The University of Fiji
(An Entity of Arya Pratinidhi Sabha of Fiji)

A Smart Business Model for Land Management in Fiji

A Thesis

By

Sereana Driu

BIT (UniFiji), PGDIT (UniFiji)

Submitted in partial fulfilment of the requirements for the degree of

Master of Information Technology

Supervisor: Professor A B M Shawkat Ali, *PhD (Monash Uni)*

Department of Computer Science and Mathematics

The University of Fiji

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EXAMINER DECLARATION

The undersigned have examined the thesis entitled '**A Smart Business Model for Land Management in Fiji**' presented by **Ms. Sereana Driu**, a candidate for the degree of Master of Information Technology, Department of Computer Science and Mathematics, The University of Fiji and hereby certify that it is worthy of acceptance. As a Master's candidate, I declare that there is no conflict of interest to use the data in this thesis for research purpose.

Supervisor: **Professor A B M Shawkat Ali**, The University of Fiji, Fiji
Signature:
Date:

Examiner: **Girija Chetty**, University of Canberra, Australia
Signature:
Date:

Examiner: **Dr Meena Jha**, Central Queensland University, Australia
Signature:
Date:

ABSTRACT

The phrase “Business Intelligence” (BI) today is inextricably linked to Information Technology, and has been developing for over 150 years. Even though computers were invented before BI, it wasn’t until they became widely used that BI gained importance. From then on, its development was closely tied to computers and databases[1].

To assist businesses in making more data driven decisions, BI integrated business analytics, data mining, data visualization, data tools and infrastructure, and best practices. This thesis investigates into how the BI tool known as Tableau can forecast and visualize land management growth in the agriculture and residential sector in the Central-Eastern part of Fiji, along the Suva – Nausori corridor. Such visualization can assist decision making in understanding the growth in the area of development and also look into areas of future growth and how demographic and economic impact has had on the growth.

This thesis presents an intelligent business model for land management. This model is based on Machine Learning and Artificial Intelligence, which can be used to optimize land management decision-making. The model consists of four key components: a data analytics platform, a deep learning model to identify patterns, a predictive analytics model, and a decision support system. The first component collects relevant land management data from various sources, including satellite imagery, land-use maps, and other sources. The deep learning model is then used to identify patterns and trends from the data. The predictive analytics model then uses the data to predict land use and management operations. Finally, the decision support system recommends optimal decisions based on the predictions. The model is designed to provide a better understanding of land management and to improve land-use efficiency. The model can also be used for decision making in other sectors, such as urban planning and natural resource management.

[1] Derived from the website - https://www.toptal.com/project-managers/it/history-of-business-intelligence that explores the History of Business Intelligence. Accessed on Friday 28th October 2022 (Limp, 2018).

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Thanks to Tableau for giving me the accessibility to use their platforms and e-learning courses to understand and learn the features and functionalities available for my experiment.

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STATEMENT OF ETHICS

The data collected was a sample for this project as there was not enough time to request all data from the significant land owning entity in Fiji. The dataset was utilized for all the graphs and forecast to achieve the required results.

The number of words is 20,084, as counted by Microsoft Word, excluding references and appendices.

Sereana Driu

Date: 19th May 2023

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GLOSSARY

Table 1: Definitions

Terms	Definitions
A&BI	Analytics and Business Intelligence (ABI) is a catch-all phrase that refers to the software, hardware, procedures, and best practices that enable access and analysis of data to enhance and optimize actions and decisions (Gartner, 2023).
AIC	Akaike Information Criterion (AIC) is a mathematical method for evaluating how well a model fits the generated data. In statistics, AIC is used to compare different possible models and determine which one is the best fit for the data (Bevans, 2022)
Artificial Intelligence	The replication of human intelligence functions by machines, particularly computer systems, is known as artificial intelligence (Burns & Laskowski, 2023).
Artificial Neurons	A synthetic neural network connection is called an artificial neuron (Tucci, 2023).
BI	Business Intelligence (BI) platforms offer capabilities in three categories—analysis, like Online Analytical Processing (OLAP), information distribution, like reports and dashboards, and platform integration, such as BI metadata management and a development environment—companies can help businesses create BI applications (Gartner, 2023).
Convolutional Neural Network (CNN)	Used for image recognition and classification (Wood, 2022).
Data Analytics	The study of examining unprocessed data to draw inferences about such information is known as data analytics (Frankenfield, et al., 2022).
Deep Learning	Deep learning is a subset of machine learning, essentially a neural network with three or more layers (IBM, NA).

GIS&RS	Geographical Information Systems and Remote Sensing is one of the ways frequently used to get physical data for GIS integration is remote sensing. Only *by* making immediate contact, remote sensors gather information from earthly objects.
iTaukei	Identifies the native or indigenous people of Fiji.
Mataqali	Refers to sub-clans, a collection of groups of extended families whose four fathers are from the same family.
NLTB – Native Land Trust Boards	A trustee that looks at landowner's land that is now re-known as iTaukei Land Trust Board (TLTB).
Recurrent Neural Networks (RNN)	An example of a neural network with loops that allows data to be saved within the network is a recurrent neural network (Deep AI, NA).
Temporal Granularity	They are also known as TG which means the finest unit of time expressed by the view (Tableau, 2021).
Tokatoka	Refers to groups of extended families.
Turaga iTaukei	Refers to indigenous man also used to address Chiefly's positions in a village or district in Fiji.
Turaga ni Mataqali	An elected leader of the Mataqali, a sub-clan of a Fijian village.
Vanua	Refers to the land and can also be used to address a particular district or village title.
Yavusa	It is a collection of sub-clans (Mataqali units).

CHAPTER 1

INTRODUCTION

As the world progresses a lot of changes have been brought about and technology is one of the key agents of change in the evolution movement of businesses. There is no doubt that the acceleration of changes in business processes would elevate the need for business intelligence to help grow business grow its their field of expertise.

Business intelligence is the technology, tools, and procedures used to gather, store, use, disclose, and analyse data to aid decision making. All of these factors combine to produce a holistic picture of a firm that enables decision – makers to take better, more effective actions. Business intelligence has developed over the last few years to incorporate additional procedures and activities to aid performance. Flexible self-service analysis, controlled data on reliable platforms, empowered business users, and speed to insight are prioritized by modern BI solutions.

Fig. 1: Source: TechTarget.com –A timeline of notable BI developments (Avidon, 2019)

It is crucial to remember that this is a relatively contemporary understanding of BI, and the term has a troubled past as a catchphrase. Traditional business intelligence, complete with capital letters, first appeared as a method of information sharing between firms in the 1960s. In 1989, the phrase "business intelligence" was introduced along with computer decision-making models[2]. These programs continued to

[2] (Tableau, 2020)

evolve, transforming data into insights before becoming a specific service solution from BI teams with IT-dependent support.

Business Intelligence (BI) refers to gathering, analysing, and presenting data to support business decision-making. The concept of BI has evolved, reflecting changes in technology and the needs of businesses.

In the 1960s and 1970s, BI was primarily focused on operational reporting. This involved generating reports that summarized data from various business processes, such as sales, finance, and inventory management. These reports were typically printed out and distributed to decision-makers.

In the early 1980s and 1990s, developing a decision support system (DSS) helped move BI beyond simple operational reporting. DSS allowed users to interact with data, generate ad-hoc reports, and conduct what-if analyses. These systems were typically based on mainframe computers and required specialized training.

In the early 2000s, the development of data warehousing and online analytical processing (OLAP) technologies allowed BI to become more integrated and user-friendly. Data warehouses allow businesses to consolidate data from various sources into a centralized repository. OLAP provided a way to analyse this data using multidimensional models that could be easily visualized and explored.

In the mid-2000s, the rise of big data and cloud computing technologies transformed BI once again. The explosion of data from social media, mobile devices, and the Internet of Things (IoT) required new tools and technologies to manage and analyse this data. Cloud-based BI solutions emerged, providing businesses with scalable and flexible platforms for data analysis.

Today, BI has evolved to encompass various technologies and methodologies, including data mining, predictive analytics, and artificial intelligence (AI). These technologies allow businesses to gain insights into customer behaviour, market trends, and operational performance and to make data-driven decisions that can drive growth and profitability.

BI can be a powerful tool for land management. It helps organizations better understand their land and make informed decisions with the data they have. By leveraging BI, organizations can better identify trends and patterns and detect potential problems or opportunities. With an intelligent BI model for land management, organizations can use data to make decisions that will improve productivity, profitability, and sustainability. This model can help organizations develop an understanding of their land, analyse historical patterns and trends, and forecast future needs. With these insights, organizations can make the best decisions to ensure the long-term success of their land management activities.

In summary, the evolution of BI has been driven by a combination of technological advancements and the changing needs of businesses. As data continues to play an increasingly important role in decision making BI will likely continue to evolve and adapt to meet the needs of businesses in the years to come.

CHAPTER 2
LITERATURE REVIEW AND RESEARCH QUESTION

2.1 Overview

The literature review and research question chapter of a thesis is a critical component that serves as the foundation for the research study. This chapter aims to provide a comprehensive overview of the existing research and scholarly work in the field, identify gaps in the literature, and define the research question the study will address.

The literature review typically begins with a general introduction to the topic and provides an overview of the key concepts, theories, and research findings related to the subject area. It then goes on to critically evaluate the literature and identify the gaps in knowledge that the study aims to fill. This evaluation should be done by comparing and contrasting the different studies, and identifying strengths, limitations, and inconsistencies in the literature.

The literature review chapter should also provide a clear justification for the research question that will be addressed in the study. The research question is the central focus of the study and should be formulated to address the gaps identified in the literature review. It should be clear, concise, and specific to allow for a focused research study.

The research question should be developed based on the key concepts, theories, and gaps identified in the literature review. The question should be designed to test a hypothesis or answer a research problem systematically and scientifically. The research question should also be feasible, ethical, and relevant to the field of study.

In summary, the literature review and research question chapter of a thesis provides an overview of the existing research and scholarly work in the field, identifies gaps in the literature, and defines the research question that the study will seek to address. It is a critical component that forms the foundation for the research study and helps to guide the research design and methodology.

2.2 Literature Review

While researching for literature reviews, research articles and other journals of Business Intelligence studies that have been carried out before the key search words used were Business Intelligence on Land Management literature review or research paper, the outcome of the search came out with several types of research in which BI was involved in various industries.

Business intelligence models for land management have been increasingly studied in the past few years. This is because land management is a complex, multi-faceted problem that requires a variety of data sources, data analysis, and decision-making tools. In this literature review, several papers have discussed the business intelligence model for land management. We focus on the different approaches used to develop the models, the benefits of using business intelligence models, and the challenges that must be overcome to make them successful. Data mining is one of the most commonly discussed approaches to developing a business intelligence model for land management. Data mining techniques are used to identify patterns, trends, and correlations within large datasets that can be used to inform decision-making. For example, a data mining model can identify which areas of land are most vulnerable to land degradation or which are most suited for certain types of land use. This type of analysis can help land managers make more informed decisions about land use and management. Another approach to developing a business intelligence model for land management is using geographic information systems (GIS). GIS allows land managers to visualize data, such as land use and land cover, to better understand.

Business Intelligence (BI) models for land management are becoming increasingly popular in land management. These models allow land management companies to make more informed decisions about the land they manage and the resources they need to manage it. The introduction of these models has brought new opportunities, as well as challenges, to the land management sector. This literature review will analyse the papers that have discussed BI models for land management. The first paper to be analysed is "Business Intelligence (BI) Models for Land Management: A Review" by Yang Lee (Business Intelligence (BI) Models for Land Management: A Review, 2018) . This paper provides an overview of the current BI models and their application in land management. This paper also addresses these models' challenges and guides their successful application. The authors conclude that applying these models can give land managers the tools to make informed decisions about the land they manage and its resources. The second paper to be analysed is "Business Intelligence (BI) Models for Land Management: An Overview" by M.A. Rahman (Business Intelligence (BI) Models for Land Management: An Overview, 2017). This paper provides an overview of the various BI models available for land management.

Table 2: Literature review paper on business intelligence from 2015 - 2021

NO.	Research Paper Name	Brief Summary
1.	35 years of research on Business Intelligence process: a synthesis of fragmented literature.	This systematic review, however far from complete, attempted to synthesize the mass of information regarding the BI process using an integrative framework that highlights areas of overlap and knowledge gaps where scholars should focus. This article aims to inspire researchers to broaden their perspectives, adopt a more thorough understanding of the BI process to contribute to its organizational context and concentrate their attention on the linkages between the BI process, related constructs, and results (Kohtamäki & Talaoui, 2020).

NO.	Research Paper Name	Brief Summary
2.	Business Intelligence & Analytics applied to Public Housing	The paper aims to suggest a method, a framework, and finally, an architecture that would enable prediction in a decision-making process from a Big Data perspective. BI&A architectures, a fresh method for gathering and storing data called Data Lakes[3] is emerging. To enable users to conduct both types of analyses, separately or together on Big Data, it is recommended that BI and BA be combined in the general context of Big Data. Specifically, the data lake will be fed by two sorts of data: internal data, or data belonging to the organization, and external data, or data gathered from the Internet. Internal data will typically be structured data that does not have issues with big data. Since this organized internal data is the foundation of the business intelligence (BI) activity, it is often managed by an ETL, which feeds a data warehouse from which reports are generated. Big Data problems might arise from external data that comes from highly diverse sources. Although internal data can also be analysed using these techniques, external data is the primary source of BA analysis. To increase the number of variables or observations accessible or to provide "advanced" indicators that may be used in BI analysis, it is thought that external data can be connected with internal data from the company. The ultimate goal will be to take advantage of the metadata system's ability to store both raw and transformed data in the lake, feed various applications (including a data warehouse and predictive models), try to fine-tune a home's attractiveness, and give social landlords the ability to better manage their operations by comparing their data to external data. (Scholly, 2020).
3.	Business Intelligence Implementation Success Framework: A Literature Review	Business intelligence (BI) is a tool for managing businesses. SMEs utilize BI systems to research the elements affecting their business to aid in decision-making. It consists of tools and applications used to gather and analyse business-related information. BI can be studied from a process and a system

[3] A data lake is a sizable collection of unstructured raw data that is sourced from many different external sources. Data lakes rely on the schema-on-read attribute, which stores data in its raw form and only specifies the schema when it is queried. Numerous apps can access the data that is kept in a data lake, which is where the data is stored.

NO.	Research Paper Name	Brief Summary
		perspective as a separate field (Alali, et al., 2019).
3.	Business Intelligence Success Factors: A Literature Review	The four additional variables of vision and strategy, organizational structure, competency development, and organizational culture are added to the paper's research on the framework for the success of information systems (Gaardboe & Svarre, 2018).
4.	Literature Review of Business Intelligence	The literature evaluation offers fresh perspectives on how various BI components affect managerial decision-making standards directly or indirectly. Additionally, it helps clarify the BI Architecture and its components and the ideal circumstances for BI implementation. It also emphasizes how BI helps many firms by enhancing flexible reporting, analysis, and better decision-making by preserving higher data quality (Jain & Sharna, 2021).
5.	Modelling of Business Intelligence Systems using the Potential Determinants and Theories with the Lens of Individual, Technology, Organizational, and Environment Context – A Systematic Literature Review	A systematic literature study was carried out to investigate the most likely drivers and hypotheses that affect the adoption and acceptance of BIS in organizations, (Ahmad, et al., 2020).
6.	Possibility of improving efficiency within business intelligence systems in companies.	Business intelligence systems offer much potential for processing and evaluating the volume of structured data produced by the firm from various data sources. These data can be used to gather crucial facts, and knowledge, and even identify competitive advantages. These problems highlight the requirement for ongoing system effectiveness improvement (Kubina, et al., 2015).
7.	Research Paper on Business Intelligence	Business intelligence's main goal is to establish a solid foundation in online buying and selling, finance (investment, insurance, etc.), and, surprisingly, in betting, food, fashion, community delivery, and governance. In every area, there will undoubtedly be a strong preference for business intelligence over user assets and extensions (Bhosale, et al., 2021).
8.	The adoption of Business	A methodical examination of the literature was conducted to

NO.	Research Paper Name	Brief Summary
	Intelligence systems in small and medium enterprises in the healthcare sector: A systematic literature review	investigate the ideas and determinants that might have the greatest influence on how business intelligence systems are accepted and used in an organization, and in this case the healthcare system was the focus (Salisu, et al., 2021).
9.	The Impact of Business Intelligence in the Era of Big Data on Business Data Analysis	Business intelligence demonstrates past, present, and future events as well as the previous handling strategy. In contrast, company data analysis may analyse past, present, and future events as well as how to handle the finest business plan moving forward. Enterprises can incorporate information technology and execute efficient and automated decision-making by effectively integrating the two, which gives them a tool to boost their productivity (Yu, 2021).

Table 3: A literature review on land management

NO.	Research Paper Name	Brief Summary
1.	Digital land management technologies	In order to build a spatial platform for digital agriculture and the digital economy, the essay discusses difficulties linked to the support of digital land management with contemporary technology. Modern digital technologies create a new system infrastructure to support land management, making it possible to thoroughly optimize the procedures in the top-to-bottom management of national land resources. Numerous issues that need to be resolved involve enormous undertakings (such as a thorough inventory of the nation's land, monitoring real estate use, efficient real estate management, etc.). It entails digitising land management procedures using cutting-edge technologies like GIS, CAD, BIM, Big Data, and B*lockchain*. They can efficiently and quickly complete complex activities while building a new database that will fully automate the gathering, storing, and interpretation of geographical and associated data. The sector can be completely modernized with the use of new, cutting-edge information, communication, and computer technology. A different state approach to land policy is necessary for the complex system challenge of digitizing land management. It is vital to link the laws governing all lands

		co*mprehensively* manner while providing systematic state support for land management. Reorganizing and upgrading equipment is necessary for modernizing land management, which will cost a sizable sum of money (Papaskiri, et al., 2021).
2.	Modelling land use sustainability in Fiji Islands	The author highlighted topics under a summary of agroforestry and land use changes in the Fiji Islands, technology that are alternatives to Geographical Information Systems and Remote Sensing (GIS&RS) for forestry applications in the Pacific Islands. The other two areas of discussion were the Socioeconomic influences on changing agricultural practices in Fiji and Viti Levu's land suitability for planting significant tree species. In conclusion, the paper stated that the pressure to increase cropping areas and decrease dry seasons between crops is growing in the Fiji Islands, severely impacting soil erosion and nutrient deficits. The gradual transition from mono-cropping to agroforestry systems has positive long- and medium-term economic and ecological effects. However, most farmers still make decisions based on the short term due to uncertainty surrounding their land tenure and a lack of knowledge about sustainable land use techniques. Future land reformation plans must be implemented gradually under local circumstances, promote production, eliminate colonial-era tenures, and rebuild a more efficient organizational structure within associations of joint landholders. (Cornelio, 2017)
3.	Urban foraging: Land Management Policy, Perspectives and Potential	This paper examines the potential of urban foraging as an alternative land management policy, exploring the perspectives of both proponents and opponents of this practice. Urban foraging is defined as the practice of collecting food from wild, uncultivated areas of urban environments. The paper argues that urban foraging can provide significant social, environmental, and economic benefits, including improved access to healthy food, increased biodiversity, and potential job opportunities. Additionally, the paper discusses some potential challenges and risks of urban foraging, such as impacts on ecosystems and safety concerns for foragers. The paper concludes that urban foraging should be further explored and evaluated as an alternative land management policy,

		considering local contexts and the community's needs (Sardeshpande & Shackleton, 2020).

2.3 Research Questions

Throughout the years, the land has been a sensitive topic of discussion amongst the people of Fiji. As of today, many developments and leases are being given to tenants who would like to utilize land for their needs concerning residential, agricultural, commercial, industrial, or minerals around the country. However, there has not been any tool used to help the trustees who are managing the land for the people to help them make better informed decisions to sustain and continue to develop the land and people of Fiji. To fulfil the study's goal, the following research questions (RQ) are addressed:

RQ1: How to identify land valuation forecast using Tableau for Fiji's Central Eastern (CE) division?

RQ2: Discover, how the growth of Residential leases in the CE division for the past 10 years?

RQ3: How to Monitor and forecast agricultural land development using Tableau in the CE division?

2.4 Conclusion

In conclusion, this thesis's literature review and research question chapter has provided a comprehensive overview of the existing research and scholarly work in the field, identified gaps in the literature, and defined the research question that the study will seek to address.

Through a critical evaluation of the literature, it has become clear that there is a need for further research to explore the relationship between the key concepts and theories in the field. The identified gaps in the literature have highlighted the need for a focused and systematic study that addresses the research question scientifically and rigorously. While going through the literature review that was published between 2015 and 2021, there is a gap in the review that deals with the questions posed as the research question mentioned above.

The research question has been formulated based on the gaps identified in the literature review and is designed to test a hypothesis or answer a research problem. The question is clear, concise, and specific and is relevant to the field of study.

This thesis's literature review and research question chapter has provided a strong foundation for the study and will guide the research design and methodology. The study aims to contribute to the existing knowledge in the field and provide insights into the relationship between the key concepts and theories.

Overall, the literature review and research question chapter of this thesis has provided a comprehensive and critical evaluation of the existing research in the field, identified gaps in knowledge, and defined a clear and focused research question.

CHAPTER 3

RESEARCH METHOD

3.1 Overview

The chapter on research methods is a critical component of a thesis paper outlining the procedures and techniques used to conduct the research study. This chapter explains the research design, data collection methods, data analysis techniques, and any ethical considerations or limitations that may have affected the study.

The research method chapter begins with a clear and concise overview of the study's chosen research design. This section will describe the research approach, such as quantitative, qualitative, or mixed methods, and the specific research methods and techniques used to collect data.

The chapter also includes a detailed description of the data collection methods used in the study. This may include surveys, interviews, observation, or other data collection techniques used to gather data relevant to the research question. The chapter should provide a clear explanation of how the data was collected and any procedures or techniques used to ensure the reliability and validity of the data.

Data analysis techniques are also a crucial aspect of the research method chapter. This section should describe the techniques used to analyse the data collected, such as statistical, thematic, or content analysis. It should also explain how the data was interpreted and how the findings relate to the research question.

Ethical considerations are also an essential part of the research method chapter. This section will describe any ethical issues that arose during the study and the steps taken to ensure the ethical treatment of study participants. This section should also discuss any limitations or constraints that may have affected the study.

Overall, the research method chapter of a thesis paper provides a detailed explanation of the procedures and techniques used to carry out the study. It is essential for ensuring the reliability and validity of the research findings and for demonstrating the rigour of the research study. The research method chapter provides the reader with an understanding of the methods used in the study, the limitations, and any ethical considerations that may have affected the study.

In the literature, various research techniques and strategies, including conceptual, quantitative, qualitative, and mixed methods, have been utilized to apply the BIS.

Table 4: Search Results in Google

Years	2016-2022
Keywords	"Business Intelligence on land management literature review", "Business Intelligence on the land management research paper", "Business Intelligence", "Land management assisted by Business intelligence", "Business Intelligence for Property Management."
Databases	ResearchGate; ScienceDirect; Springer link; Google Scholar; MDPI; IGI-Global, Sematic Scholar

3.2 Data Collection and Sample Selection

Data was collected from a land management entity in Fiji that only focused on the country's Central-Eastern division. There were a total of 14849 data gathered that were classified into different land functionality and from which the data was divided among the two types as agriculture and residential usage. The sample was scrambled to avoid any confidential information being released like the land owning unit of the lease area or the land leaseholder. Information used is only focused on the rental and quantity of the lease growth over the past years about agriculture and residential leases.

3.2 Research Method

Several types of research methods are used in the social sciences and other fields. Some of the main research methods include:

1. **Quantitative research**: This research method involves collecting and analysing numerical data to test hypotheses and explore relationships between variables.
2. **Qualitative research**: This research method involves the collection and analysis of non-numerical data, such as interviews, observations, and open-ended survey responses, to gain a deeper understanding of a phenomenon.
3. **Mixed methods research**: This method involves using quantitative and qualitative research methods in a single study to gain a more comprehensive understanding of a phenomenon.
4. **Case study research**: This method involves the in-depth study of a single case or a small number of cases to gain a detailed understanding of a phenomenon.

5. **Action research**: This research method involves the active participation of stakeholders, such as community members or employees, in the research process to identify and address issues in a practical setting.
6. **Experimental research**: This research method involves the manipulation of an independent variable to test its effects on a dependent variable, often in a laboratory setting.
7. **Survey research**: This research method involves collecting data through standardized questionnaires or surveys administered to a sample population.

Each research method has its strengths and weaknesses, and the choice of method depends on the research question, the goals of the study, and the resources available. Researchers often use multiple methods to gain a more comprehensive understanding of a phenomenon.

The approach that is used in this research is the quantitative method. Quantitative research is a research method that uses numerical data to test hypotheses and explore relationships between variables. It typically involves collecting numerical data through surveys, experiments, or observations and analysing it using statistical methods. The goal of quantitative research is to identify patterns and relationships in the data and to make objective conclusions based on that analysis.

The quantitative research process usually involves the following steps:

1. Formulating a research question: The researcher begins by identifying a specific research question or hypothesis that can be tested using quantitative methods.
2. Designing the study: The researcher designs a study to collect quantitative data that will address the research question. This may involve selecting a sample population, designing a survey or experiment, or identifying a data source.
3. Collecting data: The researcher collects numerical data from the selected sample population or source. Data collection methods may include surveys, experiments, or observation.
4. Analysing the data: The researcher uses statistical analysis methods to analyse the collected data. This may involve identifying patterns or relationships between variables, using regression analysis, or conducting hypothesis testing.
5. Drawing conclusions: The researcher draws conclusions based on the data analysis. The conclusions should be based on statistical analysis and objective and data-driven.

Some advantages of quantitative research include collecting large amounts of data, generalising findings to larger populations, and testing hypotheses objectively. However, some disadvantages of quantitative research include the potential for the research to be superficial or lacking in depth, the potential for researcher bias in data collection or analysis and the potential for the research to overlook critical qualitative aspects of the phenomenon being studied.

3.3 Ethical Concerns

Potential ethical issues in any research study must be considered and addressed. One of the most common ethical setbacks that can arise is related to data gathering. Data gathering can involve collecting personal information about participants, which raises questions about the privacy and confidentiality of that information.

For example, suppose a study involves collecting sensitive data such as medical histories, financial information, or personal beliefs, or land ownership collecting sensitive data such as medical histories, financial information, personal beliefs, or land ownership. In that case, there is a risk that this information could be used against the participant somehow. This can be particularly concerning in studies that involve vulnerable populations, such as children, the elderly, or individuals with mental or physical disabilities.

To address these ethical issues, there is a need to take steps to protect the privacy and confidentiality of participants. This would involve obtaining informed consent from participants, ensuring that all data is stored securely, and using anonymized data to protect participants' identities.

In addition to privacy concerns, there are potential ethical issues related to how data is gathered. For example, if a study involves deception or coercion to obtain participant data, this could be considered unethical. Similarly, if participants are not fully informed about the nature of the study or their rights as participants, this could also be a breach of ethical principles.

To address these ethical concerns, as researchers, it is vital to ensure that participants are fully informed about the nature of the study and their rights as participants. This may involve providing detailed information about the study in the informed consent form, allowing participants to ask questions or raise concerns, and ensuring that participants have the right to withdraw from the study at any time. By taking these steps, researchers can help ensure that their study is conducted ethically and responsibly.

3.4 Big Data

Perhaps one of the most well-known expressions emphasizing the value of data is "Data is the new oil." Although the metaphor is certainly a little off, it captures the idea of our combined online influence on the world economy and our digital lifestyle. How much data is produced daily, in any case? Honestly, there is not a straightforward solution to this simple query. Even if they tried, the world's Google, Amazon, and Facebook could not keep track.[4] According to Brank.V, the global data sphere will have 175 zettabytes of data by 2025 and every single day in 2018, more than 2.5 quintillion bytes of data were produced. The digital world has produced huge amounts of data. In addition to mining 1.25 new bitcoins every minute, nearly 3.1 million gigabytes of internet data were used that year.

As for businesses, 53% are using big data analytics, according to a recent Dresner Advisory Services report on the topic[5]. Data sets that are too big or complicated for conventional data processing programs are called big data (Naganathan, 2018). Predictive analytics and other techniques were once utilized to extract value from data.

Big data systems that contain a mixture of structured, unstructured, and semi-structured data increasingly use BI platforms as their front-end interfaces. The flexibility of modern BI software's connectivity choices often allows it to connect to various data sources. This makes it a strong fit for big data architectures, as does the user interface (UI) of most BI products, which is generally relatively straightforward. In addition to traditional data warehouses, users of BI tools have access to Hadoop and Spark systems, NoSQL databases, and other big data platforms, giving them a unified picture of the varied data kept in each.

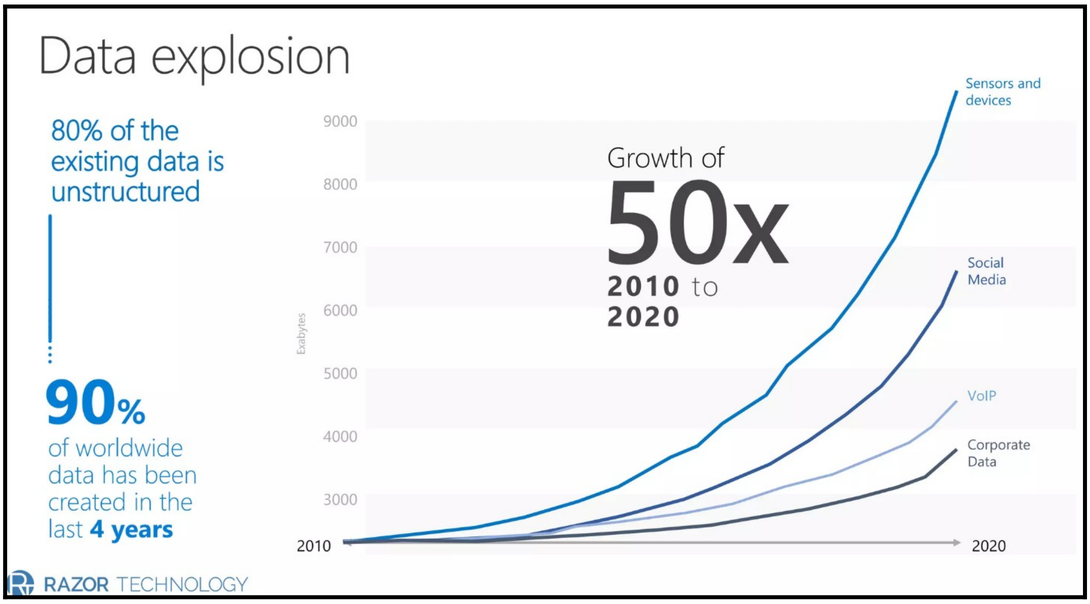


Fig. 2: Data growth between 2010 - 2020 (Rosenthal, 2019)

Big Data is part of the BI model, you cannot mention BI without Big Data. Big Data processing starts with the raw data, which is typically impossible to store in the memory of a single computer because it has not been aggregated (Naganathan, 2018). Big Data is a catchphrase for enormous amounts of data, both organized and unstructured, that constantly inundate businesses (Monnappa, 2022). Big Data can be

[4] (Vuleta, 2021)

[5] (Jovan, 2021)

utilized to analyse insights that could result in wiser company decisions and strategic business movements (Monnappa, 2022). Tom Davenport, IIA Director of Research, conducted interviews with more than 50 companies to learn how they employed big data, according to a paper on big data in significant companies. He sums up his report with the following conclusions (SAS Insights, 2018) below:

- **Cost Reduction**. When storing vast amounts of data, big data technologies such as cloud-based analytics can dramatically lower expenses (for example, a data lake). Big data analytics also aids businesses in coming up with solutions to operate more effectively (SAS Insights, 2018).
- **Making quicker, more accurate decisions.** Businesses can quickly evaluate information and make quick, educated decisions because of in-memory analytics' speed and capacity to examine new sources of data, such as streaming data from IoT (SAS Insights, 2018).
- **New Services and Products.** Businesses can provide customers with what they want, when they want it, thanks to the ability to measure customer requirements and satisfaction through analytics. More businesses now have the chance to create cutting-edge new goods in response to the shifting needs of their customers thanks to big data analytics.

3.5 Conclusion

In conclusion, this chapter is crucial as it provides an overview of the methods used to collect data and analyse the findings. The chapter discussed the importance of selecting an appropriate sample for the study and the methods used to collect data, particularly in quantitative research. The use of big data was also highlighted, emphasizing the potential benefits of using large datasets to enhance research findings.

Ethical considerations were also addressed, acknowledging the importance of ethical principles when conducting research. As a researcher, it is essential to ensure that the data being obtained are informed consent from participants, maintain confidentiality, and minimize any potential harm to the participants.

In summary, a thorough understanding of research methods is essential for conducting valid and reliable research. This chapter has highlighted the importance of selecting an appropriate sample, collecting data using appropriate techniques, and adhering to ethical guidelines. With this knowledge, the research provides meaningful insights into the research question, ensuring that the findings are accurate and ethically sound.

CHAPTER 4

DESIGN, DEVELOPMENT AND EVALUATION

4.1 Overview

The chapter focuses on designing, developing, and evaluating a Business Intelligence (BI) model for land management using Tableau as the BI tool. The chapter is divided into three main sections.

The first section introduces the concept of BI and discusses its importance in land management. It provides a brief overview of the four components of a BI model, including data sources, data warehousing, data mining, and data analysis. This section emphasizes the need for a robust BI model to help land managers make informed decisions based on accurate and timely information.

The chapter's second section discusses the available BI tools and evaluates their suitability for land management. The section provides an overview of the different tools, including Tableau, Power BI, and QlikView, and compares their features, functionality, and usability. This section concludes that Tableau is the most suitable BI tool for land management dues to its ease of use, flexibility, and ability to handle large datasets.

The final section of this chapter focuses on developing the BI model using Tableau. The section provides a step-by-step guide to building the model, starting with data collection and cleansing, then data analysis and visualization. The section also provides examples of how the BI model can be used to improve land management practices, such as identifying areas for conservation, predicting changes in land use, and analysing the impact of climate change on land resources.

The chapter concludes by emphasizing the importance of a robust BI model for land management and highlights the potential benefits of using Tableau as the BI tool. The chapter also suggests areas for future research, such as incorporating machine learning algorithms into the BI model and exploring the use of other BI tools for land management.

Fig. 3: Modern Analytics Workflow. Source from tableau.com

Another problem with many Business Intelligence (BI) definitions is that they frequently alter over time as people's perspectives on the same things shift. When the software industry first started using BI, it was considered personal insight rather than public or shared knowledge.

BI is defined as frameworks that collect, transform, and present structured data from various sources, reducing the time needed to gather essential business data and enabling its effective use in management decision-making processes (Solberg, 2015).

Institutions and companies have objectives and questions. In order to answer these questions, they collect the relevant data, analyse it, and decide which steps to take to achieve their goals to respond to these questions and monitor performance against these objectives. Technically speaking, unprocessed data is gathered from business systems. These unprocessed data are then processed, then kept in data warehouses, the cloud, applications and files[6]. Users can access the data once it has been stored and begin the analysis process to provide answers to their unanswered business questions. Other features provided by BI tools are turning data into charts or graphs and presenting them to important decision-makers.

4.2 The Four Key Components of the BI Model

BI is an umbrella phrase that covers the procedures and techniques for gathering, classifying, and analysing data from business operations or activities to improve performance. It is much more than just one particular "thing." All of these combine to produce a comprehensive image of a firm to enable people to make better,

[6] (Tableau, 2020)

more effective decisions. In order to enhance performance, BI has accelerated over the past few years to include additional activities and processes. These new processes are:

- *Data mining* - analysing massive datasets with databases, statistics, and machine learning (ML) to find patterns.
- *Reporting* - Providing stakeholders with data analysis so they can develop conclusions and take action
- *Benchmarking and performing metrics* - Utilizing specialized dashboards, performance versus goals is tracked by comparing recent performance data to past performance data.
- *Descriptive analytics* - utilizing early data analysis to ascertain what took place.
- *Querying* - BI asks data-specific inquiries and then extracts the responses from the data sets.
- *Statistical analysis* - utilizing the outcomes of descriptive analytics to explore further the data with statistics, such as how and why this pattern occurred
- *Data visualization* - transforming data analysis into visual analytics using histograms, charts, and graphs to make data easier to absorb.
- *Visual analysis* - utilizing visual storytelling to explore data, share findings quickly, and maintain an analytical flow
- *Data preparation* - assembling various data sources, figuring out their parameters and measurements, and getting them ready for analysis

a. BI, Data Analytics, and Business Analytics function together

Data analytics and business analytics are both a part of business intelligence, but they are only used in small amounts overall. Data scientists use advanced statistics and predictive analytics to delve into the details of data in order to find patterns and predict new patterns. Data analytics asks, "Why did this occur, and what might occur next?" Business intelligence utilizes these models and algorithms and transforms the output into language that can be used to take action (Tableau, 2020).

Business Intelligence is all about utilizing the data made available, there are two ways in which a business or organization can utilize these data: Predictive Analysis and Forecasting. The two terms may sound like they mean the same thing; however, there is a slight difference between the two analysis methods. The two techniques will be further elaborated in this paper, and the technique used to experiment on the data sample will be identified and explained.

4.2.1 Data Analytics Platform

Data analytics platforms are increasingly becoming the foundation of today's digital business. They enable organizations to collect, analyse, and present large amounts of data in meaningful ways. Data analytics platforms allow organisations to gain insights into their customers, operations, and processes. By leveraging data-driven decision making, businesses can become more efficient and profitable.

Data analytics platforms enable organizations to collect and analyse large amounts of collected data quickly and analyse large amounts of data quickly. These platforms allow businesses to gather data from multiple sources, including databases, applications, web browsers, and mobile devices. Businesses can gain a holistic view of their customers and operations by collecting data from multiple sources. In addition, analytics platforms enable businesses to identify trends and correlations in their data. This helps them better understand their customers and improve their products and services.

Data analytics platforms also enable businesses to create visualizations of their data. These visualizations make it easier for businesses to understand their data and identify patterns and relationships. This can help them identify opportunities to improve their operations and provide better customer service.

Finally, data analytics platforms allow businesses to share their data with other organizations. This can benefit companies collaborating with other businesses, allowing them to share data and insights to create better products and services.

In conclusion, data analytics platforms are essential for businesses to gain insights into customers and operations. By leveraging data-driven decision making, businesses can become more efficient and profitable. Data analytics platforms enable businesses to quickly collect and analyse data, create visualizations, and share data with other organizations.

a. Deep Learning Model to Identify Patterns

Deep learning is an artificial intelligence approach that uses self-learning algorithms to identify patterns in data, allowing for the automated recognition of complex patterns. It is a subset of machine learning that seeks to recognize patterns in data by using multiple layers of artificial neural networks. Deep learning models can identify patterns in large amounts of data, such as images, text, and videos, and generate predictions based on those patterns.

The main goal of deep learning is to uncover hidden patterns and correlations in data, which can be used for a wide range of applications, from image recognition and speech recognition to natural language processing and autonomous driving. Deep learning models are composed of interconnected layers of artificial neurons responsible for recognizing patterns in data. Each neuron processes data independently, allowing for the simultaneous processing of multiple data points. The interconnected layers of neurons are responsible for learning the data patterns and making predictions based on those patterns.

One of the most popular deep learning models is the convolutional neural network (CNN), used for image recognition and classification. CNNs are composed of multiple neuron layers arranged in an ordered hierarchy. Each layer is responsible for extracting more complex features from the data. For example, the first layer may extract edges, while the second layer may identify shapes. The deeper the network, the more complex the features that can be extracted.

Deep learning models can also be used for sentiment analysis, where they are used to identify the sentiment of a text. These models are composed of multiple layers of neurons that are trained on labelled data. The neurons in the layers are responsible for extracting features from the text, such as words and phrases, and for making predictions based on those features.

Finally, deep learning models can be used for time series analysis, where they are used to identify patterns in time series data. These models are composed of multiple layers of neurons trained on labelled time series.

Deep Learning (DL) is a branch of Artificial Intelligence that uses algorithms to learn from data in an unsupervised manner. DL models can learn complex patterns and relationships from large amounts of data. Tableau is a powerful data visualization tool to uncover dataset's insights and trends. The combination of Deep Learning and Tableau can be used to identify patterns and relationships in data that are not easily detected by traditional methods.

In order to use Deep Learning in Tableau, the data must first be pre-processed and prepared for the model. Feature engineering, data normalization, and feature selection are necessary before the data can be fed into the DL model. After the data is ready, the model can be trained using various DL algorithms, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). Once the DL model is trained, it can be used to generate insights from the data. For example, a CNN can be used to identify patterns and correlations in large datasets. This can be used to uncover meaningful relationships in the data that may not have been discovered using traditional methods (Meimand, 2021).

Tableau can then be used to visualize the insights generated by the DL model. This can be done by creating visualizations such as charts, graphs, and maps. These visualizations can be used to analyse the data and identify trends, correlations, and outliers.

In conclusion, Deep Learning and Tableau can be used together to uncover valuable insights from data. These two powerful tools can be used to identify patterns and relationships that would be difficult to detect with traditional methods. Organizations can gain valuable insights and make better decisions by pre-processing and preparing the data, training a DL model, and visualizing the results in Tableau.

b. Predictive Analytics Model

Predictive analytics models are an increasingly important tool in the modern data-driven world. These models use data from past events to forecast future outcomes, providing businesses and organizations with valuable insights into their processes, products, and customers. Predictive analytics models are used to identify trends and patterns in data, predict customer behaviour, and identify risks and opportunities.

At the core of predictive analytics, models use algorithms and data mining techniques to find patterns and relationships in data. These models analyse large amounts of data to detect patterns, trends, and correlations. Once the patterns are identified, they can be used to predict future outcomes. For example, a predictive analytics model may identify a pattern in customer purchase data that indicates a likelihood of a customer buying a particular product. This information can then be used to target the customer with tailored marketing messages or to develop new products or services.

In addition to predicting future outcomes, predictive analytics models can also be used for anomaly detection. Anomaly detection is the process of identifying data points that do not fit with the expected pattern. This can be used to detect fraud and other suspicious activities. Predictive analytics models can also be used to identify correlations between different data sets, such as customer demographics and product sales. This analysis can help organizations better understand their customer base and improve their marketing strategies.

Predictive analytics models are becoming increasingly important for organizations of all sizes. They provide valuable insights into customer behaviour, trends, and risks. By leveraging the power of predictive analytics models, businesses and organizations can gain a competitive edge over their competitors and make better decisions to increase profits and reduce risk.

4.3 Business Intelligence Tools: Analysis

Nowadays there are many different BI tools available for beginners to experienced level users, from non-IT background users to experienced developers, from small organization to large companies; whether hosting is required in-house or cloud hosted; with the wide range of platforms available, there is a suitable tool for everyone.

According to the most prominent research organization Gartner, the Magic Quadrant for Analytics and Business Intelligence Platforms for 2022, they have identified a total of twenty (20) platforms that rated according to their capabilities and the areas that they were measured on are (Mitchell, 2022):

i. Security
ii. Governance
iii. Cloud-based analytics
iv. Data source connectivity
v. Data preparation
vi. Catalogue
vii. Automated insights
viii. Data visualization
ix. Natural language generation
x. Reporting

Analytics and business intelligence (ABI) tools, according to Gartner, make it possible for less technically savvy employees of any team to "analyse, examine, exchange and manage data." (Mitchell, 2022) These features are the cornerstones of distinguishing the 20 vendors' offerings. Gartner has divided each vendor into four categories: leaders, challengers, visionaries, and niche players by, carefully evaluating each one (Mitchell, 2022).

Fig. 4: Gartner Magic Quadrant for Analytics and Business Intelligence Platforms 2022 (Mitchell, 2022)

a. Leaders

Leaders in the magic quadrant combine a strong vision with a track record of delivering value by demonstrating a comprehensive understanding of critical ABI capabilities and a dedication to client success. They not only provide evidence of this value but also allow for incremental purchases and corporate scalability to meet the unique requirements of businesses in various industries. As depicted above, these leaders are:

- ❖ Microsoft (PowerBI)
- ❖ Salesforce (Tableau)
- ❖ Qilk

b. Challengers

Challengers in the magic quadrant are well-positioned to thrive in the ABI market and present a demonstrated capacity to deliver value for companies with particular use cases consistently. Meanwhile, these providers' cooperation across the many items in their portfolios appears to be lacking. On the other hand, they risk lagging behind market leaders in terms of sales and marketing, industry-specific content, and innovation. These challengers for 2022 are:

- Google
- Domo

c. Visionaries

Visionaries in the magic quadrant offer a distinct, solid vision for the contemporary ABI platform and excellent functionality in their specialized fields. Sadly, in spite of their thought leadership, they occasionally lack the broader competencies needed to implement an ABI solution at scale and reliably. Falling into this visionary list are:

- ThoughtSpot
- Sisence
- Oracle
- SAP
- TIBCO Software
- SAS
- IBM
- Yellowfin
- Tellius

d. Niche Players

These suppliers can offer the perfect solution to businesses utilising a specific cloud stack because they frequently produce incredible results across particular industries or use cases. However, Gartner doubts the company's capacity to rival market leaders in innovation and execution. 2022 niche players are:

- Amazon Web Services
- Alibaba Cloud
- Zoho
- Pyramid Analytics
- MicroStrategy

- ❖ Incorta

4.3.1 Selecting the BI Tool

While deciding which tool to use for the experimentation of land data, two contenders are the top leading platforms mentioned by the Gartner matrix, ***Microsoft (Power BI)*** and **Salesforce (Tableau).**

i. *Power BI*

The industry-leading BI application Power BI is used for data analytics, data visualization, and the creation of ad-hoc reports that provide a multi-perspective view of the information. After the data has been cleaned (which entails actions like importing data, converting data to tabular format, splitting up columns, removing extra rows, and un-pivoting the region columns), and integrated (which entails combining data from various sources and producing a single data model for analysis), anyone can handle data from different sources. It enables viewing, visualizing, and data analysis. To import data from PXIB files employ robust compression algorithms. In order to make it easier to use, it offers numerous software services, over 100 connectors, and a drag-and-drop function. The created dashboards are valuable and straightforward to comprehend. Those already utilising Microsoft technologies like Excel, Azure, and SQL will find Power BI a simple win (InterviewBit, 2022).

ii. *Tableau*

Tableau is a well-liked business intelligence and data visualization solution for reporting and analysing vast amounts of data. Users can use it to generate various graphs, maps, dashboards, and stories to visualize and analyse data to aid in business decision-making. Tableau's intelligible formats make the data it generates accessible to users of all levels. Users do not need to be well versed in any technical skills to develop a customized dashboard with Tableau.

Table 5: Comparison between Power BI and Tableau (InterviewBit, 2022)

Power BI	Tableau

Low-cost software. The pro version of power bi costs $10 per month per user.	More expensive than Power BI. The pro version
While the data volume is little, it operates more quickly and effectively; but it becomes slow when processing mass data.	It offers a wide range of tools for data visualization and is appropriate for quickly handling big volumes of data.
A free Power BI account has limited customer assistance.	Due to its substantial community platform for debate, it offers great customer service.
R-based visualizations are supported.	Python and R are both fully supported and integrated.
It is appropriate for small and medium-sized businesses.	It is appropriate for Medium-sized and large-sized enterprises.
Using the Embed option, it can quickly and securely incorporate Power BI reports in internal web portals.	In Tableau, embedding reports into a new environment might be complex.
Many tasks are made simpler by the query editor that Power BI provides (used to alter data files before putting them into Power BI).	Tableau does not support this feature.
Power BI can only run on Windows because it is a Microsoft product; it cannot operate on Mac.	Both Mac OS and Windows support Tableau.
Both novice and knowledgeable users typically use it.	For their analytical aims, experienced analysts typically employ it.
Although Power BI supports a wide range of data sources, it has less access to additional databases and servers than Tableau.	Several servers and data sources are available to Tableau Software.
Power BI has a SaaS infrastructure and strict license.	Tableau has n-tier client server architecture and variable license.
It is connected with Microsoft Azure, which aids in data analysis and product pattern comprehension.	Tableau has built-in machine learning capabilities, making it suitable for doing ML operations on datasets.

From the comparison mentioned above, the tool selected was ***Tableau*** mainly for the following reasons:

- *Tableau can run on both Windows and Mac OS operating systems*
- *Provides 12 months of free access to students to their services and platforms*
- *Provides free e-learning courses for students to use*
- *Support is easily available from a wide range of forum communities.*

A Tableau can forecast land management by visualizing current and historical land management data, such as land use, land cover, land ownership, and land zoning. Tableau can create interactive visualizations that show how land management decisions have impacted the land over time and can be used to explore potential outcomes of future decisions. Tableau can also be used to track changes in land use and land cover over time and to forecast the potential impacts of proposed land management policies.

4.3.2 Predictive Analysis

Being strategic and proactive are frequently emphasized in excellent business training. For businesses to be reacting to every innovation and sporadic failure is insufficient in today's competitive market. Organizations should instead be forward-thinking, predicting outcomes, seizing opportunities, and limiting losses. Predictive analytics is now easier to use, thanks to increased data volumes and user-friendly tools, enabling businesses to be more proactive and boost their bottom line.

With methods like data mining, statistics, data modelling, artificial intelligence, and machine learning, predictive analytics calculates the likelihood of future events. Simply said, predictive analytics analyses past data from an organization to produce future projections. With the use of modern predictive analytics approaches, a business can spot trends in the data that indicate impending hazards and opportunities.

A. Common Techniques for Predictive Analytics

Predictive analytics have a wide range of potential uses, and the models underlying their insights are highly diverse. Identifying the organisation's objectives makes it easier to determine the ideal predictive analytics tools. To determine the tool to be used, is determined by the objectives the organization wants to address. Four categories classify the different types of predictive analytics models as stated below:

1. **Regression Models** determine how strong a link between two variables is. In order to anticipate future effects, the model keeps track of how actions (independent variables)

affect outcomes (dependent variables). Simple linear regressions with one independent variable and one dependent variable or multiple linear regressions with two or more independent variables are two examples of these statistical models. Depending on the context and types of variables involved, a range of regression approaches can be used. Organizations can use scenario analysis, sometimes known as "what-if" analysis informally, to plug in new independent variables and evaluate how they affect the result by describing the connection between the variables. In order to ascertain how a product's characteristics affect the chance of purchase, organizations may utilize a regression model. A firm may discover a link between the colour of the product and the chance of purchase by examining the relationship between the two. For example, blue shirts may be associated with higher sales. The company may investigate how other variables, such as size, seasonality, or product positioning, affect the probability of purchasing because the connection does not imply causation. These insights can be used to guide marketing campaigns or the development of new products to identify which goods are likely to succeed in the future.

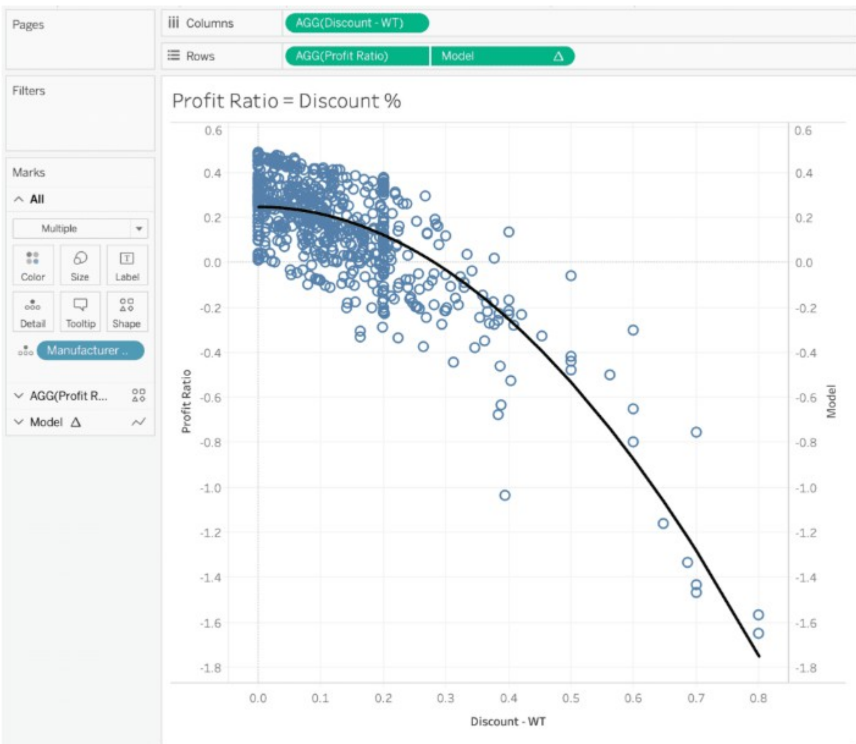


Fig. 5: Example of Linear Regression Model: Source phData Blog (Stanke, 2020)

2. **Time-series Models** accumulate information based on time. Time is one of the most frequently used independent variables in predictive analytics since so much of the world's data can be described as a time series. The usual model would be to use the data from the previous year to analyse and predict a statistic for the next few weeks. Organizations utilize time series studies for several purposes since time is a standard variable. This model can be applied to trend analysis, which charts the movement of assets over time, or seasonality analysis, which forecasts how assets are affected by specific year periods. Forecasting sales for the next quarter, estimating store traffic, or even figuring out when the flu would likely strike are some examples of practical applications.

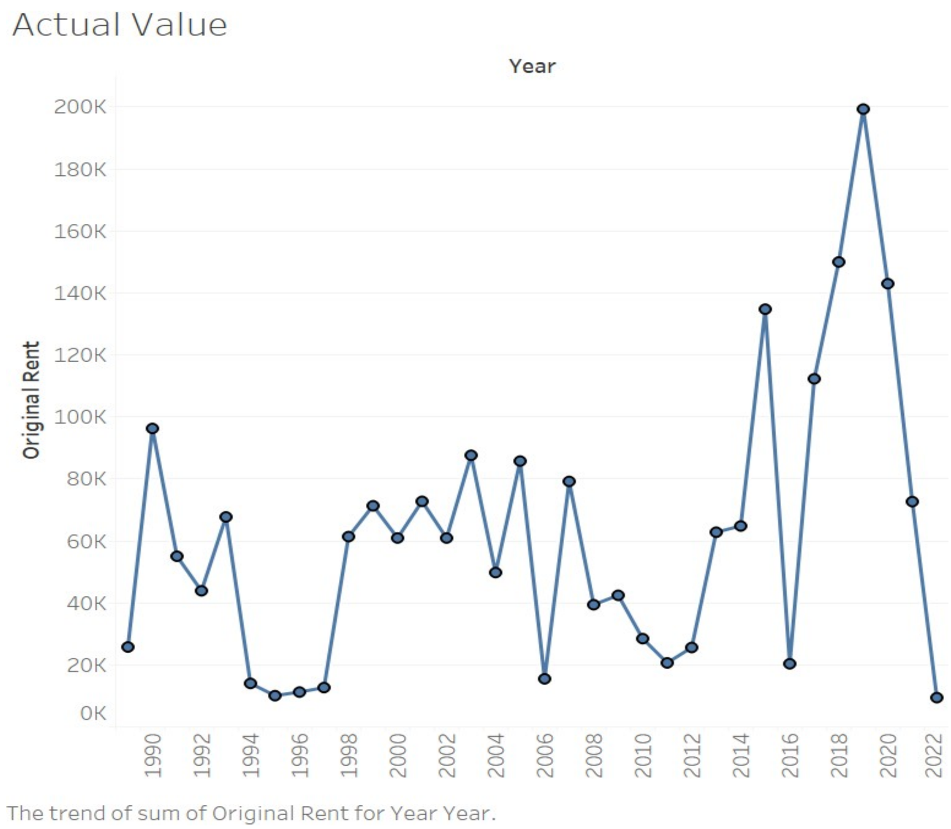


Fig. 6: Example of Time Series Model

3. **Clustering Models** cluster data based on comparable characteristics. A clustering model uses a data matrix to link individual items to pertinent attributes. The algorithm will use this matrix to group items with the same features, revealing patterns and insights that may have previously been concealed. Businesses can use clustering models to categorize their clients and develop more specialized marketing plans. For instance, a restaurant might

group its patrons according to where they are and only distribute flyers to patrons within a specified driving distance of its most recent location.

Fig. 7: Example of Clustering Model. Source from H2KInfosys blog (Kumar, 2020)

4. **Classification Models** categorize data based on past knowledge. A training dataset with all of the data labelled at the outset is used for classification. Any new data is classified by the classification algorithm when it understands the relationships between the labels and data. Decision trees[7], random forests[8], and text analytics are common categorization model strategies. Many organizations utilize classification models because they are simple to retrain with new data. To detect fraudulent transactions, banks frequently employ classification models. To predict what potential fraudulent transactions would look like, the system can examine millions of recent transactions. It can also notify users when behaviour on their account becomes suspect.

[7] Decision tree classification method generates branching options and probabilities for each one. When modelling nonlinear relationships between classes, this techniques works well, according to (Lu, 2022)

[8] Also according to (Lu, 2022), Random forest classification model is trained utilizing the output of an ensemble of randomly generated decision trees by a classification algorithm.

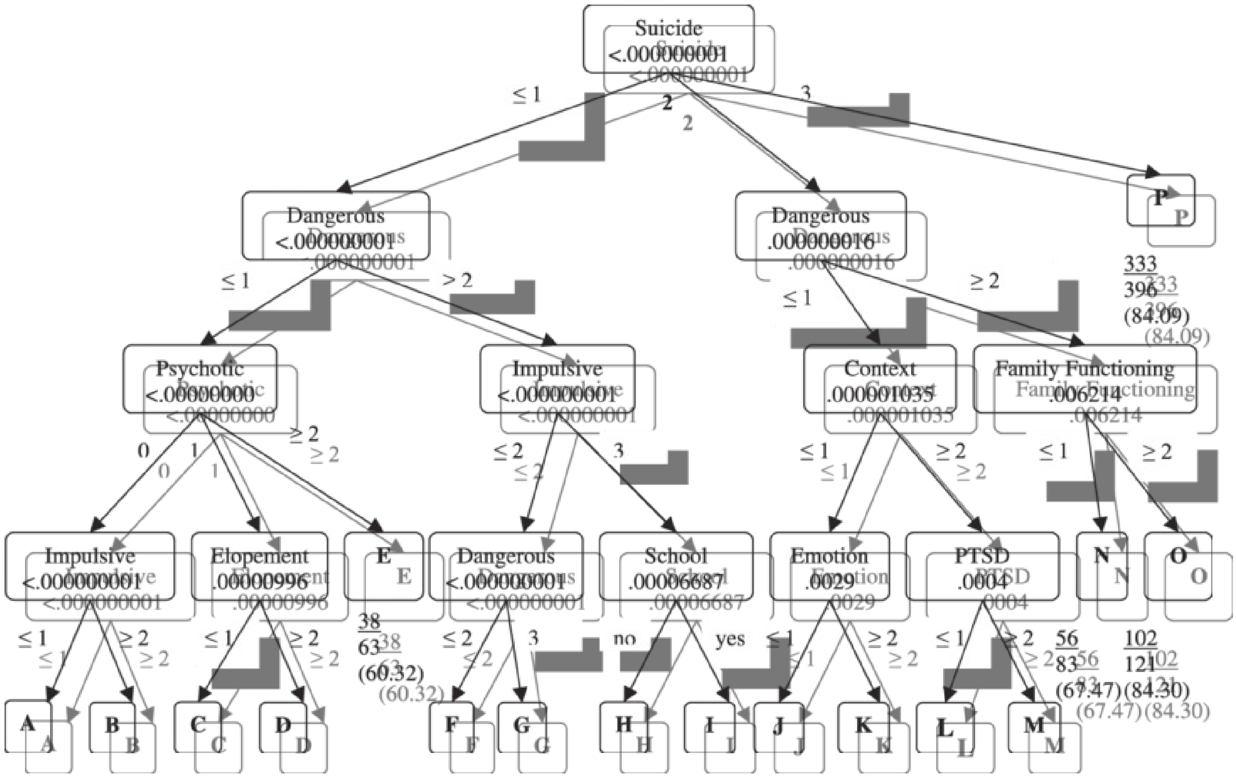


Fig. 8: Source ResearchGate (Lyons, 2007), and example of a tree model for classification model

Sometimes a combination of the models is used to look for insights and possibilities in the data being analysed. For instance, a collection of algorithms known as neural networks are used to find patterns in data by simulating the functioning of the human brain. Neural networks can handle enormous data and create incredibly complex relationships by combining regression, classification, clustering, and time series models.

B. Importance of Predictive Analytics

Organizations can use predictive analytics to be more proactive in their daily operations by seeing trends that might help them make wise decisions. Thanks to the predictive models described above, organisations no longer need to rely on informed guesses because forecasts offer more information.

4.3.3 Forecasting

Using data from the past, present, and trend analysis, *forecasting* is a planning technique that assists management in its efforts to deal with the unpredictability of the future, according to Michael (Sandnerg, 2017). Assumptions are made at the beginning of the forecasting process based on management's experience, expertise, and judgment.

These estimations are extrapolated into the upcoming months or years using various methods, including Box-Jenkins models, the Delphi method, exponential smoothing, moving averages, regression analysis, and trend projection. Sensitivity analysis is a method that assigns a range of values to uncertain parameters because each miscalculation in the assumptions will have a similar or amplified effect on forecasting (variables).

A. Types of Forecasting Methods

There are two methods of forecasting:

1. **Qualitative Method -** They depend on the judgment and opinion of experts or customers, making them subjective. Qualitative methods are utilised for medium to long-term judgments when historical data is unavailable. A type of qualitative forecasting technique is market research.

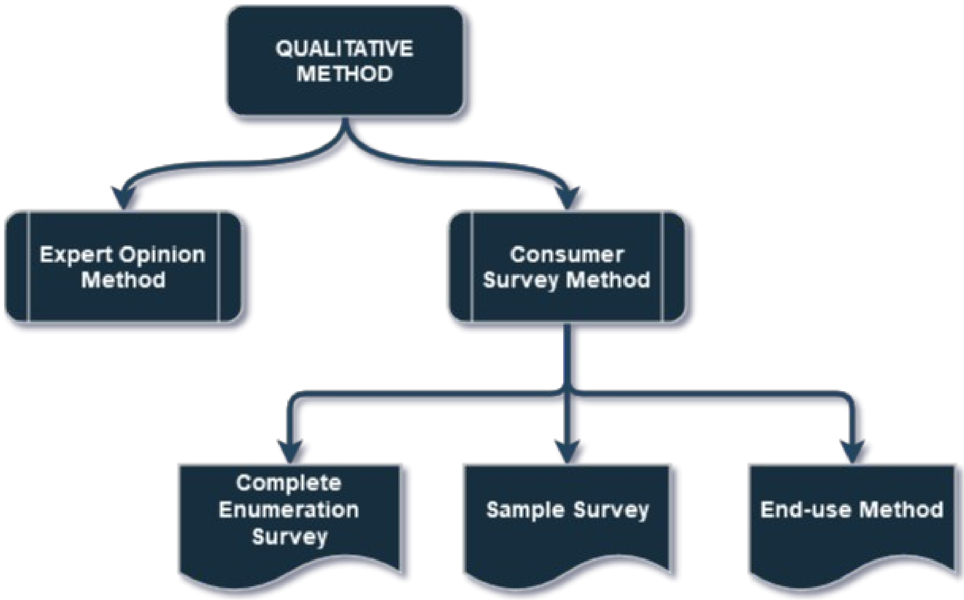


Fig. 9: Qualitative Method of Forecasting

2. **Quantitative Methods:**

These forecast future data based on historical data. When we have historical numerical data and can reliably predict that some data patterns are likely to persist in the future, these strategies are acceptable. For making decisions that may affect the short and medium-term, quantitative methods are typically used.

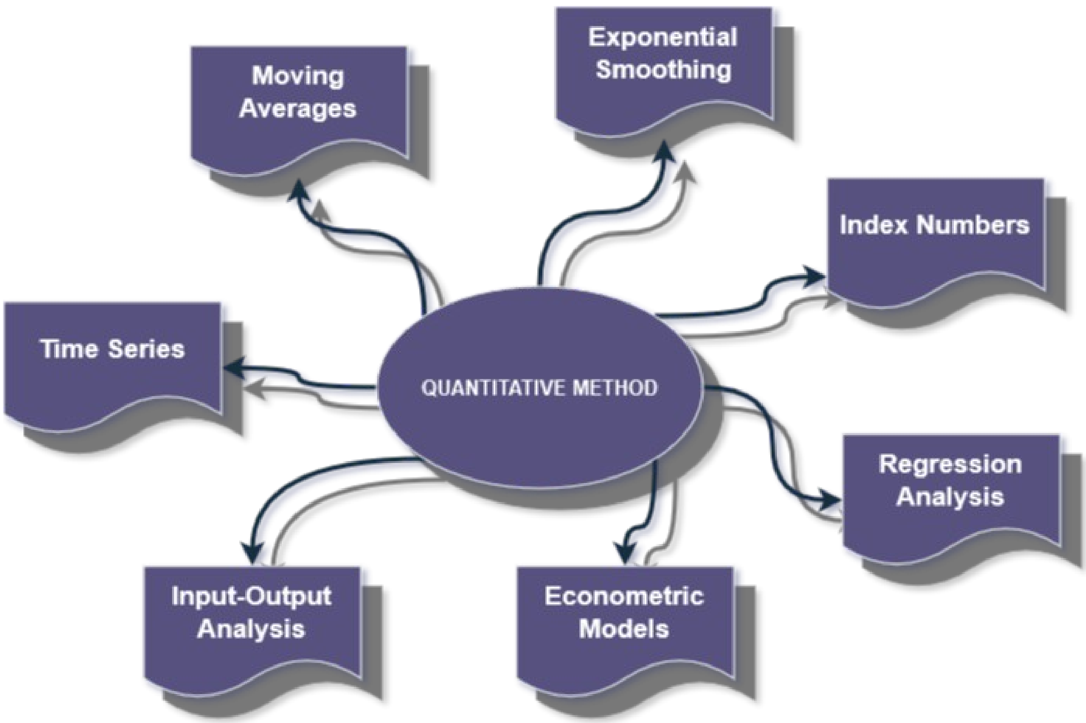


Fig. 10: Quantitative Method of Forecasting

4.4 Development

The BI tool used with sample data from a Land Management entity in Fiji is Tableau. Tableau enables individuals and businesses to become more data-driven. The Tableau analytics platform, one of the industry standards for modern BI, facilitates faster discovery and sharing of insights that potentially transform industries and the global economy. Regardless of the user's role—analyst, data scientist, student, teacher, executive, or business user—Tableau is made to help them comprehend the data they utilize.

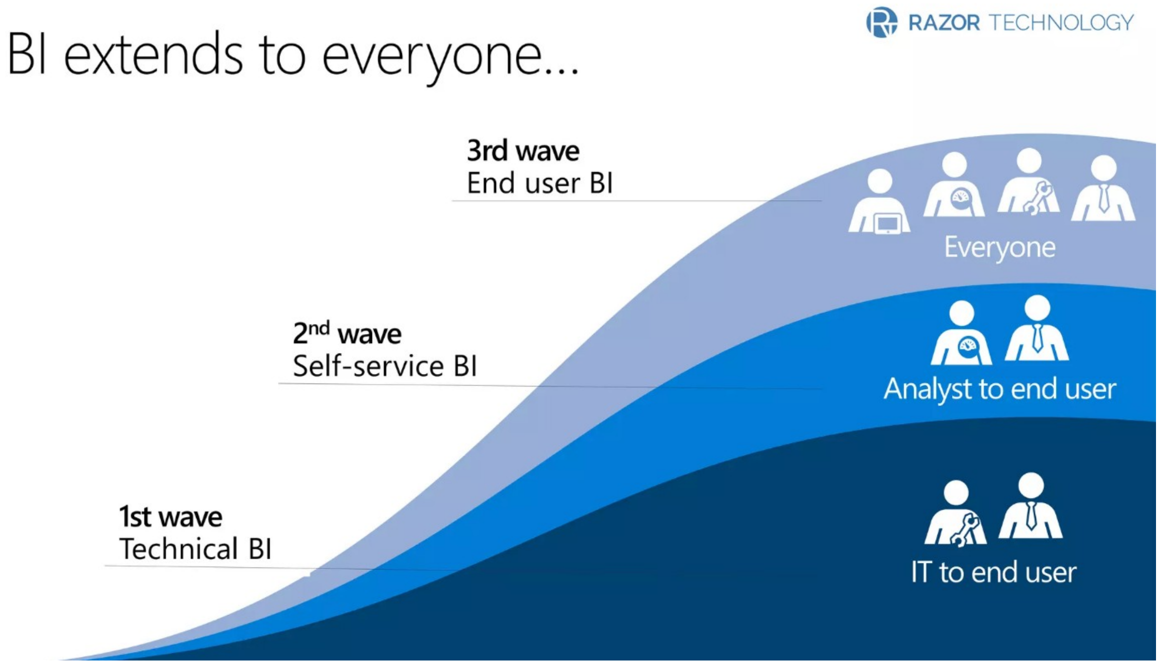


Fig. 11: Source Slideshare - Razor Technology (Rosenthal, 2019)

A computer science project at Sandford that sought to enhance the efficiency of analysis and increase data accessibility for users led to the creation of Tableau in 2003.

Fig. 12: Source Slideshare - Razor Technology (Rosenthal, 2019)

This is an opportunity to allow all users, not only IT people, to analyse data across their business or organization. It also allows decision-makers to view data from a holistic approach to their organization as departments no longer work in a silo and keep their data to themselves.

Before going into the experimental section of the data gathered and how tableau is being used, let's first understand how land is managed in Fiji.

4.4.1 Land Management in Fiji

Land management in Fiji is being looked after by two main entities, iTaukei Land Trust Board and the other is the Ministry of Land and Minerals. Only roughly 100 of the 364 islands and atolls that make up the Republic of Fiji are continuously inhabited, and the total land area is 18,333 square kilometres. Viti Levu and Vanua Levu, which cover 10,429 square kilometres, are the two largest islands.

Fig. 13: Satellite image from Google Maps of the Fiji Islands (Google, n.d.)

4.4.1.1 Land Ownership Structure – Traditional

Independent patrilineal family groups were the first type of indigenous society in Fiji, according to iTaukei Land & Fisheries Commission documents. They worked the soil by tilling it. Intermarriage groupings were drawn by their similarity, but each unit had its settlement and distinct and identifiable agricultural land. The same force that prompted these families to migrate also forced them to band together for mutual defence or protection; as a result, the tribe known as the "*Yavusa*" and its leaders developed. As the nation's population grew closer, battles for land and other conflicts broke out. While many Yavusa were left broken and dispersed, others created confederations now known as the *Vanua*.

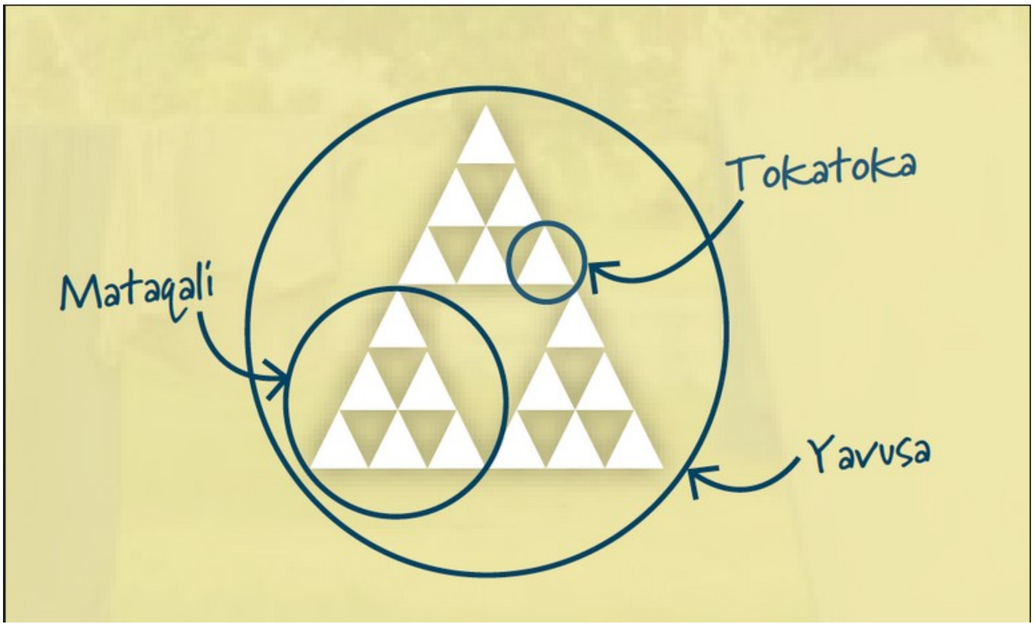


Fig. 14: Fijian Land ownership structure is also the social structure. (Unknown, 2014)

a. **Vanua** – is a separate, independent kingdom of one or more Yavusa who respect, honour and recognize a leader. Its leader, known by the title of Tui or King, would have excessive control over all Yavusa in the Vanua. For instance, some chiefs or leaders are addressed as the Sau of Mualevu, Tui Vuda, the Ka Levu of Nadroga, Roko Tui Dreketi, Vunivalu na Tui Kaba and so forth. Vanua limits came to be understood as Tikina or District boundaries under colonial rule, which was administered by the Tikina and Provincial government, according to (TLTB, 2010)

b. **Yavusa** – A group of related Mataqali known collectively as Yavusa under the leadership of a Chief who is the closest living relative of their common ancestors, or Kalou-Vu, are recognized by the generic name "A I Cavu" to other Yavusa. Simply said, a Yavusa is a group of closely related families that have come together or reside close to one another for defensive purposes. The iTaukei people had learned the value of cooperation and leadership after a century and a half of struggles and conflict. The Yavusa organization consequently gained the reputation of being a predetermined leader closely related to the Ancestral God by blood (TLTB, 2010).

c. **Mataqali** - As the primitive community grew, it gradually divided into several distinct population groups, each with its name and a unique purpose within the Yavusa. These duties were strictly passed down from father to son in the household and were not thought to be interchangeable. Since the Mataqali used in most was the sole word used in most of Fiji, this division became known as the *Land Owning Unit (LOU)* of landownership in almost all of the communities. When the Yavusa first came into being, the Mataqali comprised farming family groups that initially lived close together and were connected by marriage. It was only logical in delegating responsibilities to give the senior male in each localized linked group responsible for properly performing tribe obligations. That individual became the Head of the Mataqali (TLTB, 2010).

d. **Tokatoka** - Each Mataqali consists of two or more Tokatoka, or family divisions. Each Tokatoka has its headman, who is under the direct authority of the Turaga ni Mataqali (Head of the Mataqali). The Tokatoka is the unit of service, just like the Mataqali was the unit of government.

1874 Deed of Cession – Clause 4

"*That the absolute proprietorship of all lands not shown to be alienated so as to become bona fide the property of Europeans or other foreigners or not in the actual use or occupation of some chief or tribe or not actually required for the probable future support and maintenance of some chief or tribe shall be and is hereby declared to be vested in her Majesty, her heirs and successors."*[i9]

The three main types of land tenure in Fiji were described in the preceding section:

1. **iTaukei Land** - All of the land in the iTaukei belongs to the aforementioned communal group or land-owning unit. Usually, a section of each land area is designated as the settlement site, and the other portion is designated as iTaukei Reserve. After a procedure called "De-reservation," land within the iTaukei Reserve may be made accessible for usage and development by others through a short- or long-term lease. (TLTB, 2010, p. 7). A lease must be obtained by the developer in order for construction to proceed on iTaukei land. The iTaukei Land Trust Board (TLTB), a statutory body that oversees the

[9] (TLTB, 2010, p. 5)

management of all such lands on behalf of the iTaukei LOU, provides leases on iTaukei Land.

The protection of iTaukei ownership of the great majority of Fijian land has been a feature of the entire Fijian constitution. According to the constitution, 83% of the land is now owned by the iTaukei. This percentage is now closer to *90%* because to the 2002 transfer of Schedule A and B State lands, which were State-owned but either unclaimed or unoccupied at the time of registration (Wilson, 2008). -

2. **Freehold Land** - The Torrens System of land registration, which ensures the ownership of the land, is used to register about 6% of the total freehold land area in Fiji. According to the Land Sales Act terms, freehold land can be bought, sold, or leased, but only under certain conditions. These criteria include limitations on the amount of land that can be purchased by non-residents of Fiji and by businesses that aren't entirely controlled by residents of Fiji (TLTB, 2010, p. 6).

3. **State Land** - The Department of Lands is in charge of 4% of the country's total state land area. The soil beneath Fijian seas, the beds of navigable rivers and streams, and any shoreline lands below the mean high water mark are all considered state land (TLTB, 2010, p. 6)

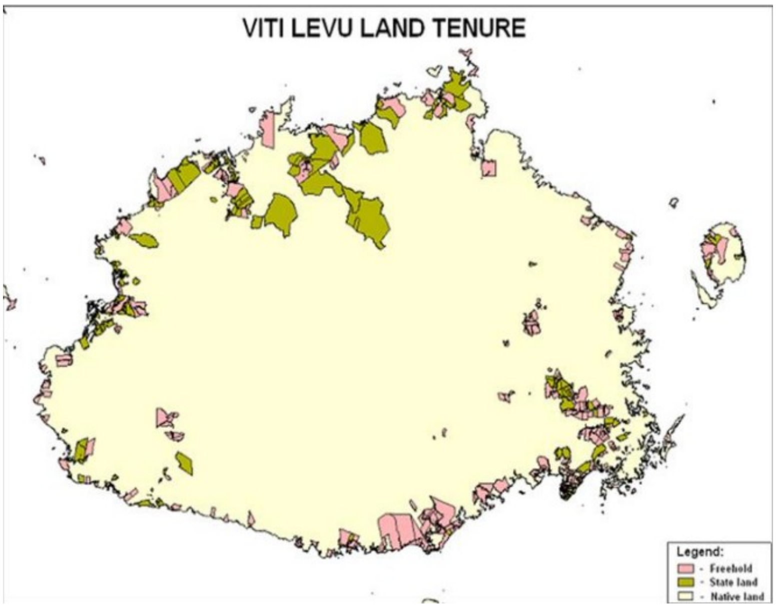


Fig. 15: Viti Levu Land Tenure depicting the three tenures (Ministry of Lands & Minerals Resources Fiji, NA)

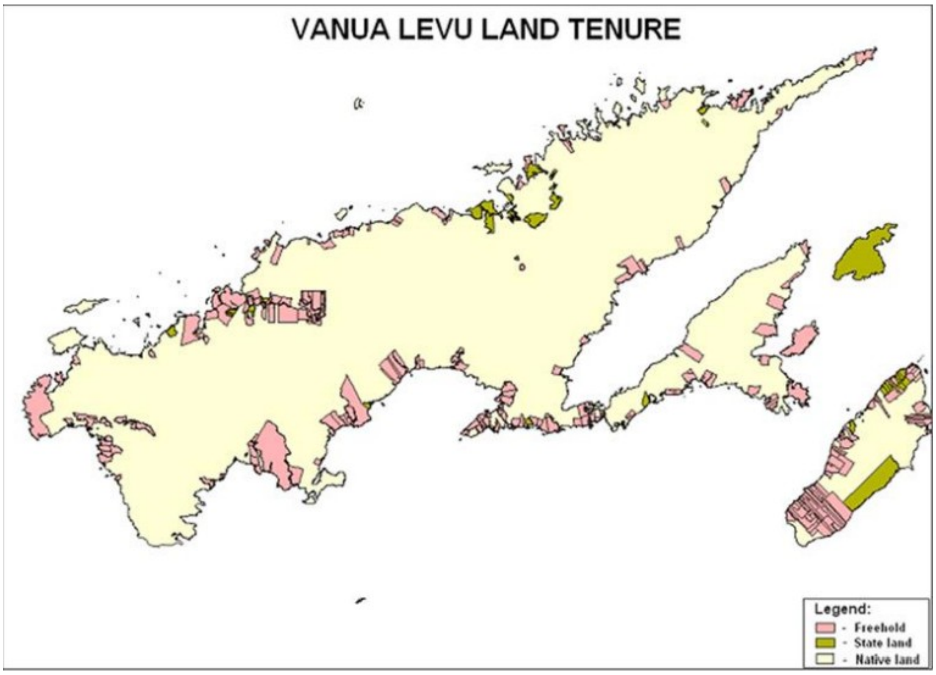


Fig. 16: Vanua Levu Land Tenure depicting the three tenures (Ministry of Lands & Minerals Resources Fiji, NA)

4.4.2 Using Tableau to Experiment Data

Data gathered for the experiment is only limited to a certain area in the Fiji region:

Fig. 17: Google map aerial view of the Central Eastern Division from Suva City throughout the Nausori area.

From the sample dummy unstructured data, Tableau Prep was used to clean up the data before being moved into Tableau Desktop to visualise the forecast of the available data. Before going further into how Tableau was used, a few things need to be understood about how land is managed in Fiji.

4.4.2.1 Tableau Prep (Tableau, 2019)

A tool in the Tableau product line called Tableau Prep Builder is intended to make the process of preparing your data simple and clear. To integrate, shape, and clean your data for analysis in Tableau, use Tableau Prep Builder.

Through the student access in Tableau, the accessibility also came with Tableau Prep which was useful. Self-service analysis is now standard practice for data-driven enterprises, thus many users may prepare the data as best they can using the tools and capabilities at their disposal. This may include copying and pasting or creating complex calculations that are not server-friendly (Tableau, n.d.). Even analysts claim that most of their work involves cleaning and transforming data through an Extract, Transform and Load (ETL) process, self-service data prep tools, or even spreadsheet applications like Excel (Tableau, n.d.). Although previously data preparation has been an IT activity, the data landscape has changed. Self-service data preparation solutions reduce the workload on IT by putting control in the hands of those who know the best data. Though self-service Data prep is still a novel skill set; it needs to be developed and implemented to allow users to comprehend and perform prep functions successfully, establish repeatable procedures, automate them for efficiency, and eventually generate trust and confidence in the data for wider use (Tableau, n.d.).

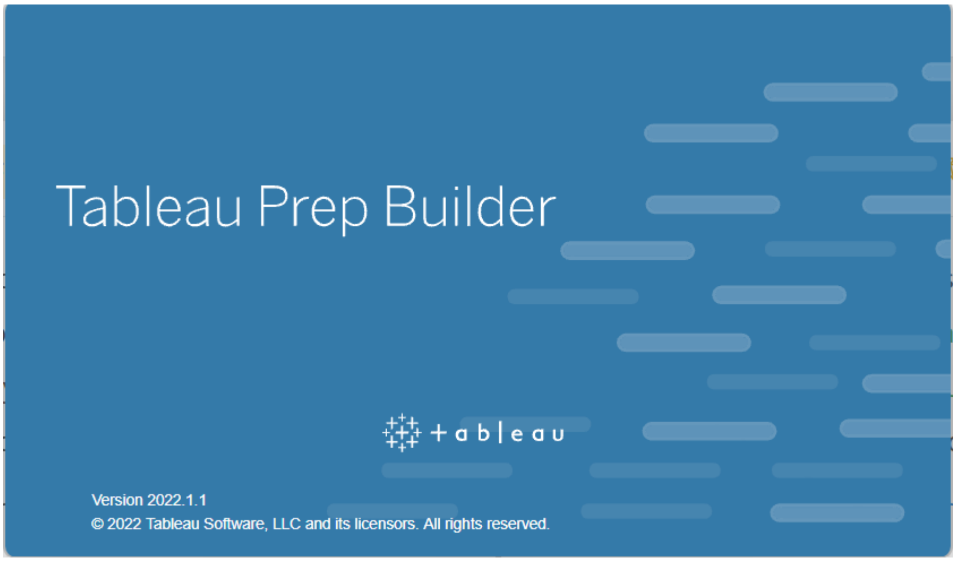


Fig. 18: Tableau Prep Builder

a. Data Cleaning Process

Here are a few steps that are guide to how Tableau Prep was used:

- The first step is connecting to your data from various files, servers, or Tableau extracts.
- Connect to several data sources and merge their data
- Tables can be added to the flow pane by dragging them or double clicking. Once there, add flow steps to clean up and shape the data with well-known operations like filtering, splitting, renaming, pivoting, joining, and unioning.

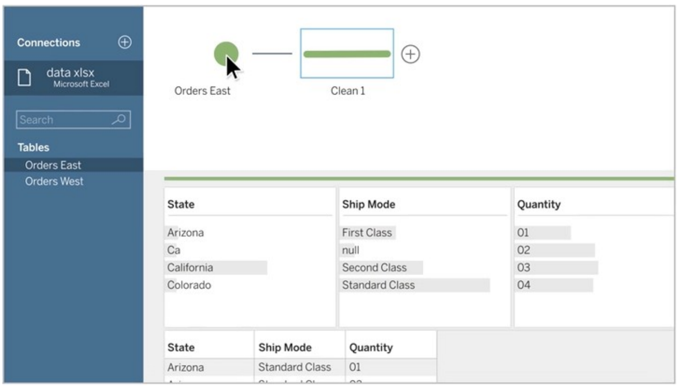


Fig. 19: Step 1 to clean up data

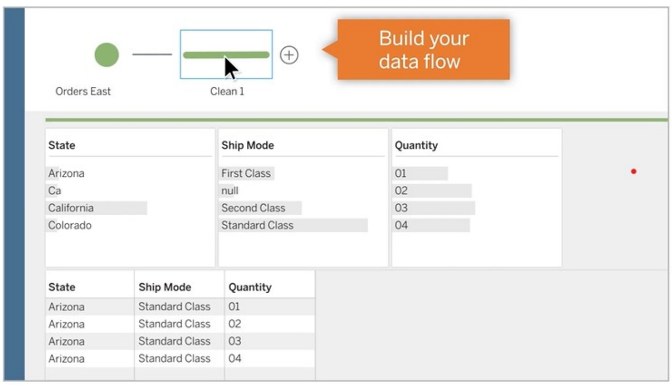
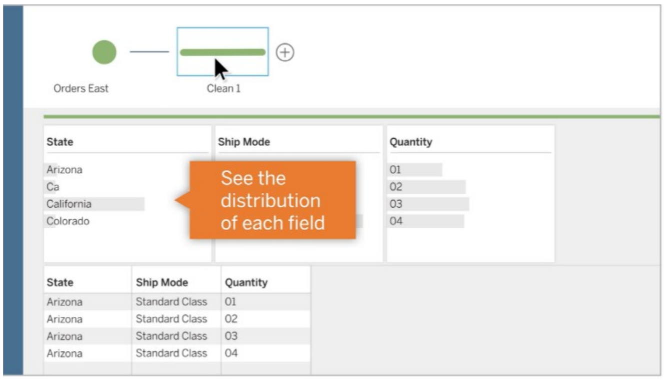


Fig. 20: Step 2 is to begin building of the data flow

Due to the confidentiality of data the actual data is not shown on its data cleaning process. However, Fig. 19 and 20 shows how the cleaning occurs in Tableau Prep, as the steps above explain.



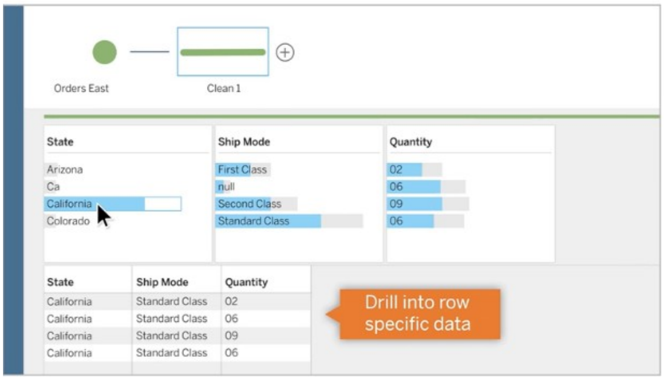


Fig. 21: Step 3 Connecting to Data - Drag and drop source files

Fig. 22: Step 4 Distribution of each field is being displayed

Fig. 21 and 22 further displays how the data was cleansed by drilling down to specific data in the collected data.

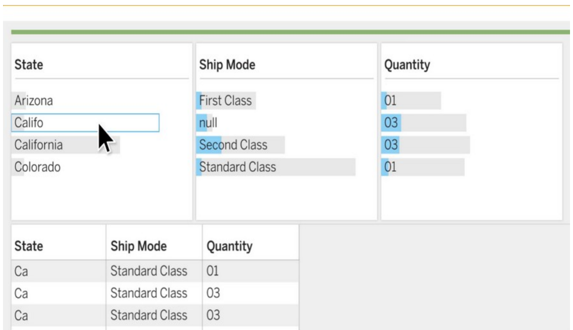


Fig. 193: Step 5 data cleaning process

Fig. 24: Step 6 of cleaning data

Clean data – Act on the data directly. Data can be edited if there is a need to do so.

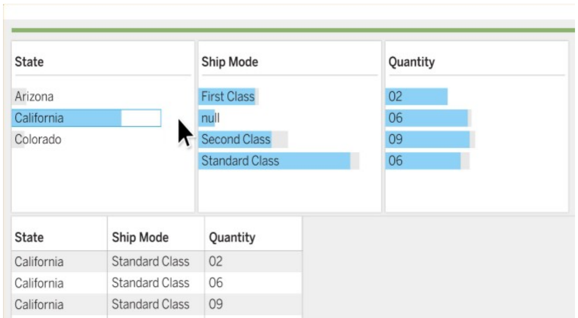


Fig. 25: Step 7 Changes occur according to the editing

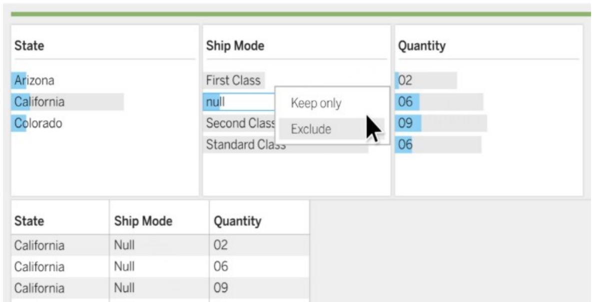


Fig. 26: Step 8 output of editing data

Once data is edited, the data displayed gets updated instantly. Even removing specific data which have no significant meaning to the data set can be done by excluding it as shown in the Fig. above.

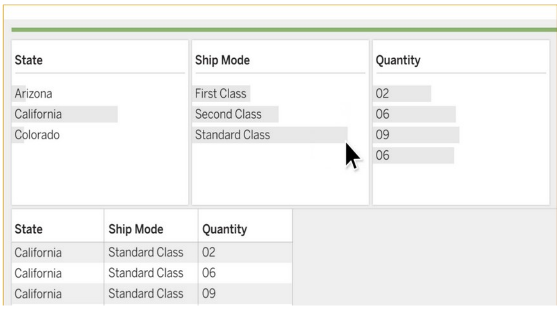


Fig. 20: Step 9 Null values removed

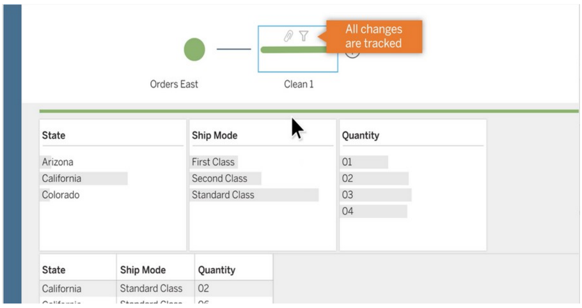


Fig. 26: All changes made are being tracked

Fig. 25 depicts the removal of null value and notes that all changes being made to the data are tracked by Tableau Prep.

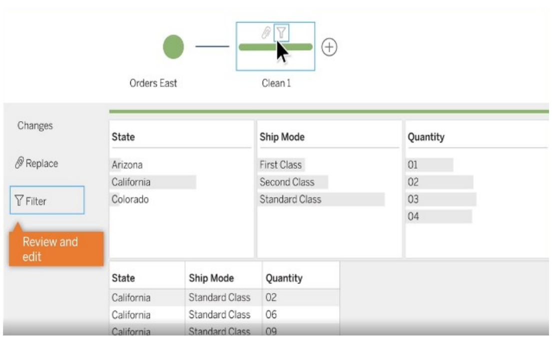


Fig. 21: Review and Edit

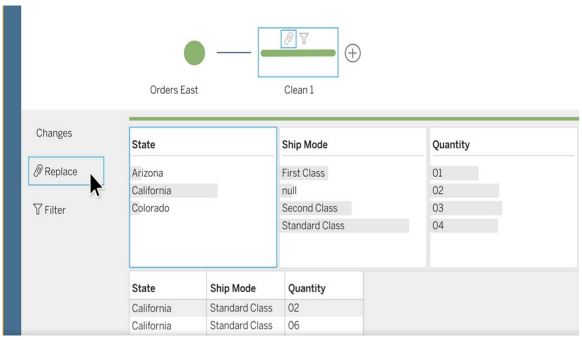
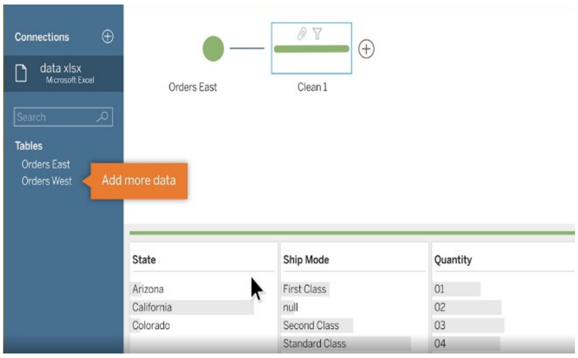


Fig. 28: Replace data if required

Fig. 27 shows the ability of Tableau Prep to review and edit the work that has already been carried out on the data and also how data can be replaced if the need arises.



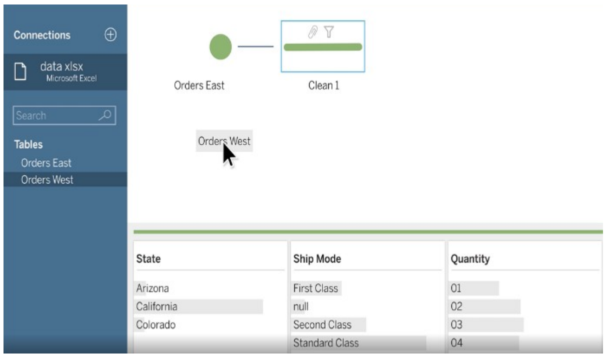
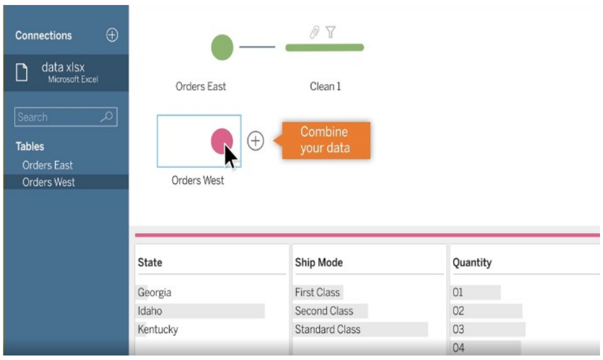


Fig.29: Combine more data: Add more data files *Fig. 30: Drag and drop more data when needed*

While working on a particular data set, tableau prep can add more data set, in this case the excel file by simply dragging and dropping it in to the workspace, as shown above. The steps to combine more than one data set is further depicted in Fig. 31 ans 32 below.



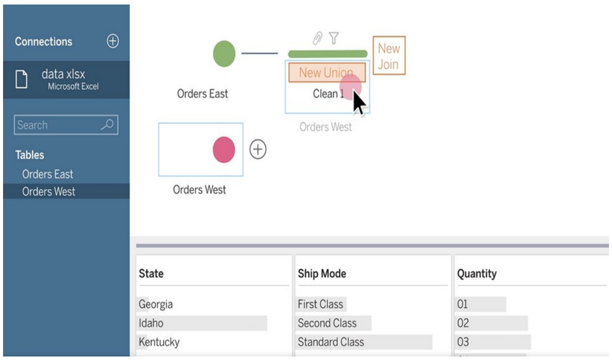


Fig. 31: Combine data *Fig. 32: Combining two sets of data*

The two data sets are joined into one data set.

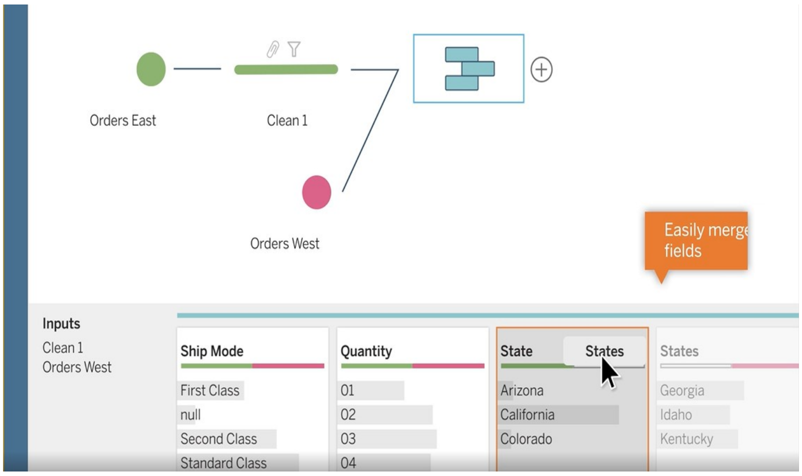


Fig. 33: Merge fields

Here it is showing that two fields in the data set are being merged into one.

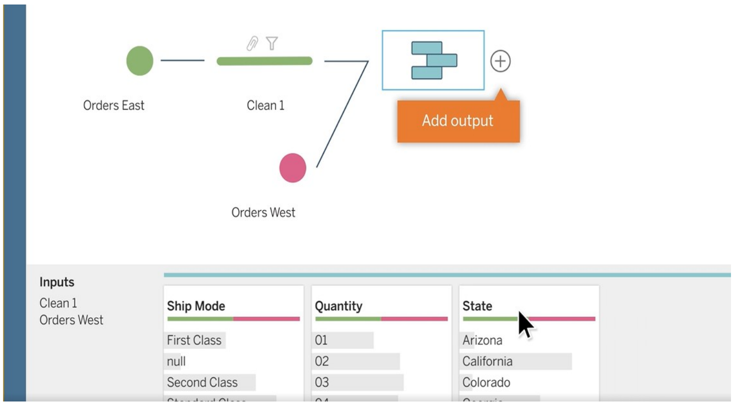


Fig. 34: Now one State column is available and all data are under that column. Add output option available now.

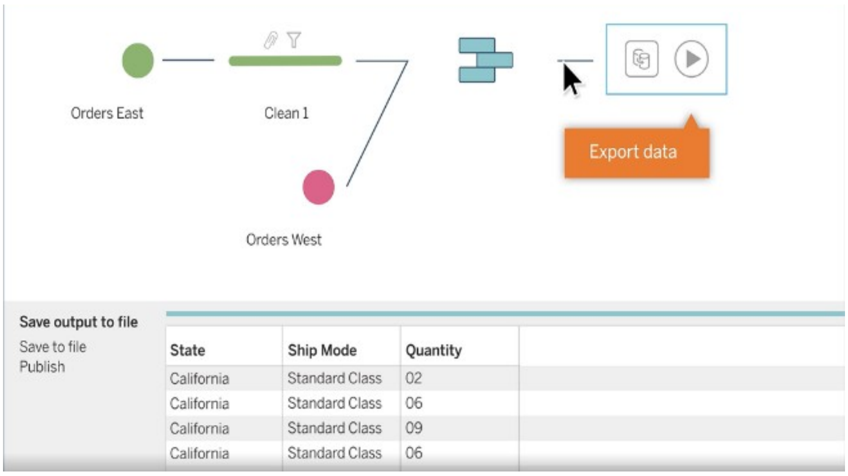


Fig. 35: Export of data in to the format users want is available

On completion of gathering all data into the format required, the output options are made available: export the data file by either as an .xlx, .pdf, .ppt or other available file types.

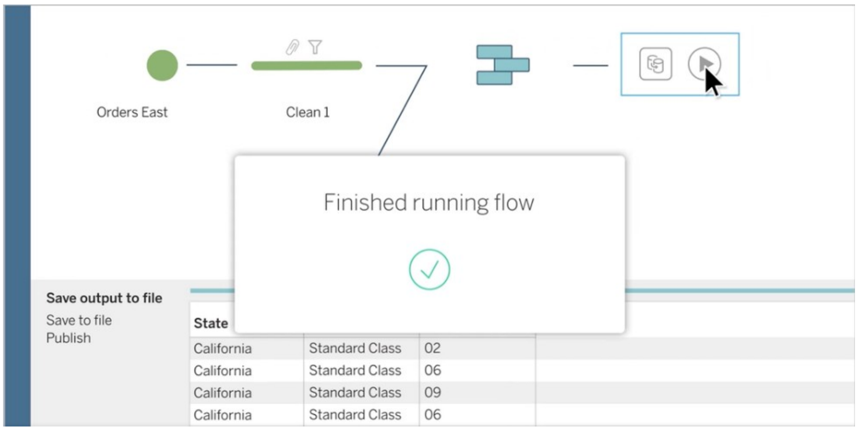


Fig. 36: Completion of running flow of the merged cleaned data set

The steps depicted in Fig. 19 to 36 are the steps that were followed when the sample data was cleaned and all those Figures are from the Tour Tableau Prep Builder version 2022.1.1 that is being used for data cleaning. Once the data was cleansed, it was sent to the Tableau Desktop platform for analysis, visualization and forecasting purposes. For more detailed instructions, the Tableau page can be visited[10].

Below is a graph that shows the sample data of just a small area in the CE division. It depicts the number of leases that have been administered to tenants between the years 2000 to 2021. This is just a high level data summary, Agriculture leases are the most affordable in terms of the rent and premium payments of the lease and have a short lease duration of between 30 to 50 years. Agriculture lease categories include beef farming, dairy farming, grazing, poultry farming, root crops, agricultural – NLTA lease, etc. Fig. 39 depicts the summary value of the leases being administered from the years 2000 to 2021 as well[11].

4.4.2.1.1 RQ1: How to identify land valuation forecast using Tableau for the Central Eastern (CE) division in Fiji?

To identify land valuation forecast through the use of Tableau in the Central Eastern division of Fiji, you can follow the below steps:

1. Data collection: Gather data on land values, land use, demographics, and economic indicators relevant to the Central Eastern division of Fiji.
2. Data cleaning: Clean and pre-process the data to ensure that it is ready for analysis.

[10] Using Tableau Prep - https://help.tableau.com/current/prep/en-us/prep_about.htm#

[11] Data shown are sample dummy data which has been slightly monitored to be used for this experiment.

3. Data visualization: Use Tableau to create interactive visualizations of the data, such as maps, scatter plots, histograms, and trend lines, to gain insights into land value patterns and trends.
4. Data analysis: Perform statistical analysis on the data to identify patterns, trends, and relationships between different variables.
5. Model building: Build predictive models using techniques such as regression analysis or time series analysis to forecast future land values in the Central Eastern division of Fiji.
6. Model evaluation: Evaluate the accuracy of the models using techniques such as cross-validation, residual analysis, and model diagnostics.
7. Results communication: Communicate the analysis results and forecasts to stakeholders, including real estate professionals, investors, and policy makers, through interactive dashboards and reports created in Tableau.

It's important to remember that while Tableau is a powerful tool for data visualization and analysis, it's essential to understand the underlying data, statistical analysis techniques, and best practices in forecasting. It may be helpful to work with a team of data scientists and real estate experts to ensure that the land valuation forecasts are accurate and actionable.

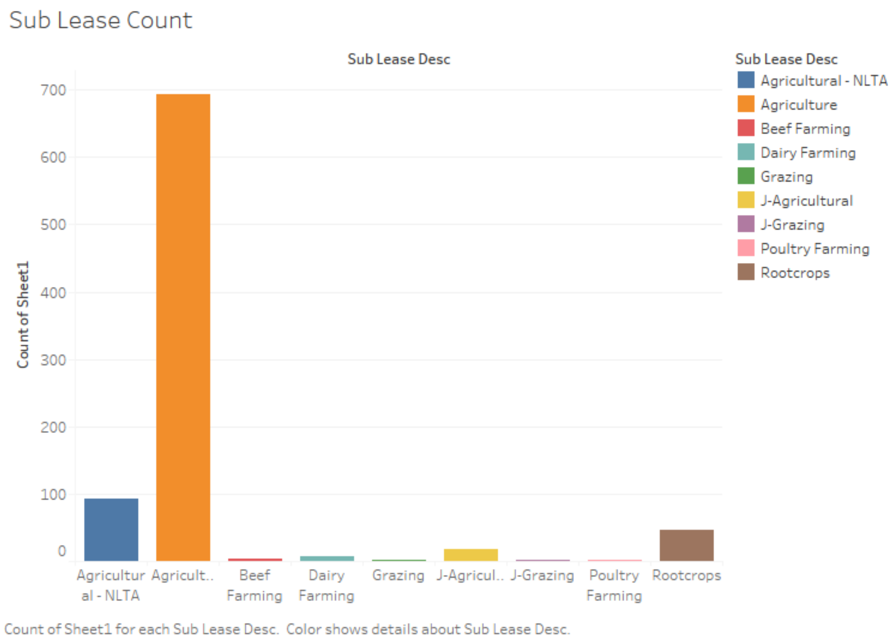


Fig. 22: Summary of Agriculture leases

This is along the Suva Nausori corridor and its different classifications as sublease types from 2000 to 2021.

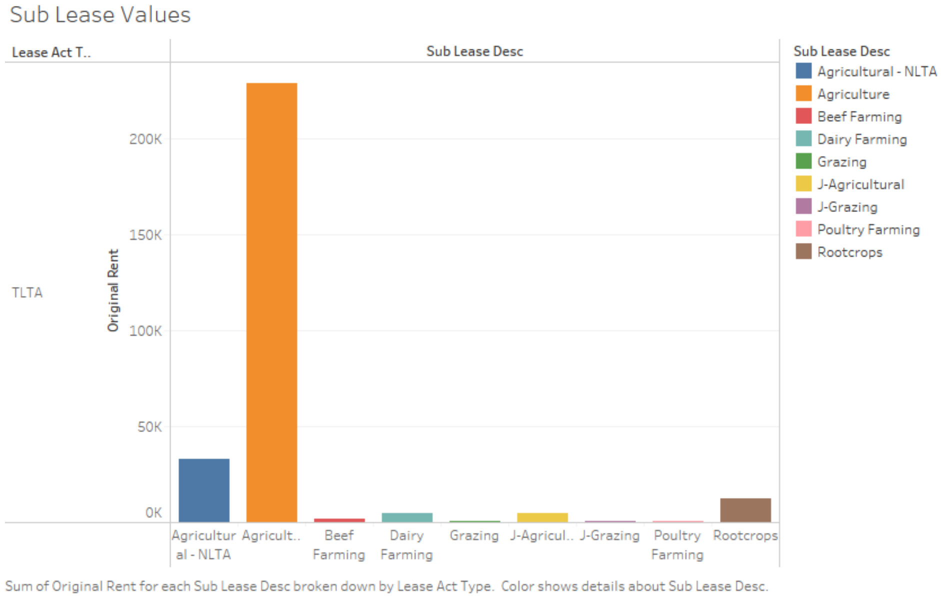


Fig. 23: Summary of Agriculture lease value for the CE region from 2000 to 2021

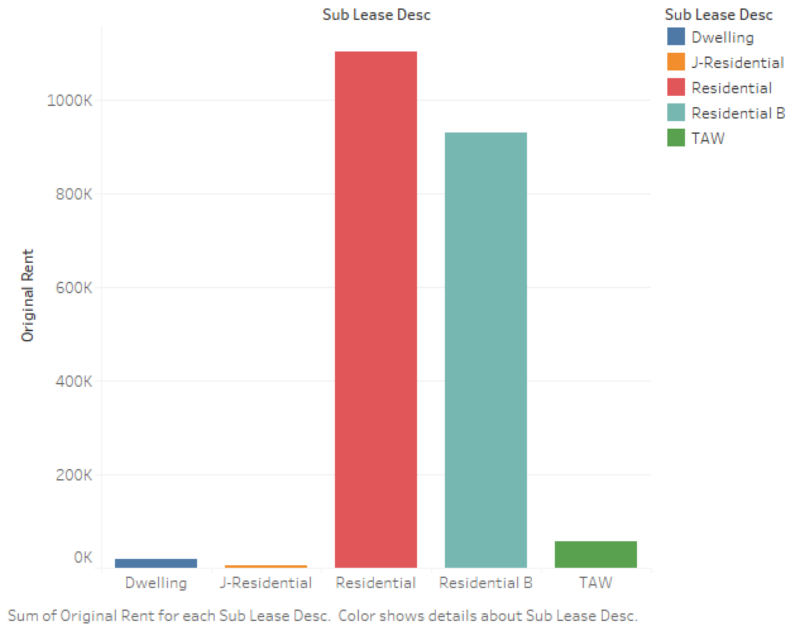


Fig. 24: Summary overview Market Value of Residential leases that have been administered to tenants from the year 1989 to 2021 – this is only within the CE region

After data cleaning from Tableau Prep this was the overview summary of residential leases. This only depicts a small area as mentioned above in Fig. 39. Under a residential lease there are five (5) categories: Dwelling, J-Residential, Residential, Residential, Residential B and Tenancy at Will (TAW), etc.

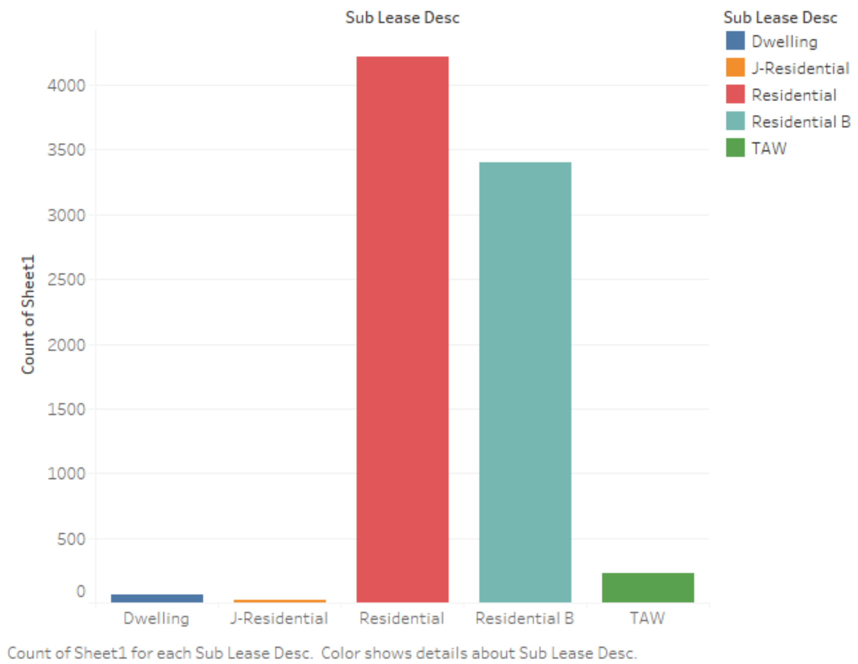


Fig. 40: Depicted is the overview summary of how many number of Residential lease have been issues in the CE region from 1989-2021 under different lease types

4.4.2.1.1.1 Tableau Desktop – Forecasting

Tableau employs an approach known as exponential smoothing for forecasting. Forecasting software looks for a recurring pattern in metrics that can be used going forward. A forecast often enhances a view with a date field and at least one metric. But if there isn't a date, Tableau can predict a view with at least one measure and a dimension with integer values (Tableau, 2019).

Every prediction algorithm is a simplified representation of a method for generating data in the real world (DGP). A straightforward pattern in the DGP needs to fairly closely match the model's prediction pattern for a forecast to be considered good quality (Tableau, 2019). Quality criteria gauge the model's fit to the DGP. If the quality is low, the precision measured by the confidence bands is not important because it measures the precision of an inaccurate estimate (Tableau, 2019).

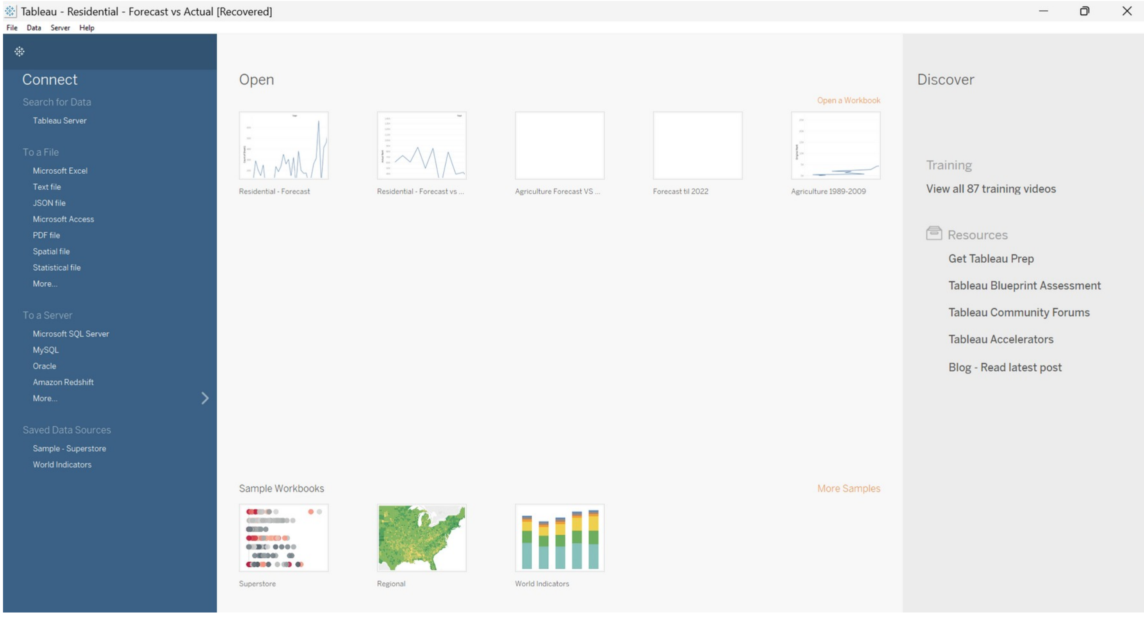


Fig. 41: The opening interface of Tableau Desktop

Up to eight models can be chosen by Tableau, and it automatically chooses the best model based on which forecast it produces. Before evaluating the forecast quality, Tableau optimizes the smoothing parameters of each model. Global optimization is used. In light of this, it is not impossible to select smoothing parameters that are locally optimal but not ideal globally (Tableau, 2019). But the parameters' original values were not the best.

When there is insufficient information in the visualization, Tableau attempts to forecast automatically at a finer temporal granularity before aggregating the forecast back to the precision of the visualization (Tableau, 2019). Tableau offers prediction bands that can be generated artificially or mathematically from a closed-form query. The closed-form equations are used in all models except those with a multiplicative component or aggregated forecasts, which feature simulated bands.

4.4.2.1.1.2 Exponential Smoothing and Trend

By using weighted averages of the series' prior values, *exponential smoothing* models iteratively predict future values for a regular time series of data. The weighted average of the previous actual value and the previous level value is used by the straightforward model known as *Simple Exponential Smoothing* to calculate the following level or smoothed values. The approach is exponential because more recent values are given a higher weight, and each level's actual values influence the influence of each level sales to an exponentially decreasing degree (Tableau, 2019). When the measure to be forecast demonstrates trend or seasonality over the time period on which the forecast is based, exponential smoothing models with the trend or seasonal components are adequate. A *trend* is an increase or decrease in the data's propensity over time. A recurring, predictable change in value is referred to as seasonality. An example of this would be a yearly change in temperature about the season (Tableau, 2019).

The quality of the forecast results will often increase with the number of data points over a series of time series. In order to model seasonality, having enough data is especially crucial because the model is more complex and needs more evidence in the form of data to obtain a fair degree of precision. The quality of the forecast will be worse; however, when data employed generated by two or more separate DGPs, as a model can only match one.

4.4.2.1.1.3 Seasonality

Tableau searches for seasonal cycles with the most usual length for the time aggregation of the time series for which the prediction is calculated. Tableau will therefore seek a 12-month cycle if the data is aggregated by months; a four-quarter cycle if aggregated by quarters; and weekly seasonality if aggregated by days (Tableau, 2019). As a result, Tableau will quickly discover a 12-month pattern with two related sub-patterns if a monthly time series has a six-month cycle.

Tableau can determine the length of a season using one of two ways. The original temporal technique uses the temporal granularity (TG) of the view's natural season length. The smallest unit of time that the view expresses is known as the temporal granularity. For instance, the view's temporal granularity is a month if it has either a continuous green date that has been reduced to a month or discrete purple year and month date portions. Using periodic regression, the novel non-temporal method—introduced with Tableau 9.3—verifies candidate length for season lengths ranging from 2 to 60.

Tableau instantaneously chooses the best approach for a particular view. The season durations are nearly likely 4, 12, 13, 7 or 24 when Tableau uses date to organize the measures in a view, and the temporal granularity is quarterly, monthly, weekly, daily, or hourly (Tableau, 2019). In order to build the five seasonal exponential smoothing models that Tableau supports, only the length inherent to the TG is used. The three non-seasonal models' AICs are compared to those of the five seasonal models' AICs, and the lowest returned. (Tableau, 2019)

The second approach is employed by Tableau when forecasting on an integer dimension. The data must be used to determine prospective seasonal lengths because this situation has no temporal granularity (TG). If the temporal granularity is yearly, the second method is also employed. Seasonality in yearly series is uncommon, but it must be extracted from the data if it does exist.

The second technique is also employed for views with minute- or second-level temporal granularity. The seasons in such series would most likely last 60 episodes if they were seasonal. If a regular process in the real world is being measured, it can have a regular repeat that doesn't match the clock. As a result, Tableau also validates the data for lengths other than 60 for minutes and seconds. That being said, Tableau cannot simultaneously model two different season lengths. In contrast, ten seasonal models are estimated, five of which have a season duration of 60 and the remaining five have a season length determined by the data. The forecast is calculated using the ten seasonal or three non-seasonal models with the lowest AIC. (Tableau, 2019)

If the pattern is evident for series arranged by year, minute, or second, a single season length from the data is evaluated. For integer ordered data, the model with the lowest AIC is returned. Up to nine slightly less distinct probable season lengths are calculated. If there are no choices for a predicted season length, just the non-seasonal models are calculated. The default Model Type of "Automatic" in the Forecast Options Dialog Model Type option does not change because all selection is automatic when Tableau determines prospective season lengths from the data. By removing the need to seek season lengths and estimate seasonal models, choosing "Automatic without seasonality" enhances performance (Tableau, 2019).

Depending on the distribution of errors for the periodic regression of each possible season length, Tableau employs a heuristic to determine the season lengths derived from the data (Tableau, 2019). The return of a single candidate implies likely seasonality because the assembly length candidates by periodic regression typically yields one or two distinct winning lengths if seasonality genuinely exists in the data. Tableau calculates seasonal models for the year, minute, and second granularities in this scenario with this candidate. The absence of more than ten candidates suggests possible seasonality. With all returning choices for integer ordered views, Tableau, in this instance, estimates seasonal models. The most significant number of candidates returned suggests that errors for the majority of lengths are similar. It is, therefore, doubtful that there is any seasonality. For an integer-ordered or yearly ordered series, Tableau exclusively estimates non-seasonal models in this scenario, and for other temporally ordered views, only seasonal models with a natural season length are estimated.

The potential season durations for the Model type "Automatic" in integer-, year-, minute-, and second-ordered views and their usage are always taken from the data. Model estimation takes significantly longer than periodic regression, therefore, the effect on performance should be minimal.

4.4.2.1.1.4 Model Types

The model type Tableau uses for forecasting is selectable in the Forecast Options dialog box. For the vast majority of views, the *Automatic* setting is ideal. Choosing *None*, *Additive*, or *Multiplicative* from the options will allow users to select the trend and season characteristics individually:

In an additive model, each element's contribution is added up, whereas in a multiplicative model, some element contributions are multiplied at minimum.

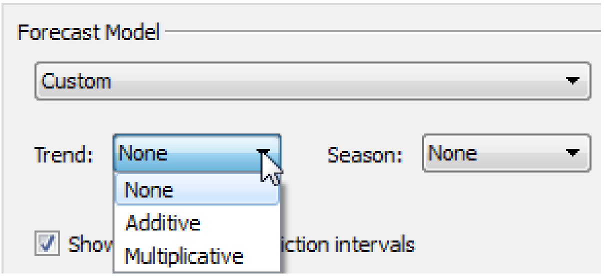


Fig. 42: Forecast Model Types. Source: (Tableau, 2019)

When the trend or seasonality of the data is influenced by its level (magnitude), multiplicative models can dramatically boost forecast quality.

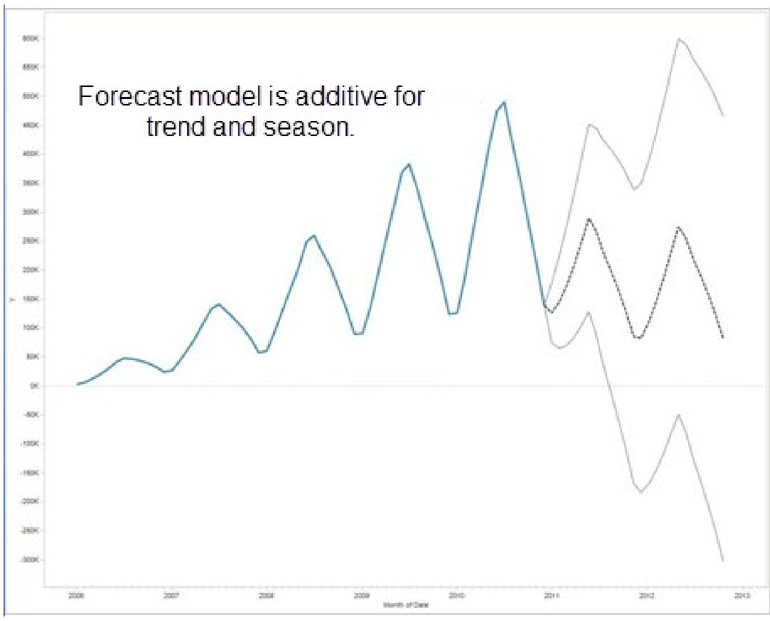


Fig.43: Forecast model is additive for trend and season Source: *(Tableau, 2019)*

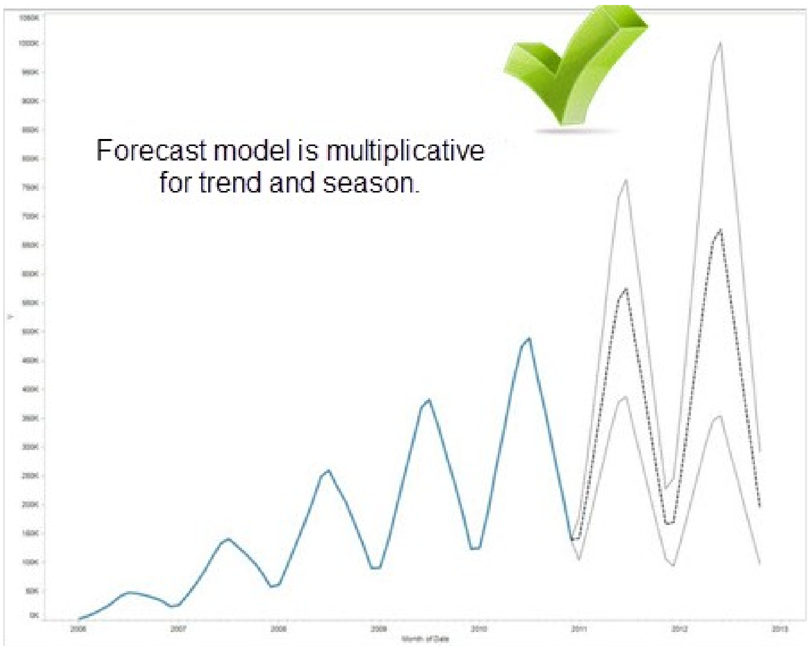


Fig.44: Forecast model is multiplicative for trend and season Source: *(Tableau, 2019)*

Remember that it may produce a multiplicative forecast without using a specific model. If it is acceptable for the data, it can be determined using the Automatic setting. A multiplicative model, however, cannot be calculated when the forecasted measure has one or more values that are lower than or equal to zero (Tableau, 2019).

4.4.2.1.1.5 Using Time to Forecast

Only one date can be present in the view when forecasting with a date. Dates in parts can be used, but they must all point to the exact underlying field. Marks, Rows, and Columns can all have dates (with the exception of the Tooltip target). These are how the data sample is being used to forecast the growth of land management in a specified region. Below are the three types of date and two of which is being used to forecast the lease growth, which Tableau supports:

- Truncated dates, such as September 2001, refer to a precise moment in time with a defined level of temporal granularity. Typically, they are continuous and have a green background. Forecasting can be done with truncated dates (Tableau, 2019).
- A specific component of a temporal measure, such as September, is referred to as a date part. A distinct, typically discrete field is used to indicate each date segment (with a blue background) (Tableau, 2019). For forecasting, at least a Year date portion is necessary. For forecasting, it can use any of the sets of dates listed below (Tableau, 2019):
    - *Year*
    - *Year + quarter*
    - *Year + month*
    - *Year + quarter + month*
    - *Year + week*
    - *Custom: Month/Year, Month/Day/Year*

Forecasting cannot be done with other date components, like Quarter or Quarter + month.

- Exact dates, such as September 1, 1997 at 14:23:45.0, refer to a specific moment with the most significant degree of temporal precision. For forecasting, precise dates are useless.

Additionally, forecasting without a date is also possible. Below is the experimented forecast data, which was made possible by the use of Tableau:

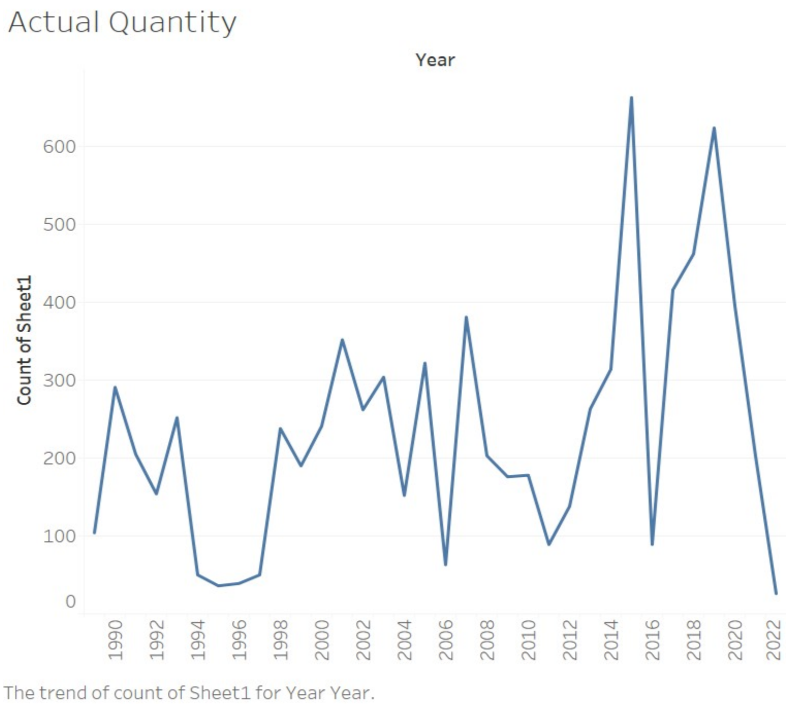


Fig. 25: Number of leases given over the years for residential lease from 1990-2022.

Data in 2022 is inconclusive as the, therefore, any misinterpretation is possible. This is dummy data not actual numbers, as it gives observers of at least an idea of the growth in the central-eastern region that comprises of Serua, Namosi, Naitasiri, Tailevu and Rewa provinces. This data will be used over the next consecutive outcomes that were being experimented with.

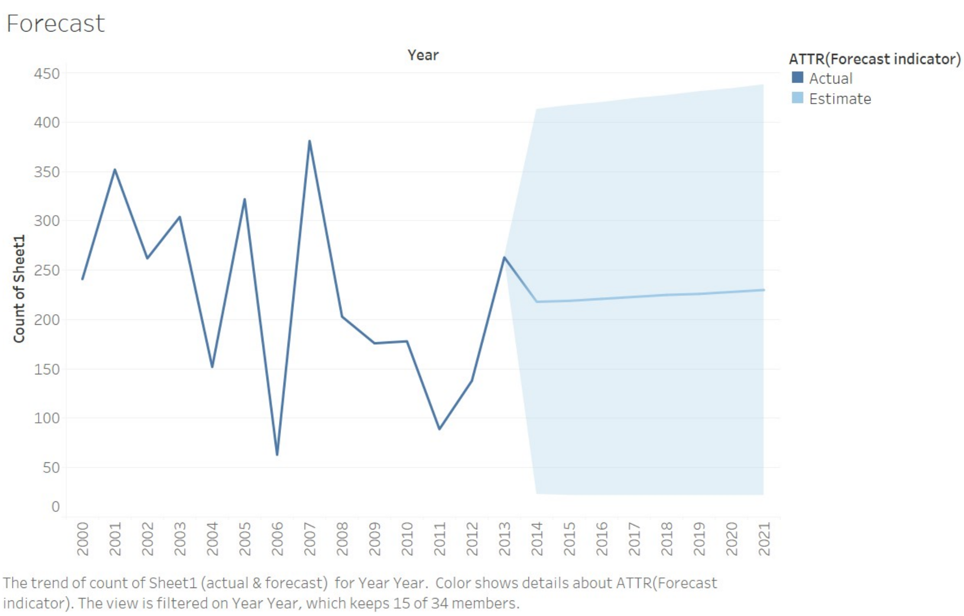


Fig. 26: Residential lease taken from the previous Fig. to begin in 2000 and end at 2014, then the forecast method was used to predict the number of leases that could potentially be administered from 2014 to 2021

Table 6: Data Set Used to Experiment Residential Growth

Time series:	Year of Year
Measures:	Count of Sheet1
Forecast forward:	Eight years (2014 – 2021)
Forecast based on:	2000 – 2013
Ignore last:	One year (2014)
Seasonal pattern:	One year cycle

Table 7: Data Set Seasonal Effect

Initial			Change From Initial	Seasonal Effect				Contribution		
2014			**2014 – 2021**	**High**		**Low**		**Trend**	**Season**	**Quality**
218	±	89.6%	5.4%	2021	-3.3%	2021	-3.3%	100.0%	0.0%	Ok

As mentioned earlier, under Forecast using Time, the same method is being applied here, and the outcome is depicted. Fig. 50 describes the forecast in detail, regarding its *Time Series* (the field with continuous dates used to specify the time series. This value occasionally might not be a date (Tableau, na))**,** *Measures* (The metrics for which estimates are made (Tableau, na)), *Forecast Forward* (Forecast duration and time frame (Tableau, na)), *Forecast Based On (*the actual data period that was used to make the forecast (Tableau, na)*), Ignore last* (Forecast data is shown for the number of periods towards the end of the actual data that are ignored (Tableau, na)), *Seasonal pattern* (length of any seasonal cycle that Tableau discovered in the data, or None if none was discovered in any forecast (Tableau, na)).

According to its ***Seasonal Effect and Contribution*** – *Trend* and *Season,* the ***Quality*** of the Forecast is classified as ***OK*** by Tableau.

- ***Seasonal Effect -*** These fields are shown for models that have been identified as having seasonality—a recurring pattern of variation across time. They display the high and low seasonal components from the most recent full seasonal cycle using a composite time series of actual and predicted values. The seasonal component, which reflects the departure from the trend, fluctuates around zero and accumulates to zero throughout the season (Tableau, na).

- ***Contribution -*** The degree to which Trend and Seasonality influence the forecast. Always stated as percentages, these values add up to 100% (Tableau, na).
- ***Quality*** - How well the projection matches the actual data is indicated. GOOD, OK, and POOR are all potential values. A forecast that forecasts that the *value of the following forecast* will be the *same as the value of the present period* is referred to as *naive*. The quality of a forecast is indicated by a naive forecast, with *OK* denoting that it is expected to have *less error* than a naive forecast, *GOOD* denoting that it has *less than half* as much error, and *POOR* denoting that it has *more error* (Tableau, na).

Table 8: Data Model, Quality Metrics and Smoothing Coefficients for Experimented dataset

Model			Quality Metrics					Smoothing Coefficients		
Level	**Trend**	**Season**	**RMSE**	**MAE**	**MASE**	**MAPE**	**AIC**	**Alpha**	**Beta**	**Gamma**
Additive	Additive	Additive	100	84	0.67	61.6%	141	0.115	0.000	0.027

The Model type is already described above in Fig. 46**,** just for more clarity, there are three options for model type; Indicates if the Level, Trend, or Season components are included in the model that produced the forecast (Tableau, na).

A. Quality Metrics

Statistics about the model's quality are provided via this set of values.

Table 9: Quality Metrics description (Tableau, na)

Value	**Definition**
RMSE: Root mean squared error	$\sqrt{\left(\frac{1}{n}\right) \sum e(t)^2}$

MAS: Mean Absolute Error	$\frac{1}{n}\sum\left\|e(t)\right\|$
MASE: Mean Absolute Scale Error MASE calculates a ratio based on the size of the error in comparison to the size of the error in a simple, one-step forecast. In a straightforward, one-step forecast, MASE determines a ratio depending on the magnitude of the mistake in proportion to the size of the error. Therefore, a MASE of 0.5 is preferable to a MASE of 1.0, which is no better than a naive forecast and indicates that your forecast is likely to have half the inaccuracy of a naive forecast. This normalized statistic, which is calculated for all values and evenly distributes mistakes, makes it a great indicator for assessing the accuracy of various forecasting techniques. Due to the fact that MASE is defined for time series that contain zero, whereas MAPE is not, it has an advantage over the more popular MAPE measure. Additionally, MAPE gives more weight to positive and/or extreme errors while MASE gives equal weight to all errors.	$\frac{\frac{1}{n}\sum\left\|e(t)\right\|}{\frac{1}{(n-1)}\sum_{2}^{n}\left\|Y(t)-Y(t-1)\right\|}$
MAPE: Mean absolute percentage error. MAPE calculates a percentage based on the size of the inaccuracy in relation to the size of the data. Therefore, a MAPE of 20% is preferable to a MAPE of 60%. The discrepancy between the response values the model predicts and the actual response values for each explanatory value in the data is an error. Since this statistic has been normalized, it may be used to evaluate the quality of various Tableau models. Because it gives some types of mistakes more weighting than others, it is unreliable for some comparisons. Additionally, it has no definition for data with zero values.	$100\frac{1}{n}\sum\left\|\frac{e(t)}{A(t)}\right\|$

AIC: Akaike information criterion. The Hirotugu Akaike-created AIC model quality metric penalizes complex models to discourage overfitting. SSE stands for the sum of squared errors, and k represents the number of estimated parameters, including beginning states.	$n * \log(SSE/n) + 2 * (k + 1)$

A. Smoothing Coefficient

Smoothing coefficients are designed to weigh more current data values over older ones so that within-sample one-step-ahead forecast errors are minimal. This depends on the rate of evolution in the level, trend, or seasonal components of the data. According to Tableau, Alpha is the level smoothing coefficient, beta is the trend smoothing coefficient, and gamma is the seasonal smoothing coefficient (Tableau, na). Less smoothing is done the closer a smoothing coefficient is to 1.00, allowing for quick component changes and a strong dependence on recent data. A smoothing coefficient's distance from zero determines how much smoothing is done, allowing for gradual component changes and less reliance on current data (Tableau, na).

According to the detailed description of the Describe Forecast summary measures mentioned above, this would enable us to identify factors on the forecast being forecasted by the experiment that was done to meet the objectives of this research. Fig. 39 was an example of how the forecast outcomes are being measured.

4.4.2.1.2 RQ2: Discover how the growth of Residential leases in the CE division has been for the past 10 years.

4.4.2.1.2.1 *Residential Growth*

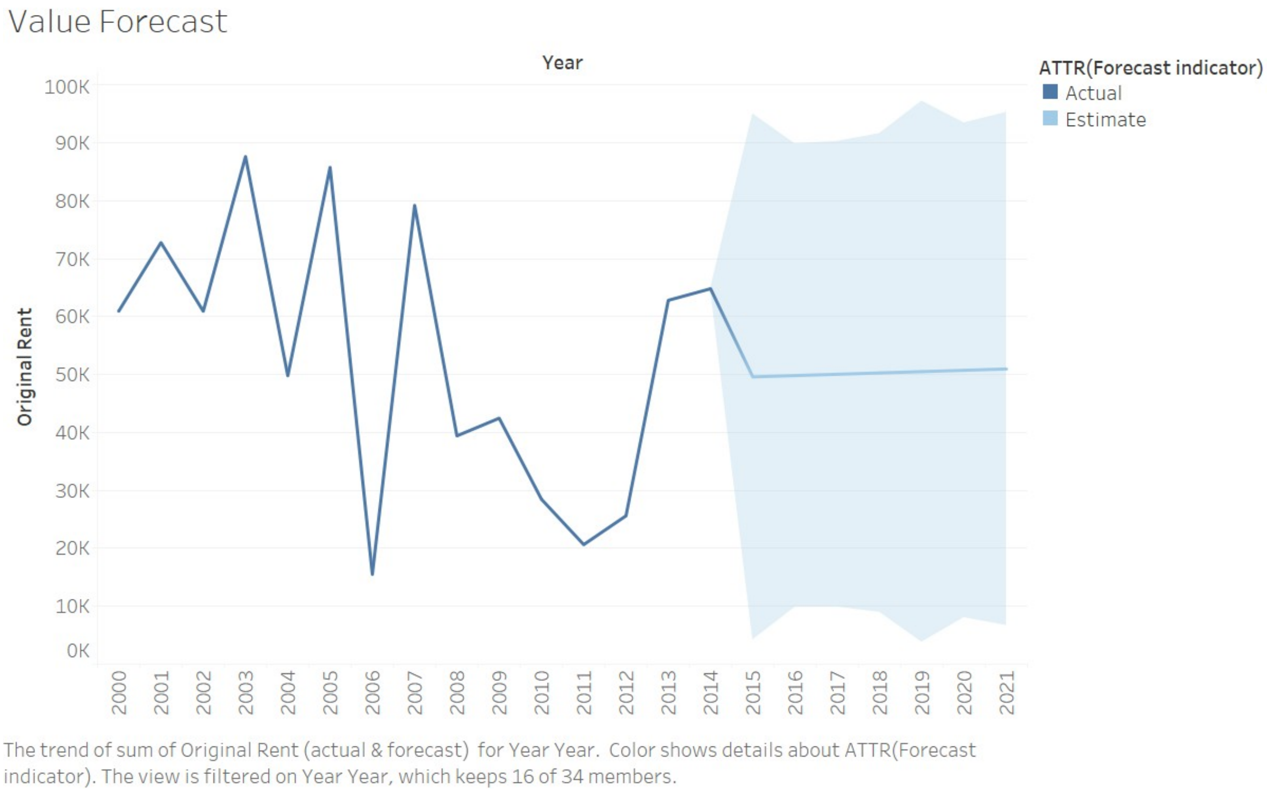


Fig. 47: This is depiction of annual rent for residential leaves using data from 2000 to 2014. From 2015 to 2021 is forecasted data

This data experiment is between the years 2000 to 2021, only covering the central-eastern region in Fiji. Data was altered during the experiment as it was unstructured, and through Tableau Prep, the data went through the ETL process.

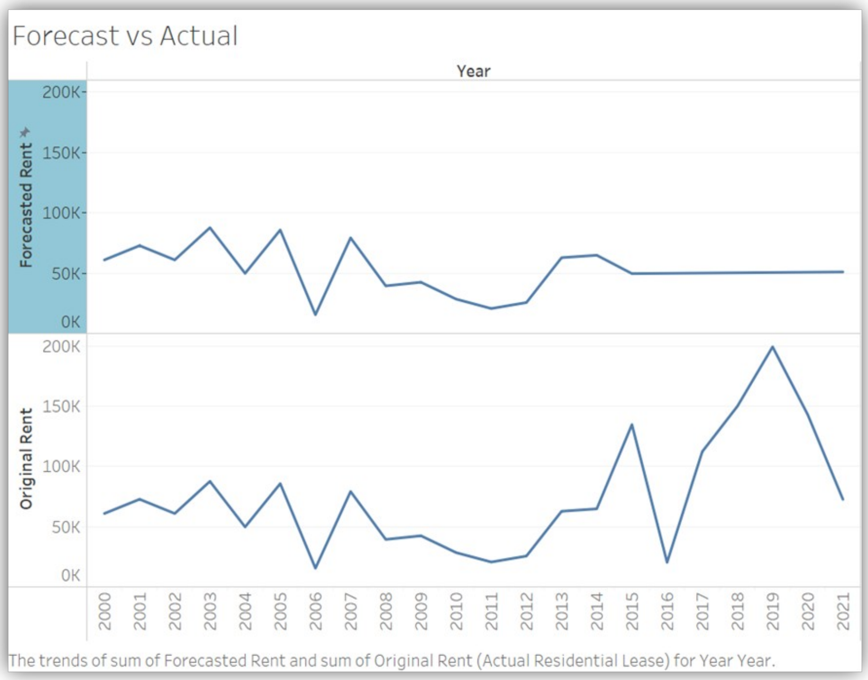


Fig. 48: Parallel values of forecasted and actual yearly rent

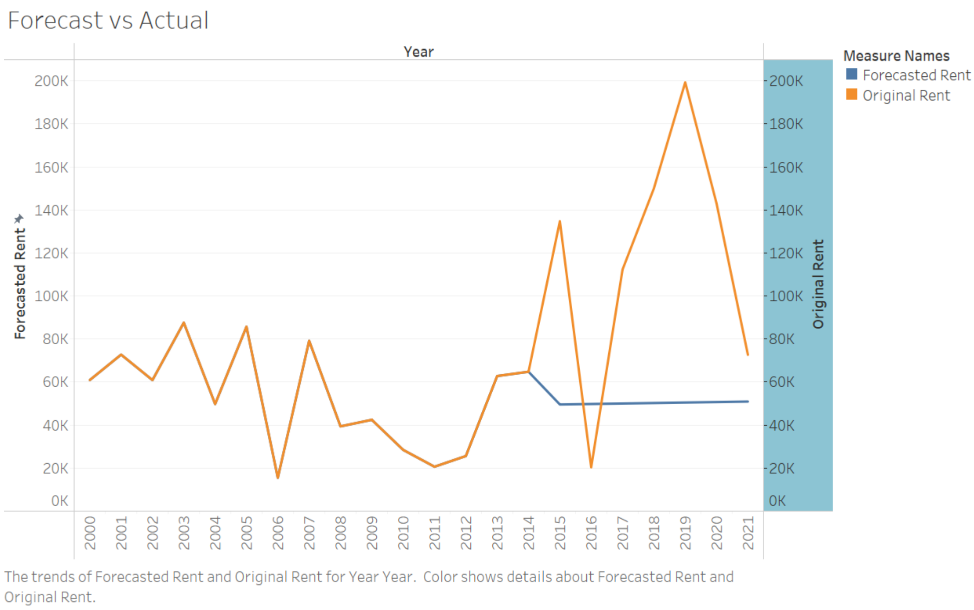


Fig. 27: Actual Value and Forecasted Value for Residential lease in

Fig.s 48 and 49 depict the actual and forecasted rent for 2015 to 2021. Due to unforeseen circumstances and other variables that are not part of this data, there is a quiet gap between these trends. Given that there is more study to bring the other variables in place, which are related to the COVID-19 period, climate change, shift in the movement and growth of population in the Central-Eastern area, the gap would likely be lesser, and there would be more understanding of what is the reason in the growth during those periods.

Table 10: Data set used to Create Forecast from 2000 to 2014

Time series:	**Year of Year**
Measures:	The sum of Original Rent
Forecast forward:	Seven years (2015 – 2021)
Forecast based on:	2000 – 2014
Ignore last:	One year (2015)
Seasonal pattern:	One year cycle

Table 11: Residential Summary by Exponential Smoothing

Initial			**Change From Initial**	**Seasonal Effect**				**Contribution**		
2015			**2015 – 2021**	**High**		**Low**		**Trend**	**Season**	**Quality**
49,587	±	45,412	1,366	2021	1	2021	1	100.0%	0.0%	Ok

All forecasts were computed using exponential smoothing.

Table 12: Forecast Model, Quality Metrics and Smoothing Coefficients for the Forecasted Residential data

Model			**Quality Metrics**						**Smoothing Coefficients**		
Level	**Trend**	**Season**	**RMSE**	**MAE**	**MASE**	**MAPE**	**AIC**		**Alpha**	**Beta**	**Gamma**
Multiplicative	Multiplicative	Multiplicative	23,838	20,683	0.79	64.1%	314		0.000	0.043	0.211

Several factors contributed to the increase in property purchase and land leasing for residential leases in the Suva and Nausori area of Fiji in 2019. Some reasons include:

1. Population growth: Suva and Nausori are two of the fastest-growing urban areas in Fiji, with a rapidly increasing population. This growth could have led to increased demand for housing and land.

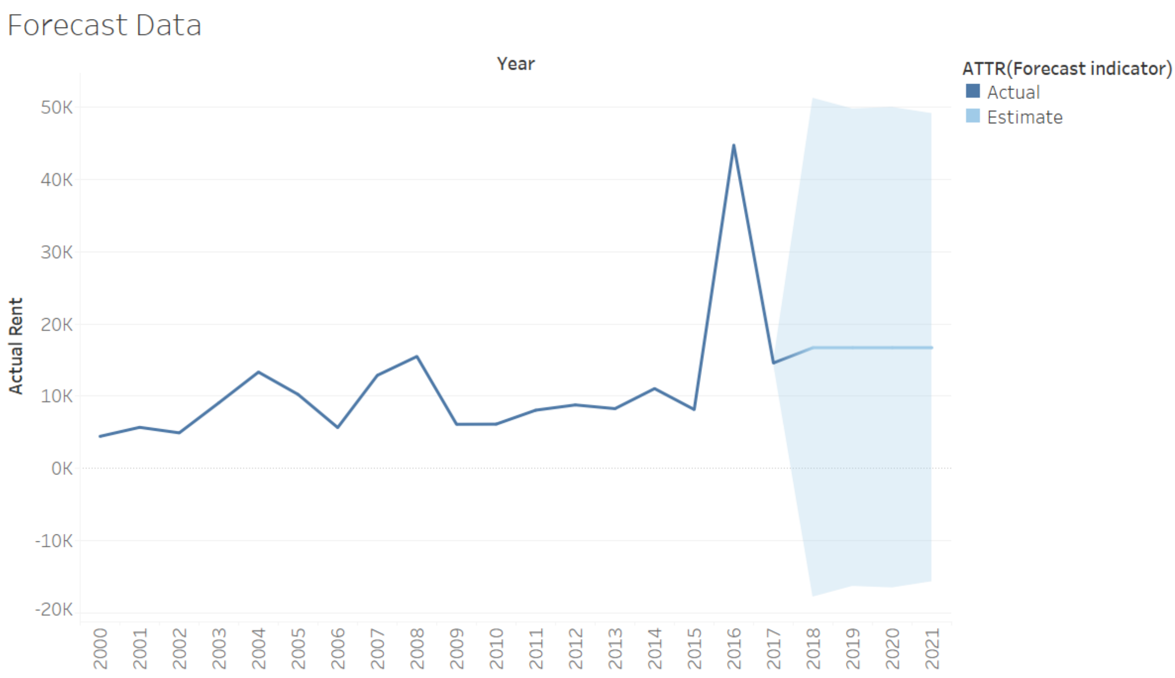
2. Urbanization: As more people move to urban areas, the demand for housing and land increases, leading to a rise in property prices and land leases.
3. Economic development: The Fijian economy has grown steadily in recent years, with increased investment and job opportunities in urban areas like Suva and Nausori. This economic development has contributed to a rise in demand for residential properties and land leases.
4. Government policies and incentives: The Fijian government has introduced various policies and incentives to support the real estate sector, such as tax breaks for property developers and homebuyers. These policies could have encouraged more people to purchase properties and lease land in the Suva and Nausori area.

It is worth noting that the specific factors that contributed to the increase in property purchase and land leasing in 2019 may be complex and multifaceted and may vary depending on individual circumstances and market conditions.

4.4.2.1.3 RQ3: How to Monitor and Forecast the Agriculture land development using Tableau in the CE division?

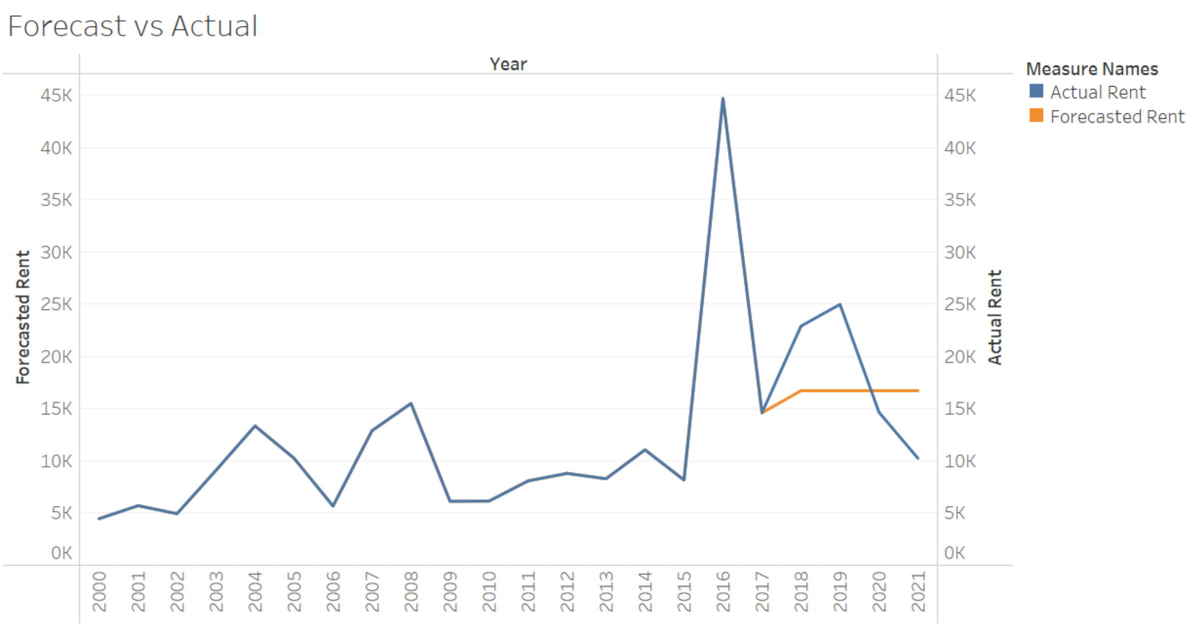
4.4.2.1.3.1 Agriculture Forecast

This data experiment is between the years 2000 to 2021, and this is only covering the central eastern region of Fiji. Data was altered during the experiment as it was unstructured, and through Tableau Prep, the data went through the ETL process.



The trend of sum of Actual Rent (actual & forecast) for Year Year. Color shows details about ATTR(Forecast indicator). The view is filtered on Year Year, which keeps 19 of 34 members.

Fig. 280: Forecast values of agriculture lease growth



The trends of Forecasted Rent and Actual Rent for Year. Color shows details about Forecasted Rent and Actual Rent. The view is filtered on Year, which keeps 22 of 22 members.

Fig. 51: This Agriculture forecast is for annual rent values from 2000 to 2017 and then the forecast begins from 2018 to 2021.

Since agriculture lease is usually low in demand, we have adjusted the forecast period to a shorter timeframe than the residential forecast I did earlier.

Table 13: Agriculture Years Forecast

Time series:	**Year of Year**
Measures:	The sum of Actual Rent
Forecast forward:	Four years (2018 – 2021)
Forecast based on:	2000 – 2017
Ignore last:	One year (2018)
Seasonal pattern:	One year cycle

Table 14: Agriculture Summary by Exponential Smoothing

Initial			**Change From Initial**	**Seasonal Effect**				**Contribution**		
2018			**2018 – 2021**	**High**		**Low**		**Trend**	**Season**	**Quality**
16,714	±	34,442	0	2021	1	2021	1	0.0%	0.0%	Ok

All forecasts were computed using exponential smoothing.

Table 15: Forecast Model, Quality Metrics and Smoothing Coefficients for the Forecasted Agriculture data

Model			**Quality Metrics**					**Smoothing Coefficients**		
Level	**Trend**	**Season**	**RMSE**	**MAE**	**MASE**	**MAPE**	**AIC**	**Alpha**	**Beta**	**Gamma**
Multiplicative	None	Multiplicative	9,092	4,507	0.68	30.8%	336	0.237	0.000	0.000

As shown in the forecast above, there is quite a margin between the forecasted and actual values. Certain factors affect the growth in the rent values of both types of leases, whether it be agriculture or residential. There are certainly external factors that contribute to this, one of which was the covid-19 pandemic, despite being a time whereby many things came to a standstill; people were still able to acquire leases to meet their needs. Quiet interesting is that the residential rental value has grown exponentially during the covid-19 pandemic, however for agriculture leases there needs to be a more strategic look into increasing the number of leases administered, as the values cannot be changed according to government regulations that govern agriculture leases which fall under the Agriculture Landlord and Tenant Act [Cap 270].

The growth of the Agriculture sector from 2017 to 2021 was made possible with some initiatives and assistance provided by the government of Fiji. According to the 2018 Real Gross Domestic Output Release Report for Agriculture Sector that was released on 5th September 2019 (Agriculture, 2019) preliminary estimates, Fiji's GDP increased by 3.5% from 2017 to 2018, and Agriculture, Forestry, and Fishing is one of the many contributing factors to this. Compared to 2017, the agricultural (including sugarcane production) and forestry industries expanded by 5.5% and 24%, respectively. Yaqona, sugarcane, and taro experienced high real growth, accounting for most of the increase in the agriculture industry. Pine and mahogany production saw a 24% increase, which drove the majority of the growth in the forestry sector (Agriculture, 2019).

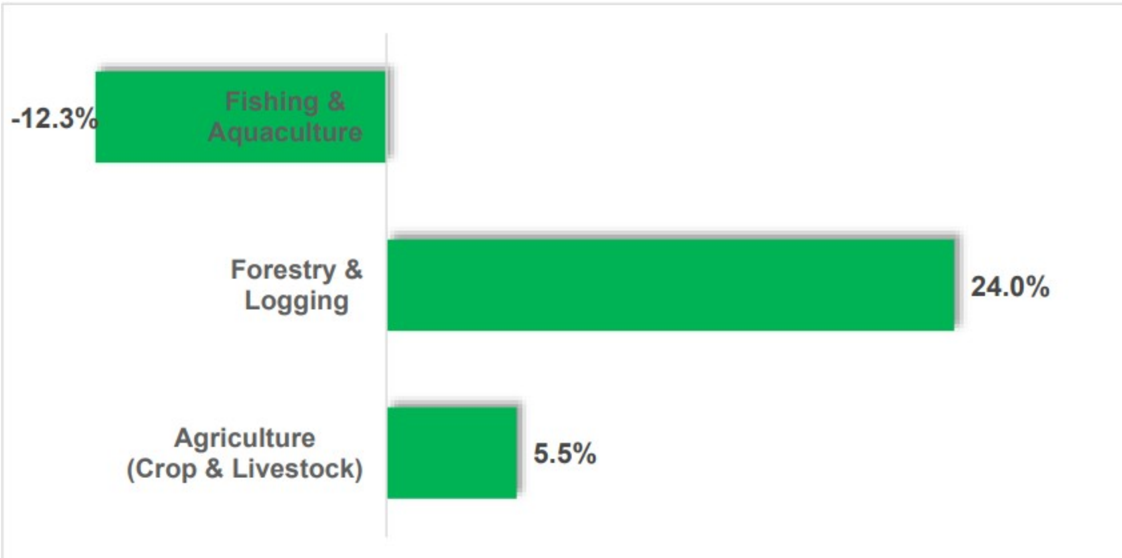


Fig. 52: Provisional GDP Growth rates for Agriculture, Fisheries and Forestry in 2018.

Source: National Accounts, Fiji Bureau of Statistics

A. Agriculture GDP [Crop & Livestock, including sugarcane]

A 5.5% rise over 2017 is seen in the preliminary estimate of the domestic agriculture product for 2018 at constant basic prices. It has increased from $650.8 million in 2017 to $686.9 million in 2018. Also, it increased its contributions to the national GDP from 6.3% in 2017 to 6.4% in 2018 (Agriculture, 2019).

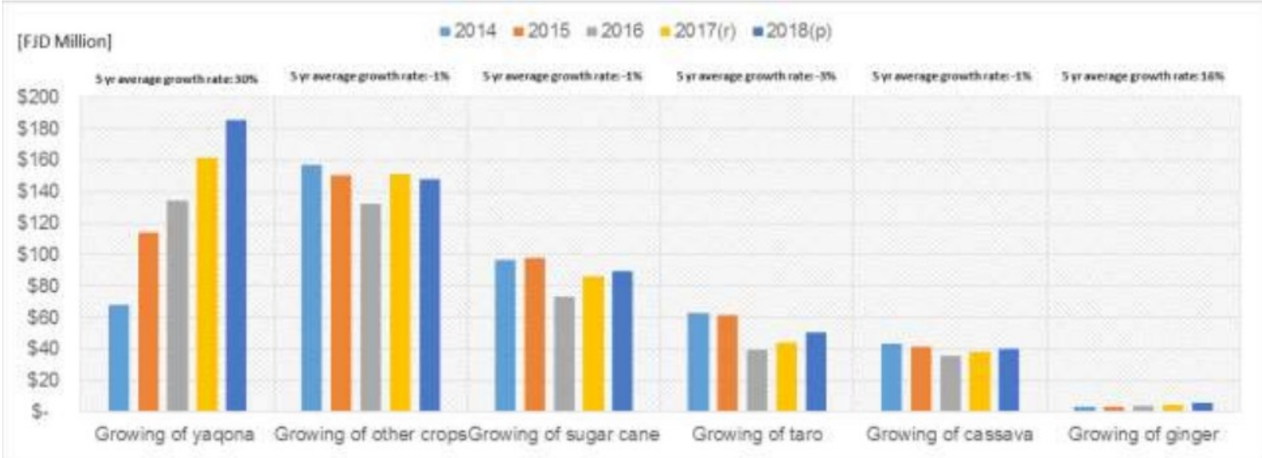


Fig. 53: GDP Growth Rate for Major Crop Commodities over the Past 5 years (2014-2018) Source: National Accounts, Fiji Bureau of Statistics (r): revised (p): provisional (Agriculture, 2019)

B. Highlights of Livestock GDP

Livestock commodities made up $64.3 FJD million of the total agriculture (crop & livestock) GDP in 2018, an increase of 2% from the previous year (Agriculture, 2019). An increase in GDP in the value of poultry, eggs, beekeeping, sheep, and goat farming increased livestock GDP (Agriculture, 2019).

Fig. 29: GDP growth rate for Major Livestock commodities over the past 5 years (2014-2018) Fiji wide. Source: National Accounts, Fiji Bureau of Statistics (r): revised (p): provisional (Agriculture, 2019)

Some statistics provided by the Ministry of Agriculture in its 2020 Key Statistics Report (Ministry of Agriculture, 2020) show the Crop Production by Division and Province:

Table 16: Major Crops: Distribution of Production by Geographical Division/Province, 2020

Division/ Province	Cassava	Dalo	Assorted Vegetables	Coconut	Yaqona	Ginger	Eggplant	Pawpaw	Turmeric
(Metric Tonnes)									
Fiji	71,890.0	535,893.7	34,419.5	21,679.5	13,187.5	11,408.8	4,146.9	3,634.9	1,632.2
Central	31,457.2	30,486.0	10,556.5	4,950.2	2,364.6	10,768.4	1,780.5	1,200.1	4.8
Naitasiri	10,117.3	12,120.4	2,813.6	930.8	675.1	7,335.4	239.2	196.3	-
Namosi	2,365.4	2,250.4	497.2	60.5	691.1	865.7	218.2	128.5	-
Rewa	2,792.2	1,706.8	1,394.8	1,373.5	291.5	42.5	260.7	90.9	-
Serua	4,815.1	4,513.0	2,152.7	413.5	298.7	2,016.4	577.9	535.1	3.2
Tailevu	11,367.2	9,895.5	3,698.1	2,271.9	408.2	508.4	484.5	249.3	1.6

Table 17: Major Crops: Distribution by Geographical Division/Province, 2020

Division/ Province	Kumala	Banana	Rice	Pineapple	Vudi	Yams	Pulses	Tomatoes	Pumpkin
(Metric Tonnes)									
Fiji	9,454.1	8,763.4	8,208.5	7,423.1	5,997.4	3,521.4	2,716.2	1,238.3	572.6
Central	4,934.4	5,216.7	535.2	2,461.8	2,706.4	498.3	186.9	300.4	129.5
Naitasiri	10,117.3	3.155.0	38.5	883.1	921.5	123.0	42.3	67.8	33.5
Namosi	2,365.4	144.6	5.4	90.4	379.1	31.2	2.3	38.4	11.5
Rewa	2,792.2	459.5	6.4	28.2	346.0	83.6	24.2	84.1	34.5

Serua	**4,815.1**	**258.6**	**439.3**	**194.9**	**254.0**	**81.1**	**58.4**	**90.1**	**30.5**
Tailevu	**11,367.2**	**1,199.0**	**45.7**	**1,265.1**	**805.8**	**179.5**	**59.7**	**20.0**	**19.6**

The above data is just a sample from the Ministry of Agriculture (Ministry of Agriculture, 2020, p. 20) that shows our farmers have the potential to utilize Agriculture leases for commercial use, which is an excellent source of income for their family and also contributes to Fiji's economy. The central division data is only shown above as it correlates to the sample data of agriculture leases being experimented with in this paper. Although papayas, pineapples, and bananas are the principal fruit products, a few businesses also process local fruits and vegetables, primarily for the domestic market, and they also make fruit juice concentrates (pineapple, orange, guava, mango, passion fruit, and other citrus fruit juices) (Commerce, 2022). A small but expanding number of high-quality specialist agricultural products are also exported, such as kava, chocolate, and certified organic coconut and ginger items (Commerce, 2022). Commodities processing for value-adding and specialized markets have potential in the agro-processing industry (Commerce, 2022).

The United States of America Department of Commerce – International Trade Administration also wrote an article on their website on Agriculture Commodities and what Fiji has to offer in this sector that could be traded with others. The statement summarizes that with the devastating effects of the COVID-19 pandemic on the nation's tourism industry, the importance of the agriculture sector to Fiji's economy for income production and food security has increased (Commerce, 2022). Including the sugar business (1.1%), agriculture is currently valued at roughly $690 million (FD$1.5 billion) and contributes to about 8.1% of Fiji's GDP (2021). More than 83% of Fiji's rural population relies on the industry as their primary source of employment, supporting the livelihoods of 27% of the country's citizens (Commerce, 2022).

There could be several reasons for the increase in agriculture leases during the COVID-19 period in Suva and Nausori areas of Fiji. Here are a few explanations:

1. Job loss and economic uncertainty: With the pandemic causing widespread job losses and economic uncertainty, some people may have turned to agriculture to generate income. Leasing land for agriculture allows individuals to grow crops and sell them to local markets, providing a source of income in times of hardship.
2. Food security concerns: The pandemic disrupted global supply chains, leading to shortages of some food items in Fiji. Leasing agricultural land can help ensure local food security by allowing individuals to grow their food and reduce dependence on imported products.

3. Government incentives: The Fijian government may have provided incentives or subsidies for individuals to lease land for agriculture during the pandemic. These incentives could have included reduced lease fees, access to agricultural equipment or supplies, or other forms of support. The Fijian government has made tax incentives available to entice private sector investment into the non-sugar subsector to improve the performance of that sector to that sector's (Commerce, 2022).
4. Increasing demand for local produce: As global supply chains were disrupted, there may have been an increasing demand for locally grown produce in Suva and Nausori. This could have motivated some individuals to lease agricultural land to meet this demand and take advantage of potential market opportunities.

Overall, the increase in agriculture leases during the COVID-19 period in Suva and Nausori areas of Fiji could be attributed to economic, social, and governmental factors. With more data this could be conclusive.

4.5 Forecast Outcome

This chapter has discussed the importance of designing a Business Intelligence (BI) model for land management using Tableau as the BI tool. The chapter provided an overview of the four components of a BI model, including data sources, data warehousing, data mining, and data analysis. It also evaluated different BI tools for land management dues to their ease of use, flexibility, and ability to handle large datasets. The chapter then provided a step-by-step guide to developing the BI model using Tableau, highlighting its potential benefits in improving land management practices.

From the outcome of this experiment, it can be concluded that while the residential lease is on the rise, there is a major opportunity for the development and leasing of agriculture leases to provide more employment to the labour market and become a major contributing factor to Fiji's economy. The previous Fijian government was working with development partners to strengthen ties between the agriculture and tourism industries and to boost the economic and social benefits for local farmers (Commerce, 2022). Hopefully, the current and new government will continue to work with these partners for the betterment of the agriculture sector and all its stakeholders. Currently, Fiji is reliant on imported goods to supply the fresh produce, meat, seafood, and dairy products needed by the tourism industry (Commerce, 2022). Fresh fruits such as papaya, tomatoes, pineapple, coconut, duruka (Saccharum edule), guava, and mango, vegetables, and herbal kava products are potential commodities in the agro-processing sector for value-added and niche-market processing (Commerce, 2022).

The data experiment is limited to the Central Eastern division along the Suva – Nausori corridor, which limits the data result to be of little impact on the organization. The experiment's outcome does not give full proof of all land use in Fiji. It is just a glimpse of how business intelligence can help and enhance better decision-making for the land management entities in Fiji.

4.6 Conclusion

The chapter's findings suggest that a robust BI model is critical for land management, as it can provide decision-makers with accurate and timely information to make an informed decision. By leveraging Tableau's features, land managers can develop a dynamic BI model that can help identify areas for conservation, predict changes in land use, and analyse the impact of climate change on land resources, provided there are more data drawn from all over Fiji to help analyse and provide more information for decision makers.

CHAPTER 5
CONCLUSIONS AND DISCUSSIONS

The literature review shows a great need for this study to be thoroughly looked into, as there is no literature review on the topic. A thorough and critical assessment of the body of prior research on the topic highlighted the knowledge gaps and created a precise and narrow study question.

Chapter 3 clearly states the significance of carrying out legitimate and trustworthy research, which requires fully comprehending research methodologies. The significance of choosing an acceptable sample, gathering data using proper methods, and abiding by ethical standards has been underlined as well. Given this information, the research done offers insightful answers to the research topic, guaranteeing that the conclusions are reliable and morally correct.

From Chapter 4, it can be concluded that the importance of adopting a data-driven approach to land management and the potential benefits of using Tableau as a BI tool. While this study focused on land management, the principles and techniques outlined in this chapter can be applied to other fields, including agriculture, forestry, and natural resource management. The chapter's findings provide a foundation for future research in the field of BI and land management, and it is hoped that this study will inspire other researchers to explore the potential of BI in improving land management practices.

BI tools are readily available now that with proper training and experiment the land management entities would be able to use them as a tool to not only make long term strategic plans but also to make operational calls through the data that is being analysed and the insight that they would be aware of from the reports that can be pulled from any BI tool that they would choose for their organization. The land management entities make better decisions on land evaluation and ensure that needs are met with specific assistance and foresight into the growth of the population and economy in some regions of the country. In due time it is possible to find useful, helpful knowledge by fusing internal and external data.

APPENDICES

APPENDIX: A

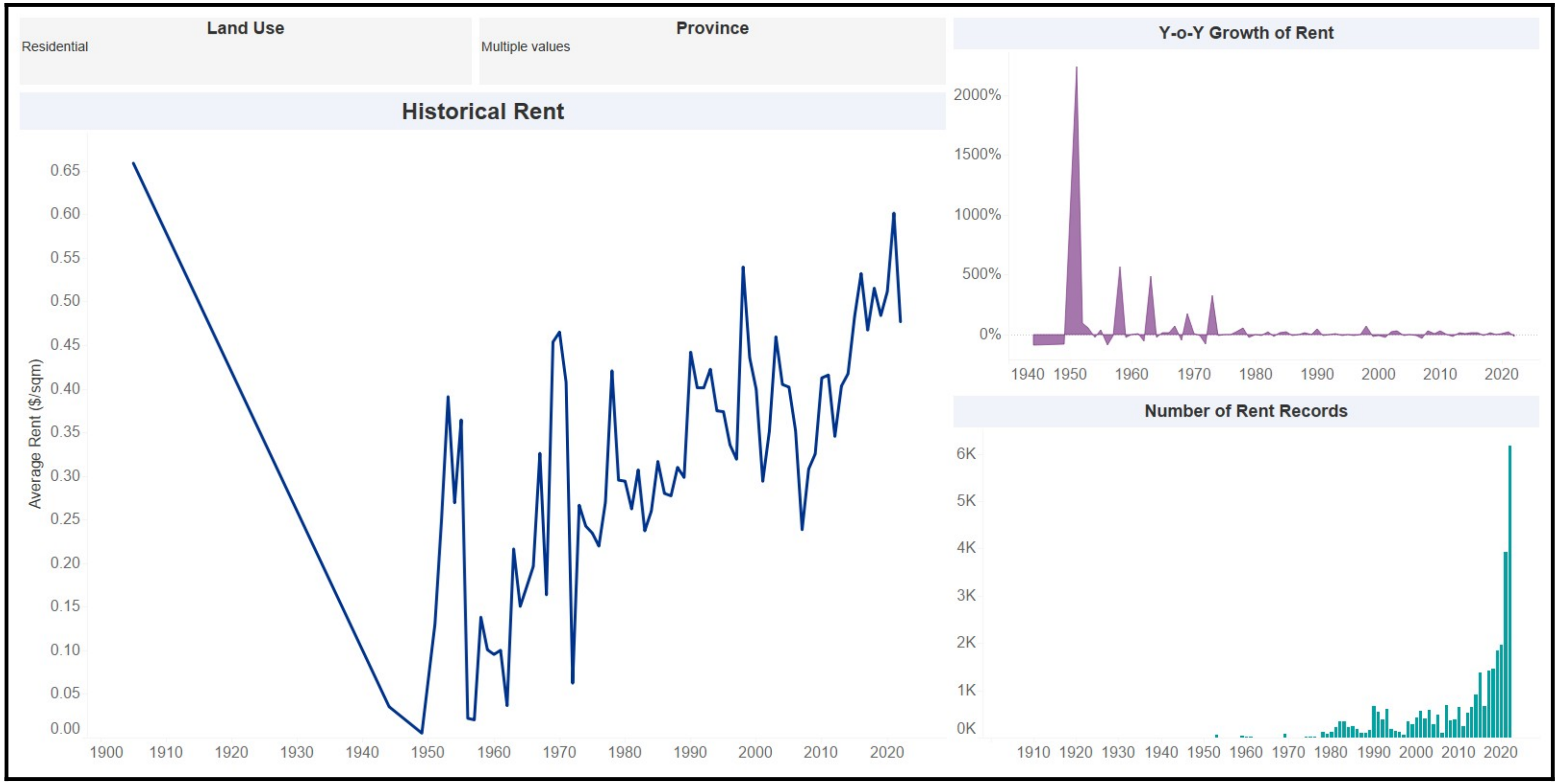


Fig 30: Overview of Average Rent per square meter for Residential lease

The approximate total area of the Province of Tailevu is 906 square kilometres, for the Province of Namosi is approximately 1,364 square kilometres, for the Province of Serua is approximately 676 square kilometres, for the Province of Naitasiri it's approximately 1,666 square kilometres and lastly for the Province of Rewa its approximately 724 square kilometres; which total it up to a land mass of 5,336 square kilometres.

APPENDIX: B

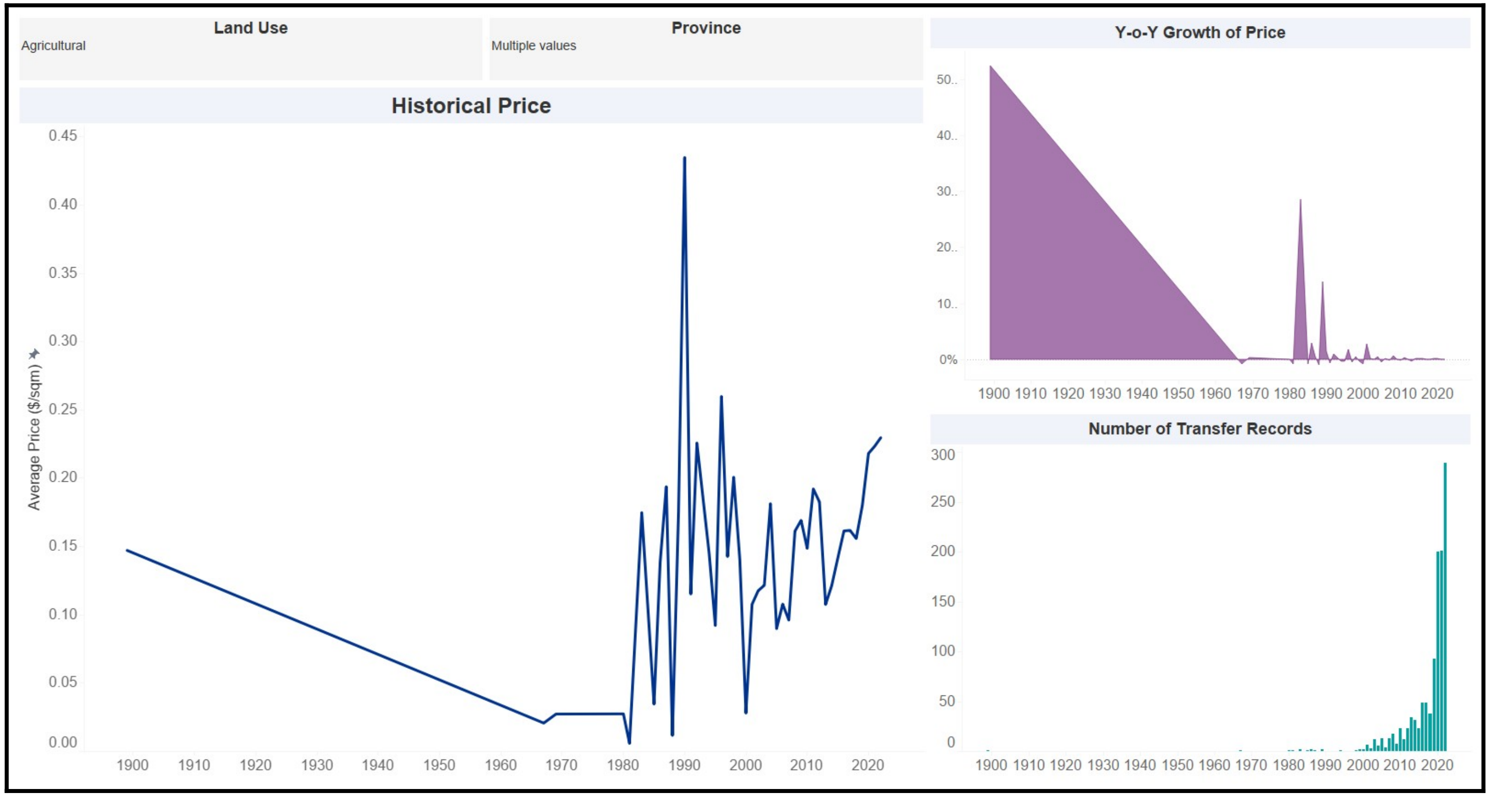


Fig. 31: Overview of Average Price per square meter for Agriculture lease

These data show the trend of the average agriculture lease per square meter for the central-eastern region of Fiji. This region comprises the provinces of Rewa, Tailevu, Namosi, Serua, and Naitasiri.

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