driver.

4.3.3. Sample Dataset Comparison

Three sample datasets generated by our team's custom LiDAR system (3DMS, see Matsushiba and Hedley, forthcoming) were brought through the workflow above to compare its effectiveness in rural, urban, and indoor environments. This approach was taken, to understand the workflow capabilities and its performance in varied settings. Three representative datasets were selected, including a rural dataset comprised of trees, low vegetation, on loose and packed dirt ground, an urban dataset on paved roadways with several buildings, trees, and road signage, and an indoor dataset in a room with walls, ceiling, floor, and a person. All three datasets were processed using the same steps, as shown in Figure 12, and then qualitatively compared.

4.4. Results: DRIVR1 – an Immersive Driving Simulator

The result of the workflow is an immersive data experience where the user drives through data once the scene has been initiated. The user navigates through the data using the Logitech G-Series steering wheel and pedals to drive a car and view the data through the head-mounted VR display. The vehicle moves on top of the ground mesh, and the point cloud is visible in the surroundings.

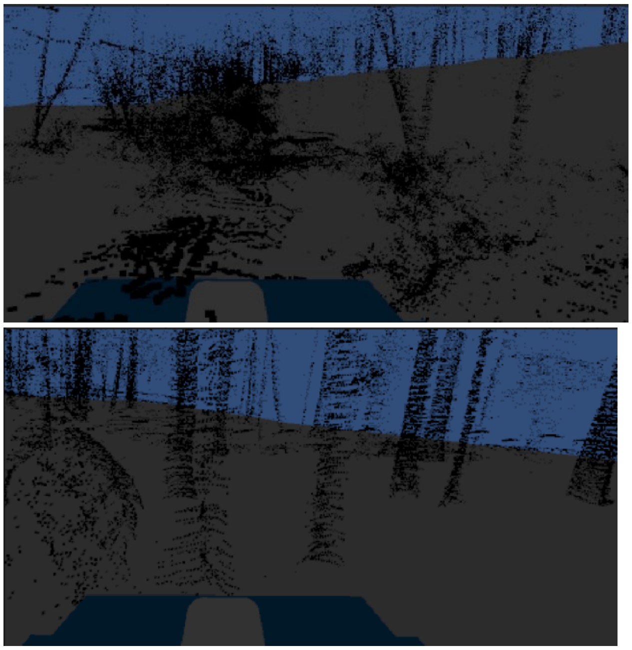

Figure 14. Screen view of point cloud and mesh.

The user can navigate through the data, and develop a spatial understanding, being able to turn their head and view different angles using the VR headset. The user is able to visualize the data in 3D, and feel the yaw, pitch, and roll as they traverse the mesh, feeling the slope changes of the ground. This is done using collisions between the vehicle and the mesh by assigning physics properties to both within the Unity game engine. In this iteration, you cannot collide with the point cloud, only the ground mesh. The data experience is immersive and allows for a holistic understanding of previously collected data. The vehicle is scaled to the dataset and allows for an intuitive spatial understanding of the dataset.

Figure 15. Yaw2 simulation chair with Logitech G-Series wheel and pedals attached (left) and Dr. Nick Hedley using DRIVR.

The user is situated in the Yaw2 virtual reality motion simulator with access to the Logitech G-Series steering wheel and pedals, as shown above in Figure 15.

4.4.1. Sample Datasets

All three datasets, rural, urban, and indoor, demonstrated the capabilities to be used in the workflow.

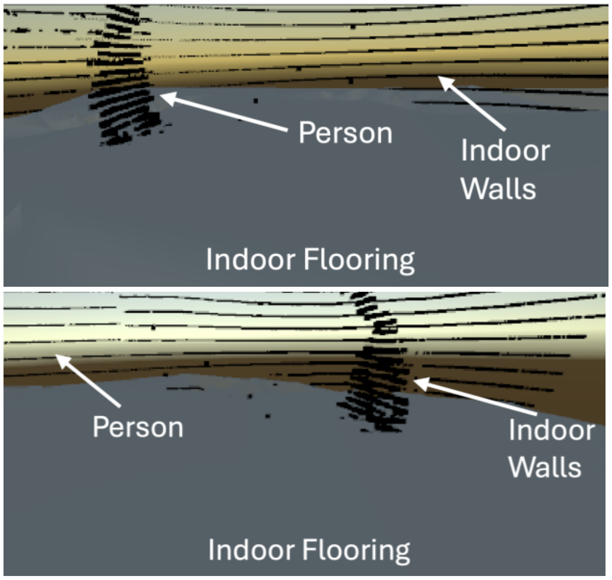

Figure 16. Processed indoor dataset as shown via Unity.

The processed indoor dataset is shown above in Figure 16 The ground mesh is very flat, generated by the points making up the floor. The point cloud looks clean, with minimal noise, visible walls and roof, and the person. The workflow had to be modified to a movable camera, instead of a vehicle, due to the small size of the area. The workflow can be applied to indoor locations and would be feasible in a larger indoor space such as a point cloud of a building.

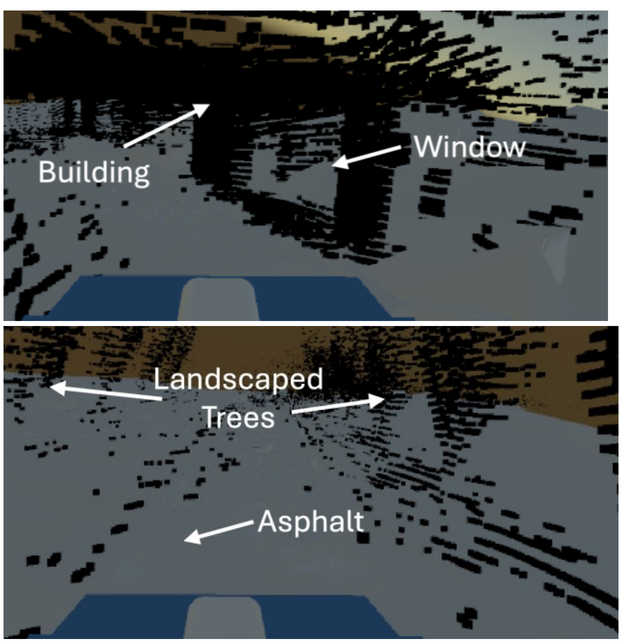

Figure 17. Processed urban dataset as shown via Unity.

The processed urban dataset is shown above in Figure 17. It shows a vehicle on a road navigating next to planted urban trees, and buildings. The roadway is smooth, and it is evident where the pavement is located when developing the ground mesh. Viewing of buildings, trees, signage, and the road is clear.

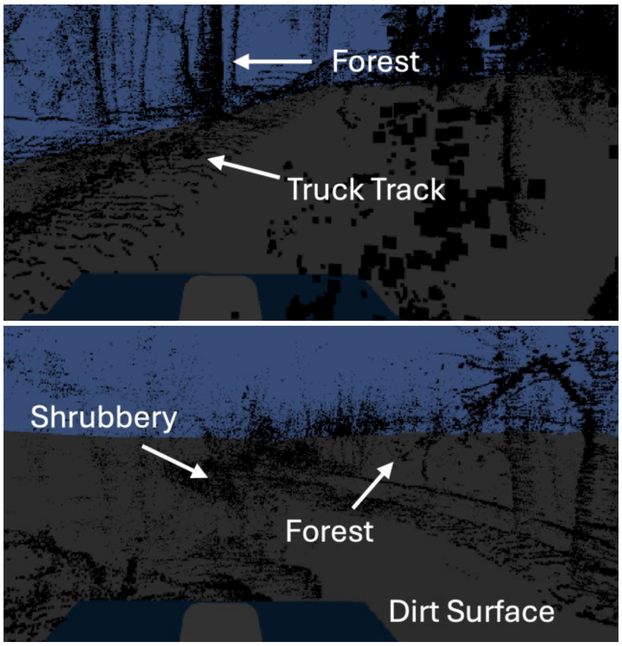

Figure 18. Processed rural dataset as shown via Unity.

The processed rural dataset is shown above in Figure 18. The trees and vegetation are visible within the dataset. A rural dataset offers the most variability in ground type and registers the slope changes. Additional noise from low lying vegetation can create a more complex viewing experience.

These three sample datasets utilized data collected from the 3DMS. The workflow has applicability to any cleaned *las* point cloud that can be navigated by ground using navigation to walk or a cleaned *las* point cloud that can be navigated via vehicle either off or on road.

Note that none of these datasets aim to record the real world with photorealistic fidelity. Their purpose is to allow vehicle operators to perceive the location and bounding volume of space they occupy. It is also intentional for us to view, explore and experience these data in their raw form. As GIScientists, we need to see these raw data in order to inspect and assess the veracity with which they have recorded (and reproduced) features in geographical reality. There is opportunity to integrate the data with digital twins or non-synchronous datasets.

4.5. Discussion

4.5.1. Decision-Making in Workflow Development

In order to develop an efficient, yet robust workflow, key decisions were made regarding how to create the ground mesh, the selection of the applicable game engine, and the use of the Yaw2 and Logitech G-Series SDK packages.

The ground mesh was classified using ArcGIS Pro. The decision to utilize ArcGIS Pro's 3D Analyst package was made primarily for ease of use and efficiency. It is a ready built tool that demonstrated success in classifying ground mesh in a number of environments including forested, flat rural, mixed elevation rural, urban, and indoor. It provides an efficient tool instead of requiring the user to develop classifiers for different environments and provides ease of use for the user. The decision to use conservative then aggressive ground classification allows the ability to identify the initial ground while ensuring differentiation between low lying vegetation and ground, while also recognizing higher planes with sharper slopes such as hilltops and outcrops. The use of Delaunay XY plane over a Delaunay best fit plane was used in CloudCompare as the XY plane is most beneficial for a relatively flat surface, and the ground classified points are generally in a relatively flat XY plane, as opposed to a plane reaching into Z. These choices allowed a ground mesh to be created with efficiency and accuracy.

The selection of Unity over Unreal Engine was made due to the flexibility and efficiency of C# and allowed current access to point cloud tools. Though Unreal Engine has improved graphics over Unity and higher rated visual effects, those were not key components in the development of the workflow which was focused on efficiency, ease of use, and accuracy. The use of C# over C++ was selected for faster compile and iteration times. Unity has up to date compatibility with the Point Cloud Viewer and Tools package, developed by a user, while the latest edition of Unreal is incompatible with the LiDAR point cloud plugin. Unity was selected for its efficiency, faster iteration and compilation times, and ability to utilize the Point Cloud Viewer and Tools package for ease of use.

The decision to use the paid Point Cloud Viewer and Tools over a particle system was made due to CPU and memory overuse. A script was developed to import a point cloud as a particle system using identified x-y-z positions, however, when this script was used beyond 10000 points, the CPU reached 100% capacity and the program crashed consistently. This is likely attributed to the lack of a spatial data structure. The Point Cloud Viewer and Tools allowed for larger point clouds to be loaded into the game engine, which improved efficiency and allows for users with less robust machines to utilize the workflow.

The Yaw2 and Logitech SDK packages were selected for their direct connection capabilities to the Yaw2 simulator and Logitech G-Series wheel and pedals. This offered immediate connectivity and ready built assets within Unity, enhancing the efficiency of the workflow.

4.5.2. Benefits of the Simulator

The immersive driving experience through collected data reaps benefits including the ability to immersively experience data, improved training capabilities for driving use cases, lower costs and easier accessibility, and improved spatial understanding of the data.

4.5.2.1 Practical Benefits for Applied Use

The capabilities to drive through data in VR with the Yaw2 simulator also allows for improved training benefits. Being able to experience the environment in XR facilitates understanding and can help train drivers who gather data in wilderness environments without the risk of inclement weather, natural hazards, complex morphology, or lack of access to services such as cellular service, GPS signal, or medical care. The simulation allows drivers to experience the actual yaw, pitch, and roll that would occur in the actual environment by driving on the simulated ground mesh. Similarly, the driver can develop improved practices for path identification by visualizing the gaps between obstacles in real scale and time.

4.5.2.2 Potential Spatial Data Visualization Benefits

The ability to immersively experience data allows for improved spatial skills and 3D understanding (Janeras et al. 2022; Harknett et al. 2022). While driving through the data, the user can understand the 3D space better, identify objects and their orientations such as the gaps between trees when driving or experiencing the yaw, pitch, and roll while traversing a slope. This allows the user to best comprehend the environment. This can also allow for data to be collected once out of the field, such as conducting a forest inventory by navigating through the environment or identifying potential outcrop locations that can be revisited upon returning to the site. The immersive data experience has potential for better 3D comprehension and data analysis.

The workflow allows the user to access an area they may not have been able to view in real life. Provided data has been previously collected in an area, either ground-based or airborne, the user can visualize and experience the point cloud in 3D. This could allow for future route planning in the area, understanding of a region, and lowers costs and accessibility barriers for sites that may be a far distance away, or morphologically challenging to access.

The immersive data experience lets the user understand the dataset and develop a 3D spatial understanding. The scale and distance can be better understood by being inside the data and improve spatial skills. By having the perspective of being inside of the dataset, and traversing it, the user can experience the real scale, navigation capabilities, and develop an improved understanding of the location without having to travel there.

4.5.3. Workflow Limitations

The workflow developed focusses on ease of use, efficiency, and accurately displaying the collected data to improve spatial understanding and experiential data comprehension. However, the workflow has limitations which can be addressed in future iterations including the use of proprietary software instead of open access, point cloud limitations in number of points, and potential ground classification issues.

The use of proprietary software over all open access software was selected for ease of use. ArcGIS Pro allowed a one-step tool to classify ground points, instead of developing classifiers for a series of different use case environments to be executed through CloudCompare, QGIS, or other open-source software. The use of game engines was required to simulate the driving environment, and regardless of engine would require cost at a certain level. The workflow also utilizes the Yaw2 simulator and Logitech G-Series steering wheel. Though these selections include additional costs, there are benefits weighing against the financial impact in efficiency, ease of use, and ability to experience the data in an immersive environment.

The importing of the point cloud into Unity has limitations regarding point cloud size that are linked to CPU. Beyond 432 million points, the Point Cloud Viewer and Tools package is unable to keep up with the demands of the point cloud, rendering the workflow unusable. This can potentially be overcome by limiting the point cloud to a specific area and exploring data in set intervals or tiling the area, which has not yet been explored.

The ground classification is limited as it is general tool that classifies the ground points based on slope and undulations. It is not specific to an environment, and thus lacks the ability to classify ground most accurately. Some of the ground points are not classified, and thus create additional noise in the point cloud. There is a trade-off between accuracy and efficiency in this case where the ability to use a single tool for multi-use cases and environments can prove beneficial when weighed against the development of specific single use classifiers for varying environments.

A key limitation regarding its immersivity is the input from both the headset and the steering wheel limits the yaw. The Yaw2 will pitch and roll but cannot orient itself with yaw due to the conflicting inputs from the turn of the steering wheel and headset. This is a future consideration that may potentially be overcome by only inputting steering wheel input for the Yaw2 simulator.

The workflow prioritizes usability and efficiency. Though it may come with a high cost due to simulators, and proprietary software, this cost may amount to less than travelling to a location to understand the initial data collected or travelling to train for wilderness driving. The workflow has limitations in capabilities, particularly with point cloud density and the yaw, and cost but works to balance them with speed, efficiency, and ease of use.

4.5.4. Comparison of Sample Datasets

The workflow was performed on sample datasets of indoor, urban, and rural environments. It showed varying degrees of capability for each, with main differences in the composition of the ground mesh, navigability, and the overall immersive data experience and point cloud viewing.

The composition of the ground mesh is different in the three environments. The indoor and urban environments generate a flat ground mesh to navigate on. Both created a ground with very little variance. The rural ground mesh has large variances in slope, and aspect, and has more extrusions.

The navigability of the data also varies based on the type of dataset. Indoor scenes allow for easy navigation, with clear cut walls and separation of objects. Urban scenes have a clear roadway to drive on. Rural scenes demonstrate more complex navigability with different path choices, which can also be beneficial for route selection training.

The full data experience also varies. Given an indoor scene is on a smaller scale, it is navigable “on foot” using the Quest 2 handheld joysticks. This reduces the immersive feeling, as the user does not physically walk through the environment but can navigate using keyboard keys or the VR headset remotes. On the other hand, the rural or urban settings allow for drivability through the scene, and given the yaw, pitch, and roll of the Yaw2, the pedals, and steering wheel, creates a more immersive environment for the data to be experienced in.

The urban scene allows for easier navigation and clearer boundaries in the data, but a less immersive experience. While the urban scene allows for easy navigation and an immersive experience. The rural data scene includes immersivity, potential for path selection with more complex navigation, and variance in the ground mesh. On the whole, the workflow shows best immersive capabilities in the rural dataset with applications in path navigation, understanding of trees, outcrops, and vegetation, and the best experience with yaw, pitch, and roll of the sensor.

4.6. Conclusion

The development of DRIVR represents a significant demonstration of the potential of a novel approach to data exploration and analysis using in geovisualization technology. Through the integration of immersive experiences and cyclical data collection processes, our system presents a potentially transformative solution to the challenges faced in traditional linear data production and user workflows, and immersive interpretive experiences with data from remote locations.

By introducing DRIVR as a tele-sensory geovisualization interface (a system that allows you to immersively view and physically feel spatial data from remote places), this paper addresses these proposes a paradigm shift towards interconnected data cycles. The methodology demonstrates a comprehensive workflow that integrates point cloud data processing, VR technology, and simulator systems. This methodology ensures the creation of immersive data experiences that are efficient and effective.

Results from sample datasets so far, showcased the capabilities of DRIVR across different environments, ranging from rural landscapes to urban settings and indoor spaces. The immersive data experiences provide users with a holistic understanding of spatial data, with the potential to develop improved spatial skills, and could improve training capabilities, and decision-making processes. The workflow's strengths and limitations revealed opportunities for future development using open-source technology and refining the ground classification technique used.

The implementation of DRIVR offers a versatile platform for immersive data experiences. By bridging the gap between field and lab environments and fostering iterative data collection processes, it has the potential to influence the way spatial data is utilized across various industries.

And while off-road driving context was our initial starting point, our vision for this system, and the research surrounding it goes considerably beyond any single application context. If we can generate data in or from remote locations, then this system allows us to explore and experience those places through tele-sensory geovisualizations. This becomes even more significant when we extend the scope of where and how remote data may be produced. In addition to terrestrial data, this can include deep-sea data surveys, and off-planet robotic surveying missions, such as

Artemis (Moon) and Mars. These capabilities will be demonstrated in upcoming future projects. There is also opportunity to conduct cognitive science and user testing with the DRIVR system in future research.

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Chapter 5. Conclusions

5.1. Summary of outcomes, objectives and research questions

The objectives of this thesis were to identify the feasibility of a remote field data production system and the capabilities of data to work between field and lab; establishing a cyclical data generation ecosystem; and conclude by attempting to build an immersive data experience with a simulator and VR – that acts to 'close the loop' between remote spaces and lab environments, through data acquisition, visualization and immersive information experiences.

This work presented three research papers tied together by the overarching theme of a data generation ecosystem, and the framework surrounding them, including an approach to combining remote sensing data collection with in-field processing, data analytics, and mixed reality.

Through these efforts, this research highlights the current practices of geovisual interfaces within the geosciences, helping to identify gaps and areas for future growth. It has also explored the feasibility of in-field data processing and the capabilities of a homegrown laser scanning system by demonstrating and documenting an empirical methodology to systemically quantify systems performance, as a basis for determining feasibility in the context of 3DMS use across a spectrum of field operations to laboratory use. This work also continued the cycle of data collection and experience into an immersive data experience in virtual reality and simulation.

Chapter 2 presented a review of the state of geovisualization, specifically geovisual interfaces, in the context of the geosciences sector. The current state of practice was reviewed using a literature review and explored limitations and future growth areas. The objective was to reveal existing gaps, limitations and future potential to allow for targeted development in a cyclical data generation ecosystem. By reviewing prevalent and relevant literature in the field, significant sector limitations were identified and areas of focus for future growth were highlighted.

Paper 1 (reported in Chapter 2) therefore achieved the first research objective "*Identify the current state of practice of geovisualization in the geosciences including key limitations, prevalent issues, and future potential"* by engaging the first two thesis research questions "*What is the current state of practice of geovisualization in the geosciences?"* and *"What are the limitations and key issues prevalent in geovisualization in the geosciences?*"

Chapter 3 presented an assessment of the data architecture and resource utilization of the 3DMS, a custom vehicle-mounted LiDAR system. The paper explored the feasibility of in-field data collection and processing of a homegrown, low-cost LiDAR system. The objective was to document the CPU, memory, and power use of the 3DMS, the data quality, and the file storage capabilities to reveal the feasibility of in field data collection and processing, fitting into the framework of the greater data collection ecosystem. Through an exploration of the 3DMS capabilities and resource utilization, a repeatable methodology for analyzing the resource utilization and data quality of different geovisual systems was developed.

Paper 2 (reported in Chapter 3) therefore achieved the second research objective "*Report on the needs and feasibility of the 3DMS in the context of a remote field data production system by identifying resource utilization needs including CPU, memory, power, and file size, and understanding the fidelity of the data produced by the 3DMS using point density*." by pursuing the third, fourth, and fifth research questions "*Is a remote field data production system feasible?", "What are the resource needs of the 3DMS?",* and *"To what extent does the 3DMS produce usable data?"* as the core of a granular systems performance assessment.

Chapter 4 explored an immersive data experience workflow where the user can drive through previously collected point cloud data. A workflow from initial point cloud data to a fully immersive driving experience was documented in the paper. The initial objective was to have the ability to navigate through collected point cloud data in an immersive environment using a combination of VR, steering wheel and pedals and simulator. This allowed for the review of data in an immersive environment, enhancing 3D spatial awareness and presenting a new perspective for data viewing.

Paper 3 (reported in Chapter 4) therefore achieved the third research objective "*Produce a workflow for an experiential data loop involving a simulated experience to gain the ability to simulate driving through data collected with the 3DMS and discuss decisions working towards an efficient workflow*." by implementing an immersive simulator system that connects the data produced remotely in the field, to user experiences in a research lab environment.

Together, these chapters help establish a greater cyclical data generation ecosystem that analyzes the feasibility of a remote field data production system, and the capabilities of data to work between field and lab, promoting a vision for what the future of data production and review can become.

5.2. Research Contributions

On the whole, this work contributes to the fields of geovisualization, geographic information science, and data architecture, and has presented the ability to explore a data collection, processing, and review cycle.

Chapter 2 identified gaps and challenges in 3D geovisualization for geoscience modelling. It serves as a foundation for future research, highlighting the need for the development of solutions to overcome limitations in the areas identified. Researchers can utilize this paper to allocate resources and make informed choices in data management and technology. It also aims to support advancements in 3D geoscience geovisualization, with the aim of improving modelling accuracy, enhancing data interpretation, and supporting more effective decision-making in the geosciences domain.

Chapter 2 builds upon past work in the geovisualization field that has reviewed the state of practice, identified limitations, and the uses of geovisualization including Çöltekin et al. 2020, Nelson 2023 and Elwood 2009. Elwood addresses emerging questions and linkages in GIScience in 2009 (Elwood 2009), and by revisiting similar questions on emerging practices and limitations in 2024 in geovisualizations, this work builds upon her past review. Çöltekin et al. review problems and research challenges in XR specifically (Çöltekin et al. 2020), this work builds upon similar research challenges in XR but through the lens of the geosciences. Nelson explores the design and evaluation stages of personal geovisualizations (Nelson 2023), this work has a related overarching goal, investigating the design and evaluation stages in a review format, but looks at it from a geosciences lens and expands beyond personal geovisualizations. Paper 1 (reported in Chapter 2) contributes to the fields of geovisualization in a broader context, identifying limitations and future growth areas for the state of practice in 2024, while introducing applications and information on the state of practice and limitations for geoscientists utilizing geovisualizations. It can help focus future works in applied research and development to relevant limitations and growth areas in the field and opens up opportunities to address field-wide limitations in geovisualization and adapt research to future growth areas.

Chapter 3 presented data analytics for visualization architecture, exploring the "under-the-hood" perspective and contributing to the development of in-field data processing and handling, analyzing a homegrown LiDAR system's capability. It offers a repeatable framework for other researchers to analyze the capabilities of their geovisual interfaces or data collection systems. The feasibility of the 3DMS is illuminated, demonstrating a wide range of applied use cases based on point cloud quality including basic surface models, forest inventory, flood and dam modelling, and basic 3D models. By highlighting the feasibility of field collection, processing, and storage in the 3DMS, we can change our relationship with remote spaces, making them accessible through data acquisition and mobilization.

Chapter 3 builds upon past works in resource utilization such as Romano et al. 2016, and is a complimentary paper to Matsushiba et al. 2024 (forthcoming). Romano et al. explore and identify performance tracking and optimization strategies for resource utilization, specifically CPU (Romano et al. 2016). This work builds upon past strategies in this field by introducing a workflow usable for geovisualization systems in an approachable way, specific to data processing and collection systems. This paper is a companion paper to Matsushiba et al. 2024 (forthcoming) which will detail the design and development of a homegrown LiDAR system. Paper 2 builds upon this by analyzing its resource utilization and capabilities to illustrate its in-field abilities. It has linkages to the geovisualization and data analytics communities while also being influential in industries such as forestry, mining, and the geosciences. It illuminates new opportunities for those versed in geovisualization to analyze and better understand their data collection and processing pipelines and create more efficient systems.

Chapter 4 put forth an immersive data experience for collected point clouds and demonstrated a new way to visualize and experience data while developing 3D spatial understanding. It presented a reproducible methodology to bring a point cloud from its initial format to a space where it can be experienced immersively; this workflow can be altered based on present hardware by removing steps and be used for different practitioners who seek to spatially understand their data. This has applications in a variety of use cases for path navigation, developing 3D spatial understanding of data, and immersive training experiences in fields such as forestry, urban design, civil engineering, mining, and geology. This furthermore encourages the accessibility of remote spaces by offering the ability to experience difficult-to-access locations in an immersive data experience.

Chapter 4 contributes to a body of spatial interface research that specifically that is both imagining and building the future of geovisual GIScience interfaces that combine and connect real and virtual worlds through data, visualization and new forms of user experience. This work includes that by Lochhead and Hedley 2019, Rydvanskiy and Hedley 2021, and Lochhead and Hedley 2021. Lochhead and Hedley 2019 develops evacuation simulations in real-world environments, Rydvanskiy and Hedley 2021 develops a mixed reality flood visualization, and Lochhead and Hedley 2021 designs virtual spaces for immersive analytics. This work builds upon those past papers by further exploring the blurring of the boundary between virtual and real worlds, and new ways to experience data. This paper also furthers previous works in virtual driving, such as Clement et al. 2022 and Min-Chi Chiu et al. 2020. Min-Chi Chiu et al. creates a virtual driving training environment and explores its use for people with limb differences (Min-Chi Chiu et al. 2020); this chapter develops a virtual driving system in a broader context, working to establish a clear workflow for a virtual driving experience. Clement et al. works to understand the psychological impacts between virtual driving and trust (Clement et al. 2022); this paper highlights the technical development of the virtual driving experience without the psychological component, focusing on a different aspect. This paper also has applications to the fields of geovisualization and the geosciences with potential industry applications in driver training and understanding of spatial data. It opens up new opportunities to explore spatial data understanding through immersion, driver path selection, and potentially develop driver training experiences.

The thesis develops a strong vision for changing the relationship between humans and remote spaces, presenting the potential to create more accessible data use and experiences through data acquisition, mobilization, and viewing. There are applications in a variety of use cases in forestry, civil engineering, mining, and geology, and methodologies that can be applied by users in 3D geovisualization to further systems development and data understanding.

5.3. Future Directions

Future directions for the work produced focus on applying the methodologies to broader applications and expanding on the vision for a cyclical data generation ecosystem.

Chapter 2 can be expanded upon by revealing limitations and growth areas at different intersections, to find sector-specific focuses, in fields such as mining, forestry, and civil engineering, where the methodologies developed in later chapters have applications. It can also be developed upon by keeping the review current. There is a rapid development of the technology and systems in the field. As technology changes, so does the field, and its applicable limitations and growth areas. Geovisualization is an ever-evolving discipline and as new methodologies, technologies, and systems emerge, so do new limitations and growth areas.

Chapter 3 has the potential to be expanded to other geovisual systems and interfaces. The methodology for analyzing the resource utilization of a geovisual or data collection system can be applied beyond the 3DMS in instances such as different types of remote sensing collection or LiDAR scanners (e.g. Leica vs Ouster) and in varying geovisual systems to analyze their feasibility. In order to elaborate on the field-lab connection, data transfer will be required. This should be explored, specifically ways to transfer data such as hard drive, using Starlink, or other methods, and compared to find the best way to bring data from the field to lab settings and enhance the ecosystem.

Chapter 4 can be improved by analyzing the data architecture of the system to create the most efficient methodology and documenting its performance. The workflow could be tested with different hardware to show its versatility, changing the simulator away from the Yaw2 and testing with a different VR headset, or functionality without a simulator or pedals. The ability to navigate through the point cloud can be enhanced by exploring the use of obstacles with physics properties (e.g. individual trees, buildings, etc.) to aid in training capacities and improve immersiveness. The workflow can be tested with improved hardware such as the MetaQuest 3 and a laptop with higher CPU and memory capabilities, to limit the lag, improve frame rate and help make the experience more realistic. By improving the immersive nature of the experience, the data can be better understood and the workflow can be used for various training capabilities, thus enhancing the link between field and lab.

In conclusion, this thesis presented a cyclical data generation ecosystem, including data collection, processing, and review which has been focussed by identifying the current limitations and growth areas at the intersection of geovisual interfaces and the geosciences. At the intersection of 3D geovisualization and geosciences, growth areas and limitations were identified, allowing the targeting of research gaps with the developed methodologies. The feasibility of a homegrown LiDAR system was analyzed through the documentation of its resource use and has permeating applications for other geovisual interfaces and data collection systems. Finally, an immersive data experience workflow was developed, allowing for improved spatial understanding and viewing of 3D data. All these components change the way we view the relationship between humans and remote places, making the inaccessible, accessible. By allowing the user to acquire, mobilize, and view data in a cyclical data ecosystem, it brings remote space closer and advances the ways we understand our data.

5.4. References

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