

Developing a digital twin model for improved pasture management at sheep farms

by
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Declaration of independent work

I, NTEBALENG JUNIA LEMPHANE, student number _____, declare that this work is an original report of my research project submitted to the Central University of Technology, Free State, for the Degree MASTER OF ENGINEERING: ELECTRICAL ENGINEERING; that the work contained herein is my own and complies with relevant policies of the Central University of Technology, Free State; and this work has not been submitted before to any institution for any other degree or professional qualification.

SIGNATURE OF STUDENT

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Abstract

Sheep farming plays an integral part in the South African livestock sector through the production of meat and wool. In sheep production, a pasture is of utmost importance. A pasture is deemed as a natural source of nutrients for animals, especially to small scale farmers who cannot afford to buy artificial feed for sheep. Pastures therefore need to be maintained to ensure good quality and quantity feed to get the best produce from the animals. The process of maintaining pastures is referred to as pasture management, and pasture management strategies require a farmer to be aware of factors such as climate and soil.

Climate change is reducing pasture production which lowers livestock productivity and, as a result, small scale livestock farmers suffer great losses. Pastures are dependent on climatic conditions, therefore, climate change has a great impact on pasture management. With the progression of climate change, farming seasons have changed, and it has become a challenge for sheep farmers to implement proper pasture management techniques due to changing weather patterns. As a result, farmers struggle to keep their sheep alive due to unavailability of animal feed caused by poor pasture production due to climate change.

The use of technology in livestock farming introduced the concept of smart farming which has made pasture management easier and more cost effective. Smart farming integrates advanced technological methods that include connectivity, Internet of Things (IoT), and data analytics. Thus, to alleviate the challenge of changing weather patterns that affect pasture management, digital twin technology is proposed as solution in this study. Digital twin development includes smart farming technologies, and the literature shows that digital twins help in identifying and anticipating issues before they happen. Hence, a digital twin is developed to improve pasture management by predicting pasture height to determine the anticipated amount of pasture and secure enough feed for the sheep for sustainable production.

The system is comprised of the physical system and its digital twin. The physical system is set up using the IoT sensors and devices. These include soil moisture sensor that measures soil moisture content, ESP32 CAM that captures the pasture images, raspberry pi that processes captured images and calculates pasture height, weather station which measures rainfall and temperature and the modem that provides wireless connectivity. The digital twin is developed using both historical and the real-time data from the sensors. Sensors data was streamed in ThingSpeak[®] cloud in real-time. Transfer of data from the sensors is the link between the physical system and the digital twin. The data analysis is performed in MATLAB[®] using an Artificial Neural Network (ANN) machine learning algorithm. The prediction of the height of the pasture is then modelled using the SIMULINK[®] platform.

The analysis of the digital twin results shows that the digital twin can accurately predict the pasture height based on historical and current data. Prediction of pasture height relies predicted temperature, rainfall and soil moisture. The results presented temperature and soil moisture prediction model to have a good performance with prediction error of ± 1.62 and -1.7 , respectively. Rainfall prediction model had a slightly higher prediction error of ± 6.03 . The outcome on the rainfall prediction model is the evidence of the impact of varying weather patterns. Nonetheless, based on the predicted temperature, rainfall, and soil moisture, the digital twin predicted pasture height to be 52 cm and observed pasture height was 56 cm, with the prediction error of -4 . The difference on the pasture height predictions is 4cm which reflects a good prediction. Therefore, the digital twin was able to reflect good dependency amongst the models, on that account, the digital twin can serve to enhance pasture management through its capabilities to monitor pastures in real-time and perform pasture height predictions for the future that assist farmers in decision making.

Table of contents

Declaration of independent work.....	ii
Acknowledgements.....	iii
Abstract.....	iv
List of Figures.....	viii
List of Tables.....	x
Chapter 1 – Basis of the Study.....	1
1.1 Introduction.....	1
1.2 Problem Statement.....	4
1.3 Research hypothesis and objectives.....	5
1.3.1 Research hypothesis.....	5
1.3.2 Research objectives.....	5
1.4 Research methodology.....	6
1.5 Research layout.....	7
Chapter 2 – Literature Review.....	9
2.1 Introduction.....	9
2.2 Sheep farming in South Africa.....	9
2.3 Impact of climate change in pasture management.....	10
2.4 The need of technology in pasture management.....	12
2.5 Smart farming.....	14
2.5.1 Artificial Intelligence in farming.....	15
2.5.2 Internet of Things in farming.....	16
2.6 Pasture-based technologies.....	18
2.7 Smart farm systems for pasture management in sheep farms.....	19
2.7.1 Information and Communication Technology (ICT)-based rising plate meter.....	20
2.7.2 Weather monitoring stations.....	20
2.7.3 Farmote Technology.....	20
2.8 Smart farming systems, challenges and solution technique.....	21
2.9 Digital twin.....	22
2.9.1 Predictive modelling.....	25
2.9.2 Digital shadow.....	28
2.9.3 Types of digital twins.....	29

2.9.4 Digital twins in livestock farming	30
2.10 Limitations of the existing research	32
Chapter 3 – Research Methodology	34
3.1 Introduction	34
3.2 Phase A – Monitoring	34
3.2.1 Central University of Technology’s farm – A case study	35
3.2.2 Developing the physical system	37
3.2.3 Structural design of physical system	40
3.3 Phase B – Algorithm development	41
3.3.1 Selecting the right algorithm	42
3.3.2 Predictive modelling using an ANN algorithm	56
3.4 Component C – Digital twin development	57
3.4.1 Stage 1 – Developing a digital shadow	57
3.4.2 Stage 2 – Developing a digital twin	63
3.5 Conclusion	69
Chapter 4 – Results and Analysis	70
4.1 Introduction	70
4.2 Digital shadow model development and results	70
4.2.1 Results on collected farm data	70
4.2.2 Findings on pasture height for both seasons	74
4.2.3 Digital shadow model predictions and results	75
4.3 Digital twin development and results	82
4.4 Analysis of the digital twin results	90
Chapter 5 – Research contributions and conclusions	92
5.1 Introduction	92
5.2 Summary	92
5.3 Discussions	93
5.4 Research Contributions	94
5.4.1 Contributions to the literature	95
5.4.2 Contribution to farming	95
5.4.3 Development of a digital twin model	95
5.4.4 Contributions to the Fourth Industrial Revolution	96
5.5 Future work	96
5.6 Scientific outcomes	97
References	98

List of Figures

Figure 1. 1 Incorporating smart farming technology in digital twin	3
Figure 1.2 Proposed system methodology	7
Figure 2. 1 Representation of technological advancements happened over the years in livestock farming	13
Figure 2.2 AI in smart farming	16
Figure 2.3 IoT in smart farming	18
Figure 2.4 Digital twin concept	22
Figure 2.5 AI algorithms and machine learning with digital twins	23
Figure 2. 6 ANN block diagram	27
Figure 3.1 Map showing the structure of the Agri Training Centre farm.....	36
Figure 3.2 Architecture of the physical system	37
Figure 3.3 IoT sensors setup	40
Figure 3.4 Process followed in selecting the suitable predictive algorithm	43
Figure 3.5 Importing and training prediction temperature model using regression learner app	44
Figure 3.6 Predicted temperature values in regression model	46
Figure 3.7 RMSE value obtained while training regression rainfall prediction model	47
Figure 3.8 Predicted weekly rainfall values using regression model	47
Figure 3.9 neural network training architecture	51
Figure 3.10 Temperature prediction model performance	51
Figure 3.11 Deployed ANN model to SIMULINK®	51
Figure 3.12 Predicted temperature values in ANN model.....	52
Figure 3.13 ANN rainfall model performance	53
Figure 3.14 Predicted rainfall values in ANN model	53
Figure 3.15 Measuring pasture height and the soil moisture	59
Figure 3.16 April farm data in Excel®	59
Figure 3.17 Models in digital shadow	60
Figure 3.18 Digital shadow temperature and rainfall prediction models	61
Figure 3.19 Digital shadow soil moisture prediction model.....	62

Figure 3.20 Digital shadow pasture height prediction model.....	62
Figure 3.21 Digital twin development process	64
Figure 3.22 Data analysis and predictive modelling in the digital twin	66
Figure 3.23 Sensor data retrieved from ThingSpeak® to SIMULINK® in real-time....	67
Figure 3.24 Deploying prediction models in SIMULINK®	67
Figure 3.25 Predictions with the Digital model in SIMULINK®	68
Figure 4.1 Weekly average temperature observed in Autumn 2021 and Spring 2021 while monitoring pasture growth.....	71
Figure 4.2 Weekly total rainfall recorded in Autumn 2021 and Spring 2021 during pasture growth	71
Figure 4.3 Weekly average soil moisture recorded in Autumn and Spring in 2021 while growing the pasture	72
Figure 4.4 Pasture height recorded in Autumn and Spring seasons in 2021	73
Figure 4.5 Grazing sheep on the pasture	75
Figure 4.6 Predicted temperature and observed temperature for Autumn 2022.....	76
Figure 4.7 Predicted and observed rainfall for Autumn 2022	76
Figure 4.8 Predicted and observed Soil moisture for Autumn 2022	77
Figure 4.9 Predicted and observed pasture height for Autumn 2022	78
Figure 4.10 Temperature analysis on predicted and observed results	79
Figure 4.11 Rainfall analysis on predicted and observed results.....	80
Figure 4.12 Soil moisture analysis on predicted and observed results	81
Figure 4.13 Structure of the physical system on the farm	82
Figure 4.14 Data collected daily from the sensors and stored in ThingSpeak®	83
Figure 4.15 The sensors' weekly data	84
Figure 4.16 Prediction period within the digital twin.....	85
Figure 4.17 Digital twin temperature predicted results compared with the observed results.....	85
Figure 4.18 Digital twin predicted rainfall results compared with the observed rainfall results.....	86
Figure 4.19 Digital twin predicted average soil moisture compared with the observed rainfall results	88
Figure 4.20 Digital twin predicted pasture height compared with the observed results	89
Figure 4.21 Monitor pasture height as animals graze.....	91

List of Tables

Table 2.1 Challenges facing livestock farmers.....	12
Table 2.2 Phases in developing data-driven digital twin	29
Table 2.3 Physics-based digital twin design.....	30
Table 3.1 Dataset used for temperature predictions	45
Table 3.2 Comparing temperature predicted and observed values on regression model	49
Table 3.3 Comparing rainfall predicted and observed values on regression model.....	50
Table 3.4 Evaluation of ANN temperature prediction model.....	54
Table 3.5 Evaluation of ANN rainfall prediction model	55
Table 3.6 Comparison on ANN and Regression predicted temperature results	55
Table 3.7 Comparison on ANN and Regression predicted rainfall results.....	56
Table 4.1 Number of weeks in a year in Autumn and Spring seasons in 2021	74
Table 4.2 Analysis of predicted average temperatures by the digital twin.....	86
Table 4.3 Analysis on digital twin predicted rainfall results	87
Table 4.4 Predicted soil moisture results analysis	88
Table 4.5 Analysis on predicted pasture height results	89

Chapter 1 – Basis of the Study

1.1 Introduction

Livestock farming contributes significantly to food security. However, in South Africa, livestock production does not only provide food security, but it serves to satisfy the basic needs of the people, including clothing, and also provides several social and economic contributions [1] to the country.

South African livestock production covers approximately 70% of the agricultural land [2]. Therefore, livestock farming forms a substantial part of the country's agricultural sector and includes the production of cattle, dairy, pigs, sheep, goats, game species and ostriches [1]. The country also boasts a thriving poultry and egg industry [3].

Livestock production systems depend on the utilisation of forage species or pastures to feed the animals, and this has become an essential element in managing the pastures [4], also known as pasture-based livestock production [5]. In South Africa, there are many animals that depend on pastures for survival, and statistics indicate that these animals include 13.6 million beef cattle, 1.4 million dairy cattle, 24.6 million sheep, 7.0 million goats, 3 million game species (farmed) and 1.6 million ostriches [1].

Hence, the statistics show that sheep farming is most practised in the country and makes a substantial contribution in wool and meat production [6]. There is also a high demand for lamb and mutton across the country, as well as the export of wool. Thus, to get good produce from these sheep, farmers need to ensure good quality and sustainable feed.

Pasture is a grazing land for all ruminants and thus provides a healthy feed for sheep too [7]. Pasture management is an important aspect of farm management, and pertains to managing healthy grass and associated plants to provide sustainable feed to the animals to ensure profitable livestock production [8]. A well-managed pasture provides notable benefits that include enhanced forage yields, and reduced feed costs, thereby leading to healthy livestock [7].

Farmers who rely on grazing pasture as their key source of animal feed, need precise and timely measurements of pasture height for effective grazing management [9]. Accurate measurement of pasture is important because productivity is driven by the degree of pasture utilisation which is a function of increased pasture growth. Various pasture measuring tools are therefore used to measure the pasture height. These include a pasture ruler, falling plate and rising plate [10][11].

Nevertheless, the major constraint facing sheep farmers is lack of good-quality pasture [12]. This problem can be caused by poor management practices, grazing systems, and a decline in pasture production as result of climate variability [13]. To overcome these challenges, technological developments were introduced to enhance pasture management strategies for better production. The introduction of Artificial Intelligence (AI), IoT, Big Data, and data analysis in livestock farming has dramatically transformed this sector, making it efficient and more profitable [14]. This further led to the emergence of the smart farming concept.

Smart farming utilises IoT sensors that allow remote monitoring, virtual fencing, provide tools for weather and soil information, as well as inspect grazing systems [12]. Utilising technology in pasture management brings a huge variance in productivity. It is critical to improve the contemporary management, herding style, and set up digitalised farming that use the latest technology. However, even with the current systems in place, farmers still encounter challenges in pasture management practices.

Pasture production is climate-dependent and hence sensitive to climate change [15]. Escalated oscillation of extreme temperatures, droughts and floods caused by climate change negatively affect the pasture species, creating unforeseen scenarios occurring earlier than expected with larger impacts [16].

Climate change also causes consequential changes in pasture management that include factors such as changing rain patterns, increased evaporation rate and decreased soil moisture which lead to poor pasture availability [17]. Consequently, pasture production becomes low and so sheep farmers end up losing the animals due to lack of good pasture to feed them [18]. This, in turn, results in collapse of small-scale farmers because they cannot afford to buy additional feed [19].

As mentioned, climate change has a negative impact on pasture management because pasture production is mainly dependent on climatic conditions. In other words, climate change affects the pasture ecosystem. There is a mutual relationship between pasture species and climatic conditions along with environmental factors.

Temperature and soil moisture affect the growth of pasture plants [20]. In spite of that, soil moisture depends strongly on rainfall [21], and the response of soil moisture content to rainfall is an important hydrological process in pasture growth. However, climate change influences soil moisture, temperature and rainfall levels thereby affecting pasture growth.

Traditionally, managing a livestock farm has been based on the experience of the farmer and human observations. Digital twin technology has the potential to shift that practice, to have farming that is based on real-time data, manipulated by AI analysis which results in better business decisions [22]. Digital twins are building upon existing technologies including IoT and simulation and, as a result, they are seen as a new phase in smart farming [23]. Figure 1.1 shows how smart farming technology is aligned to digital twin.

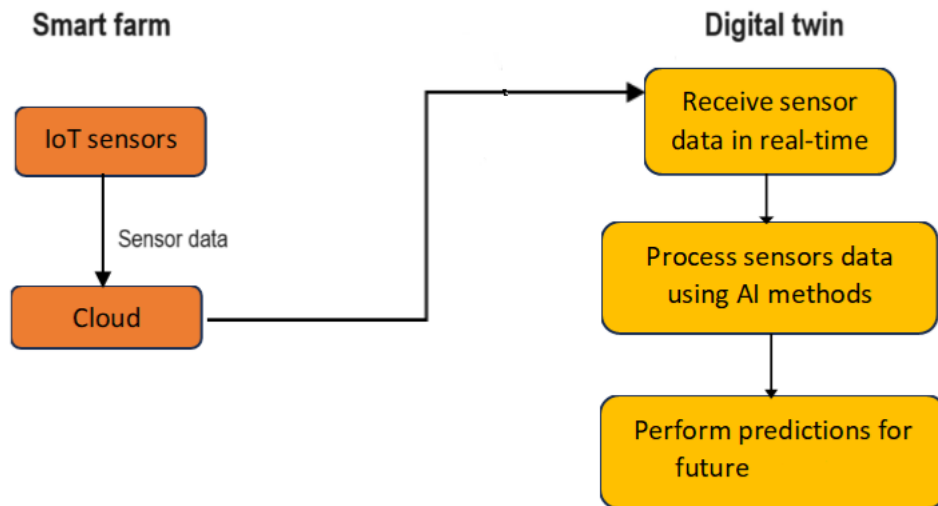


Figure 1. 1 Incorporating smart farming technology in digital twin

Digital twins have taken advantage of using current technology to improve management techniques in livestock farms to avert problems and prevent downtime, enhance general operations to escalate uptime, and even develop future prediction [24]. Livestock farmers are already using digital twins to portray information collected at the farms. Additionally, digital twin technology is sure to assist livestock farmers in predicting animal behaviours, monitor and prevent diseases, improve breeding operations, as well as improve management strategies to prevent livestock losses [22].

This study aims to build a digital twin that can assist in predicting pasture growth based on three variables, namely: Temperature, rainfall and soil moisture. The main purpose of the study is to create an improved pasture management system with predictive scenarios that can be detected at early stages for better decision-making and risk-management procedures.

1.2 Problem Statement

Sheep graze for an average of eight hours per day and their primary food source is pasture. However, lacking adequate pasture can result in having unhealthy animals. As climate plays a vital part in establishing the quality of the land type and the pasture that grows there, with the onset of climate change, it has become a challenge for sheep farmers to manage their pastures due to unpredicted weather patterns. This affects the pasture growth which leads to poor quality feed, limits farm produce, and results in collapse of small-scale farmers. This study aims to address this gap by investigating the following research questions:

1. Is it possible for small scale farmers to successfully use and engage digital twins in their farms to alleviate climate change challenge?
2. How can farmers use digital twins to improve their pasture management strategies to help them make proper decisions on time to avoid the collapse of their farms?

1.3 Research hypothesis and objectives

This section details the hypothesis of the study and the research objectives.

1.3.1 Research hypothesis

Digital twins can minimise the effects of climate change in pasture management by integrating real-time data and historical data to form predictive models that will help small-scale farmers predict pasture height. Climate change in South Africa is more affected by change in patterns of climatic conditions which includes rainfall and temperature. Precise predictions of rainfall and temperature can be helpful to farmers as it will also give a picture of expected soil moisture content that will be available to grow the pasture. Hence, this will enable farmers to properly make decisions based on the predictions.

1.3.2 Research objectives

Climate change poses some challenges in pasture management. These include unpredictable weather conditions that affect pasture growth, which results in unhealthy feeding of the animals. Moreover, these varying weather patterns make it hard to determine how climatic conditions affect pasture growth in order to weigh pasture availability to feed the animals. To address these challenges, the research focuses on the following objectives:

- Monitoring the conditions on the farm to manage factors that affect the growth of the pasture.
- Analysing, structuring and processing data to develop predictive algorithms.
- Developing a digital twin with predictive models that are updated by real-time data to predict pasture height and identify issues beforehand, hence providing instant solutions for composite problems.

1.4 Research methodology

As stated in problem statement, climate change has had a direct impact on pasture management which, in turn, affects sheep production. The aim of this research is to improve pasture management techniques by developing a real-time data collection tool that incorporates a predictive model that predicts pasture height based on three variables, namely: temperature, rainfall, and soil moisture. This will help to unravel unforeseen scenarios for better planning and monitoring.

A digital twin model is the proposed solution to overcome these challenges. Therefore, the following procedures will be undertaken in developing a digital twin:

1. Gathering historical data and real-time data from the farm. The focus will be to collecting data on temperature, rainfall, soil moisture and pasture growth.
2. Developing a digital shadow model in MATLAB[®]/SIMULINK[®] to simulate the farm operation. The model will be built with the data collected in the previous step (1). This model will aid in understanding the relationship between variables and the expected outputs on the real systems.
3. Setting up the physical system with cloud storage. This is the connection of IoT sensors to monitor the growth of the pasture. The system will be composed of the sensors to measure the parameters affecting pasture growth in real-time. The cloud platform will be incorporated into the setup to store the measured data in real-time.
4. Developing a digital twin model of the physical system in MATLAB[®]/SIMULINK[®]. The model will be developed using historical data and updated with the collected data from the sensors. The live data from the sensors will enable the model to run in real-time. The predictive system's algorithm will then be used to perform the predictions of the pasture height.
5. Analysing the predicted results from the digital twin. The predicted values and the measured values will be compared to measure the model performance. This process is demonstrated in Figure 1.2.

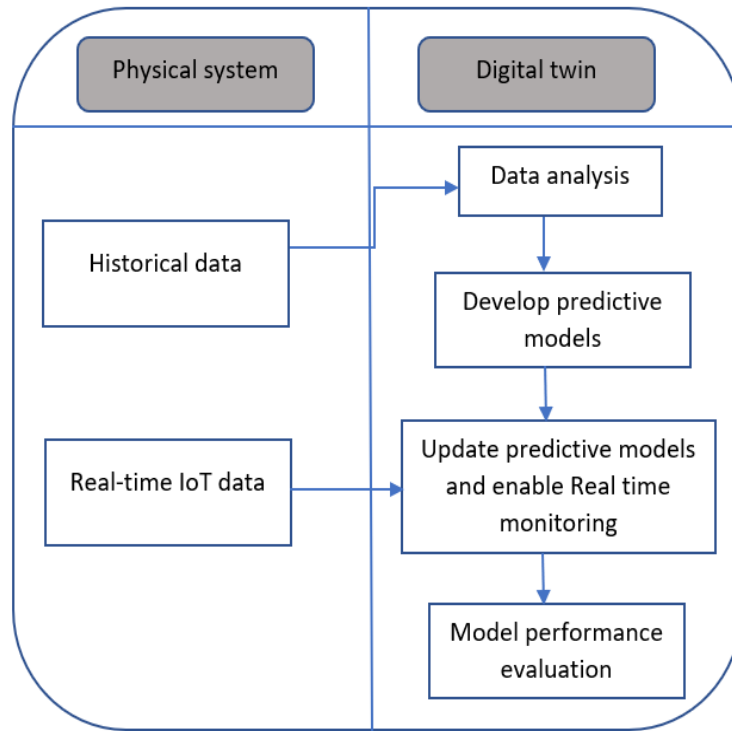


Figure 1.2 Proposed system methodology

1.5 Research layout

Chapter 1: The aim of chapter 1 is to formulate the basis of the study. Aspects including the problem statement, hypothesis, research objectives and research methodology are introduced in this chapter.

Chapter 2: Chapter 2 details the literature of the research. It explains the effects of climate change in pasture management which ultimately affect sheep production. It shows the importance of smart farming technology in pasture-based systems. This chapter illustrates how digital twins can be used to solve the challenges outlined in chapter 1 based on the literature. Lastly, the limitations of the existing literature are looked into.

Chapter 3: This chapter demonstrates the methodology carried out to develop the proposed solution in this research. Firstly, the researcher shows how data was collected. Secondly, it demonstrates how the historical data was used to identify a suitable algorithm to develop a predictive model in the MATLAB[®]/SIMULINK[®] environment.

Chapter 3 further shows how the same platform was then used to build a digital shadow model as the predecessor of a digital twin. Thirdly, the chapter details how the physical system was set up using IoT sensors to enable real-time data collection and, next, how the digital twin was then developed to perform the predictions using historical and live data.

Chapter 4: Chapter 4 shows the outcomes from the tests performed on various models for implementation. The analysis of the results is also performed. This is where the comparison of two sets of data is done to assess the performance of the model. The predicted results are also analysed to determine the effectiveness of the digital twin.

Chapter 5: The aim of this chapter is to give the summary of the work done in the research, outline the goals achieved, and highlight the researcher's unique contribution to the project.

Chapter 2 – Literature Review

2.1 Introduction

This chapter reviews the literature on previous studies that were carried out to identify the research gap. The literature review helps to identify the drawbacks of technologies currently used to support the need to carry out the study. This chapter will detail how climate change has affected the pasture management which has impacted sheep production. The chapter will also discuss how smart farming technology contributes towards pasture management. The gaps in smart farming will also be explained as well as the proposed solution.

The robust evolution of Information and Communication Technologies (ICT) and processing devices, allowed the upward push of many superior technological answers for the farming sector, primarily based totally on electronic sensors, processing factors and automation. Solutions to remote monitoring of plants and farm animals are already within sight of the market. This is proof of the growing penetration of ICT in this area, wherein concepts such as smart farming and IoT play an integral role [25].

2.2 Sheep farming in South Africa

Sheep husbandry plays an important role in socio-economic and cultural lives across all the provinces of South Africa [26]. Sheep farming serves as a source of income to small-scale businesses that produce meat and wool. There is a high demand for lamb and mutton in South Africa, over 200 000 tonnes per year [27], and a produce of over 100 million kilograms (kg) of wool [28], of which over 55 million kilograms (kg) of wool are the exports [27].

Most common sheep breeds in the country are Merino and Dohne Merino [28] as these are dual purpose breeds that produce a good quality of both meat and wool. Yet, good production of meat and wool depends on adequate and sustainable sheep feed.

Sheep feed on a forage that is found on pastures [28]; thus, pasture management practices are implemented to produce good quality pasture to feed the sheep. Nonetheless, climate change impacts pasture management which results in the decline in quality and quantity of pasture production [29]. As a result, lack of suitable pasture for feeding the sheep makes it hard for the farmers to keep their animals alive [28].

2.3 Impact of climate change in pasture management

Climate is the determination of weather conditions at a particular area on earth and it is expressed in terms of expected temperature, rainfall and wind conditions [30]. Climate change is defined as the switch in climate patterns largely brought about by greenhouse gas emissions [31]. This results in changes in climate indicators that include temperature, precipitation, sea-level rise and ocean acidification [32], consequently forming climate hazards involving droughts, severe storms, floods, heatwaves, hurricanes, cold spells, wildfires and landslides.

Climate change poses a significant risk for humans and natural systems, and is similarly threatening livestock production and productive performance [19]. Livestock products are considered to be a fundamental agricultural commodity for global food security as they contribute significantly to global kilocalorie consumption and global protein consumption; meanwhile, climate change is a threat to livestock production because of its impact on the quality of feed crop and forage, water availability, and animal reproduction [33].

South Africa is no exception to these effects, and livestock production in the country is therefore vulnerable to climatic risks. In mid-2020, commercial livestock farmers in South Africa indicated the impact of extreme temperatures which included negative implications for reproduction, loss of livestock, and severe loss of income [34].

Sheep farming is widely practised in South Africa [6], hence the focus of this study is in pasture management in sheep farms. Sheep production has been negatively impacted in the country due to climate change as small-scale sheep farmers experience water scarcity and extreme drought across the country [35].

The extent of climate change's impact is indicated by survey data from commercial farmers which shows that in a period of three years, between 2012 and 2014, most farmers withdrew from sheep farming altogether because feeding conditions became too difficult due to drought [36]. The Free State and Northwest provinces were most affected by drought due to climate change. In fact, in 2014, farmers from both provinces lost an approximate 80% of their sheep due to drought [37]. These small-scale farmers were vulnerable during drought because they could not afford to buy animal feed [37].

Pasture, commonly known to be the land used for grazing, is therefore crucial. These lands contain forage crops which are either cultivated or grow naturally to feed livestock such as cattle and sheep. There are two types of pastures namely natural pastures and artificial pastures. Natural pasture is a piece of land where forage crops grow naturally on their own to feed the livestock, whereas cultivated pasture is a piece of land where forage crops are cultivated and managed by farmers for livestock feed [38]. The cultivated pastures produce high-quality forage crops as compared to the natural pastures [39], thus the focus of this study is on cultivated pastures.

The management and maintenance of cultivated pastures is very important in sheep production. In pasture management for sheep, there are several practices and strategies implemented to ensure suitable forage availability for sheep to graze on. A well-managed pasture produces high-quality feed that enhance the health and productivity of sheep.

Climate change affects pasture management and may make the job of managing grazing lands even more complex. The combination of temperature, rainfall and soil moisture has a direct effect on pasture growth [40]. Rises in temperatures, intense rainfall and high evaporation rates caused by climate change have a negative impact on pasture production [17] [41]. Periods with low rainfall become drier than they would normally be at this time, and there is not much that can be done to increase pasture growth. Climate change therefore plays a major role in increasing the severity of drought through its climate-related factors, such as temperature and evaporation. Droughts are periods of relative dryness and reduced soil moisture due to lack of adequate rainfall [42]. Drought conditions therefore further influence pasture productivity.

As climate change results in deterioration of pasture towards reduced quality, which affects animal health, growth and reproduction, the unpredicted weather patterns affect the planning of farmers as the seasons have shifted. Previously, the rainy seasons were known, thereby allowing farmers to prepare the land for plantation at the right time. Thus, variability is the most controversial feature of climate change and is the limiting element in the prediction and assessment of its effects [43].

In addition, climate change is ongoing, but there is a combined application of multiple technologies and tools in integrated systems that can be used to overcome issues related to pasture management because of climate change [44].

2.4 The need of technology in pasture management

Globally, the livestock sector is facing several significant challenges. On the one hand, there is increased demand for meat and other livestock products. Additionally, livestock farmers are under increasing pressure to improve animal welfare using fewer resources. Table 2.1 summarises these challenges.

Table 2.1 Challenges facing livestock farmers

Productivity	Environment	Consumers	Climate Change
Need to produce more livestock products	Lower gas emissions	Animal welfare	Efficient use of resources
	Biodiversity	Human health	

Table 2.1 shows challenges that livestock farmers are experiencing. There is an increase in the world population and there is a growing demand in livestock products which contribute to food security. Livestock production is likely to be affected by climate change [45]. Climate change is caused by greenhouse emissions and the livestock sector contributes 14.5% of global emissions and, as a result, there is an increase in land degradation and decline in biodiversity [46].

At the same time, climate change affects livestock production through competition for natural resources, quantity and quality of feed, leading to a decrease in nutrient availability for livestock [31]. Consequently, the challenge is to maintain the balance between productivity, environmental preservation, customer satisfaction, and climate change mitigation strategies. Hence, new technology-based approaches are needed to produce more and to address these various issues.

Technological advancements in livestock farming have been seen over the years. In traditional farming practices, farmers visited their frequently to get the overview of farming activities. The current sensor and communication technologies offer a precise view of the farm with higher accuracy and detect issues at early stages and facilitates the use of smart tools. Figure 2.1 shows a representation of technological advancements happened over the years.

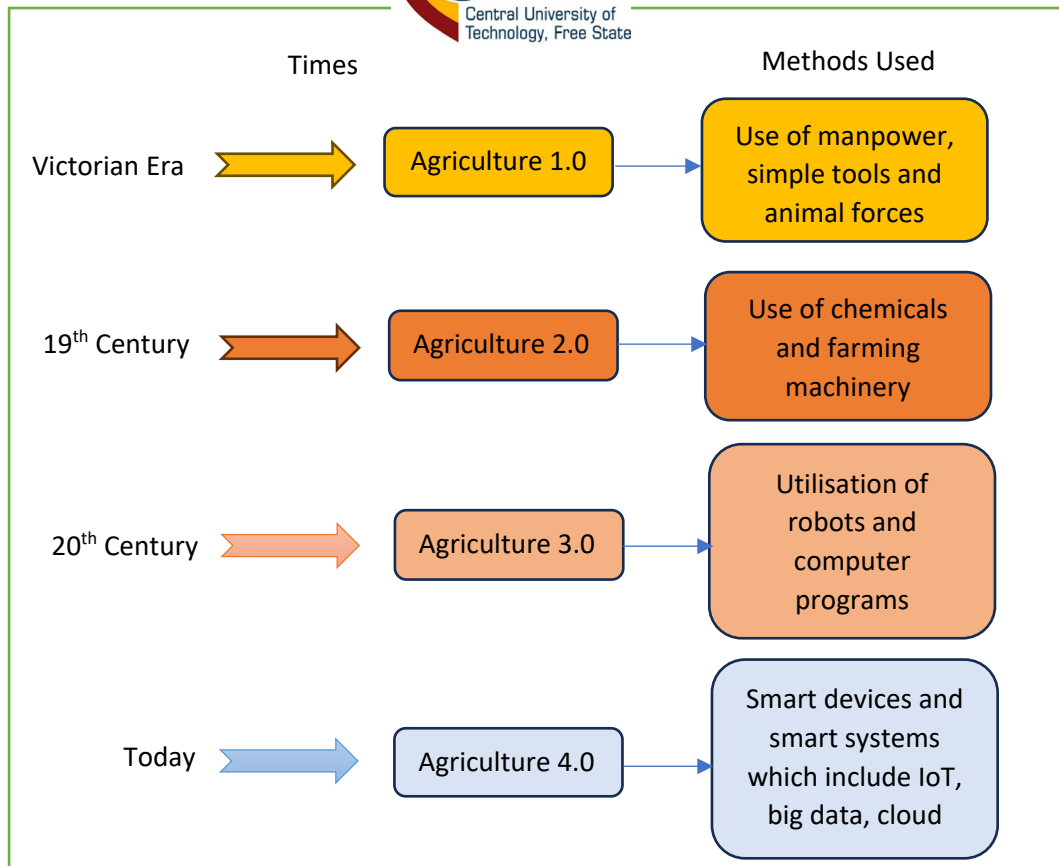


Figure 2. 1 Representation of technological advancements happened over the years in livestock farming

Smart farming is introduced to address agricultural challenges and pasture-based practises are no exception. The use of sensors and integrated technology practices helps to improve pasture management strategies for enhanced productivity. Still, current farm management practices are insufficient to meet all these challenges. In addition, the next wave of growth and gains in the livestock sector could all be attributed to the adoption of newer technologies. The focus of this study is therefore directed at the challenge of climate change which essentially affects other parameters, like productivity.

Climate change can affect the amount and quality of produce, reliability of production, and the natural resources on which livestock production depends [47]. Climate change impacts the pasture-based temperate livestock systems. The stability between different elements is challenging to assess as grazing systems are diverse, with varied management goals and strategies, and future climate projections show a high level of uncertainty [48].

2.5 Smart farming

Smart farming includes the gathering, processing, and analysis of data, as well as the cybernetics on the universal supply chain [49]. Smart farming also uses satellites, sensors and other connected devices to understand key changes in the farm and helps farmers make better decisions that solve the root problems. This allows for the collective mobilisation of operations and the management of advancements in a farm.

Smart farming provides improved decision-making and management techniques to farmers, whilst incorporating information and communication technologies into farm tools and sensors for use in crop and livestock production systems [50]. The aim of smart farming is proper farm management which is achieved by integrating smart methods to achieve multi-functionality related to remote farm management supported by alternative solutions to maintain the farm in real-time [51].

Smart farming technology is based on the use of AI and IoT for managing virtual and physical farms. Consequently, the use of sensors improves the efficiency of the farm by enabling farm activities such as animal monitoring and soil observation. These capabilities are reinforced by IoT [52].

The advantages of smart farming include the following:

- Managing escalating amount of data related to farming in real-time.
- Remote farm monitoring and control.
- Improved livestock management.
- Precise evaluation of soil, crops and livestock.
- Improving agricultural production.

2.5.1 Artificial Intelligence in farming

Artificial Intelligence (AI) has revolutionised the way agriculture operates by providing farmers with significantly better access to data regarding their operations. The principle aim of AI is to simulate human intelligence so that machines can easily mimic it and perform tasks from the simplest to the most complex [53]. The goals of using AI include learning, reasoning, and problem solving. Intelligent software and systems are developed by studying how humans think, learn, make decisions, and work while solving a problem [54]. These systems are fed with training data, and provide the desired output for every valid input, much like the human brain.

Machine learning and deep learning are core components of artificial intelligence [54]. Machine learning refers to a wide range of algorithms that perform intelligent predictions based on the data set [55]. These algorithms are typically referred to as models. The choice of the specific model is determined by the characteristics of data and the expected outcome. Machine learning can more accurately detect abstract patterns than human experts due to its high-level semantic understanding and information extraction. Machine learning is therefore used for predictions based on historical data [56].

Deep learning is a subcategory of machine learning and constitutes a network model made of neurons having various parameters and layers between the input and output [56]. Deep learning provides automatic learning of features that are presented in a hierarchical structure at several levels. Deep learning architecture is used for feature extraction and alteration, as a result these powerful processes make deep learning robust in comparison with traditional machine learning methods [57]. Processing of input data is performed as the initial layers, where the easy features are learned, and the output goes to the upper layers which perform complex features in learning. Thus, deep learning is suitable in dealing with complex and vast amounts of data [58].

In farming, AI allows automation of farm activities, which is a key component in smart farming. AI further assists in yield prediction and optimisation [59]. Feeding the machines with the right datasets can therefore result in accurate yield prediction that will enable farmers to make data-driven decisions about farm management.

Big companies are already implementing AI solutions to develop autonomous farm equipment that a farmer can control remotely [60]. Autonomous drones, for example, enable farmers to capture images and monitor farm conditions remotely. AI as a concept in smart farming is illustrated in Figure 2.2.

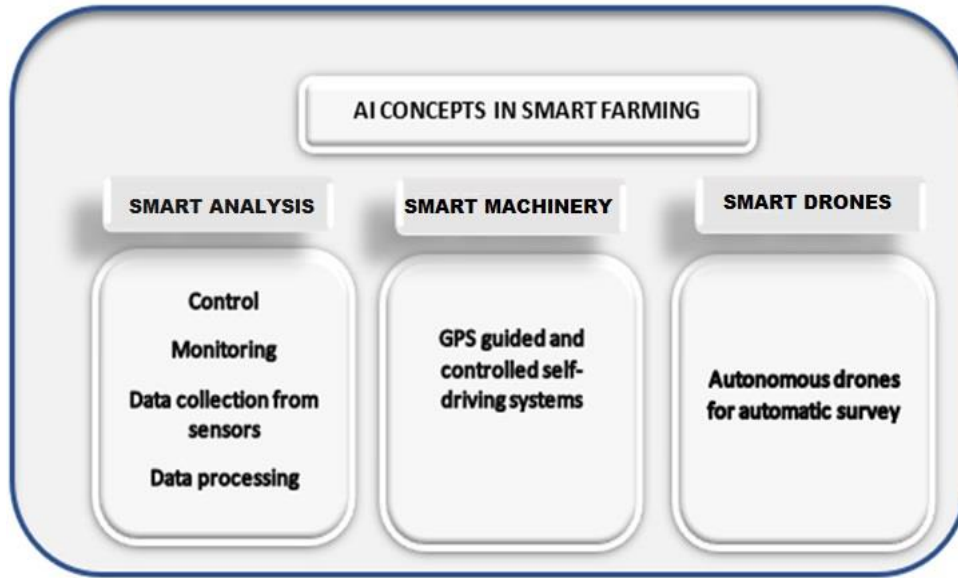


Figure 2.2 AI in smart farming

The use of AI-based equipment and machines has taken the agriculture system to a new level. Technologies which are AI-based can be used to improve efficiency in all fields and to manage many challenges in various sectors including the agricultural sector, such as crop yield sensing, soil content sensing, and crop monitoring [54]. The agricultural sector is facing a crisis as the global population grows, but AI has the potential to provide a solution. Using AI-based technology, farmers can produce more with fewer inputs and improve the quality of their production. They are also able to deliver their yields to the market faster.

2.5.2 Internet of Things in farming

Internet of Things (IoT) is a system of interconnected sensors that collect data and use communication networks to send data for analysis and decision making [24]. The analysed data will then help in the better management of the farm. IoT can also be understood as a domain where objects, animals or people are supplied with distinctive identifiers, competent of data transmission over the Internet without the need for human or computer involvement [61].

In farming, there are various sensors to read parameters such as temperature, soil moisture, water level, wind speed and direction. Each of these devices send and receive data over a network. This enables sensor measurements to be sent to a server, often a cloud where the measurements can be aggregated and monitored in real-time.

ThingSpeak®, for instance, is an IoT platform that visualises and analyses data in real-time on a cloud [62]. ThingSpeak® can also set triggers and send alert messages to the farmer via third party platforms [63]. The farmer can thus monitor the farm conditions remotely. Having access to these aggregated measurements enables farmers to make decision or act on the data.

These modern technological enhancements in farming ease simple adoption and use of smart farming with IoT. Furthermore, IoT enables integrated sensors to collect data and communicate through a network, providing for analysis of data for better decision making. IoT connection adopted technologies that include Global Positioning System (GPS), Global System for Mobile Communications (GSM), Long Term Evolution (LTE) and Wireless technology.

The concept of Big Data was introduced to IoT systems as they provide a huge amount of data [64]. Big Data also allows easy collection, storage and processing of data. This allows storage of data from different type of sensors and solves the problem of traditional storage for not being able to handle an increase of data and inability to properly handle data from different sources. Big Data can also be characterised into volume, variety and velocity [65]. IoT's therefore provide a cloud platform that allows integration of Big Data and web applications. Without IoT, smart farming is incomplete. Figure 2.3 shows how IoT plays a part in smart farming.

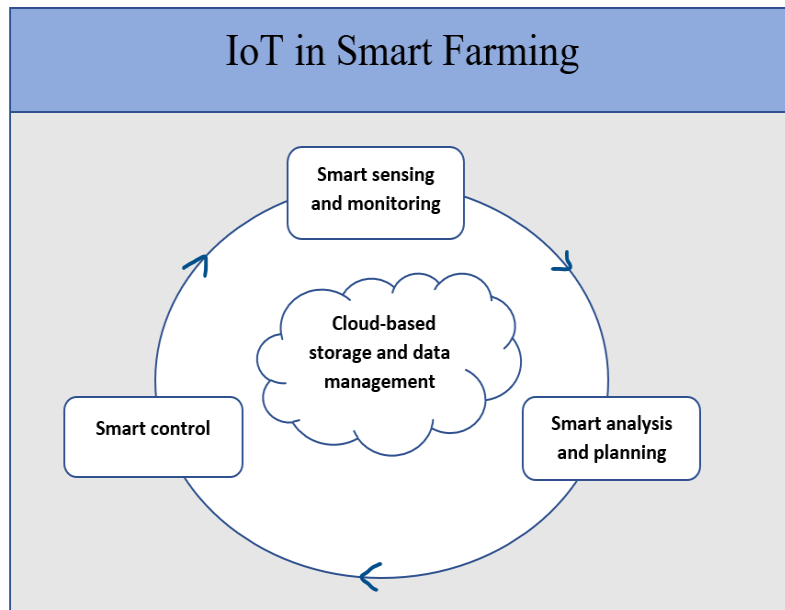


Figure 2.3 IoT in smart farming

Behaviour of farm animals in a pasture, such as the movement course and the real-time location, must be closely monitored to ensure proper pasture management. The acquisition of information on these factors may be achieved by using the pasture Internet of Things [66]. The pasture Internet of Things system structure is primarily based on Wireless Sensor Network (WSN) which can enable the transmission among divergent sampling nodes.

Automating agriculture tasks is best achieved using AI and IoT together. Thus, livestock farmers have adopted intelligent decisions informed by AI and IoT based on the needs of the farm with little human input.

2.6 Pasture-based technologies

Recent technological advances in pasture management have certainly made predicting, tracking, and managing livestock easier [67]. Presently, several self-learning algorithms are being developed to help livestock farmers collect and monitor farm data in a continuous manner. Using these smart decision support tools, farmers can make informed and proactive decisions before anything goes wrong. Moreover, these technologies promise to improve animal productivity, growth, and profitability.

Nowadays, livestock farmers are being pressed to do more with fewer resources, which presents a major challenge [67]. This is where the use of digital technologies to optimise farming processes and operations can be extremely beneficial.

In this context, digital technologies can be referred to as the following [67]:

- Smart satellite and drone services: These devices use a variety of sensors and multispectral images from above to monitor pastures and grazing fields.
- Smart measuring devices: These are devices that calculate the pasture height to estimate pasture forage mass. They are helpful in determining the amount of feed to the animal and are also important in rotation grazing practises to avoid overgrazing and manage grazing systems.
- Smart infrastructure systems: These systems use sensors to detect environmental changes to meet needs of the animals and to allow remote monitoring.
- Smart animal welfare systems: These systems use a variety of sensors, wearables, probes, and imaging technologies to monitor animal welfare parameters in real-time. These devices assist farmers in identifying and solving problems remotely.

Integration of these services have helped farmers to improve pasture management strategies for enhanced production. This has brought about the emergence of IoT pasture management solutions that have various benefits, including:

- Close pasture and livestock monitoring.
- Monitoring soil conditions.
- Managing pasture growth.
- Giving warnings on pest attacks and low growth.
- Tracking major soil parameters to measure production.

2.7 Smart farm systems for pasture management in sheep farms

New technologies are already implemented in pastures-based systems to improve efficiency. The innovation includes technology that captures and exploits the variation of pasture production that will potentially allow more specific and efficient nutrient use from high quality pasture. These pasture management systems include various components, which will be further discussed to follow.

2.7.1 Information and Communication Technology (ICT)-based rising plate meter

This is a pasture measurement tool with GPS technology that is capable of capturing pasture measurements [9]. This system links to a web-accessible database that allows for automatic data transmission to a paired smartphone application in real-time. The measuring of pasture yield leads to greater efficiency in pasture utilisation. This system also allows quantification of pasture growth, whereby pasture measurements are recorded on a regular basis, and generates reports automatically for management purposes.

This technology measures the pasture available to the animals, so that they can access the optimum amount of feed to maximise their production capability to ensure sustainability as it impacts farm management strategies [9].

2.7.2 Weather monitoring stations

Weather monitoring stations are devices that are installed in pasture paddocks that measure temperature, rainfall, relative humidity, radiation, wind speed and wind direction [68]. They are composed of wireless sensor nodes which collect, process and transmit weather data to a storage location via a gateway [69]. They process captured data that include data compression and timestamping. Although these devices collect and transmit data automatically, they require interfaces through which their operations can be monitored and configured. The software therefore supports web services on the gateway that enable remote access to weather data. These devices have the climate forecast capabilities, meaning, they can predict ongoing climatic conditions.

2.7.3 Farmote Technology

Farmote uses outlying static devices to capture pasture measurements and soil conditions, which can then be cross-referenced with images captured from several regions on the electromagnetic spectrum taken by satellite to come up with pasture estimates of biomass; hence, the measurements are communicated via electromagnetic waves to an accessible web portal [70]. This technology allows systematic remote measuring of pasture height.

Estimates of biomass can then be used to provide pasture Dry Matter (DM). The system is also capable in measuring the soil and atmospheric conditions and to take into account seasonal changes to enhance perfection on calibration. This is a technology that operates on real-time data from ground nodes that communicate through a Long Range Wide Area Network (LoRaWAN) technology [71]. Nodes are IoT devices with laser sensors that collect the moisture and quality of the pasture on a daily basis. Based on the analysis on grass growth statistics and satellite images, the system provides suggestions on what should be done on the pasture to keep it in good condition.

2.8 Smart farming systems, challenges and solution technique

Smart farming is a concept that is intended to solve problems that can hinder production in farms. The systems outlined in section 2.5 are used to enhance pasture management to improve livestock production. Nonetheless, there are drawbacks experienced in using these systems.

As the world is facing a challenge due to climate change, there is a need for forecast models to predict weather conditions which influence pasture growth to determine their height. However, uncertainty remains on how farmers would use such information in pasture management decisions and whether those decisions will be beneficial [72].

Additionally, these forecast models do not include soil moisture as one of the outstanding parameters that determine pasture growth [73]. They also lack proper detection and tracking of pasture growth [74]. This results in the inability to obtain an in-depth view of physical systems in real-time, thus resulting in laborious remote monitoring and control [75].

Sensing technologies offer the ability to monitor farms in real-time and this offers the opportunity of developing farm-specific models that an individual farmer can use to plan activities in response to changing circumstances. Incorporating these models while managing complexity and usability still presents a research challenge [76][77]. This adds to the problem of integrating the sensors and binding the sensor data to the analytics, piloting automation and response activities [78], resulting in improper processing of data and leading to generating wrong outputs. However, literature shows that digital twin technology is promising to improve smart farming for better farm management and greater productivity [23].

2.9 Digital twin

Digital twins are being given extra attention with the realisation of the fourth industrial revolution [79]. A digital twin is the virtual representation of a real-life object of which it mirrors the behaviour and states over its lifetime in a virtual space [80]. A digital twin enables analysing, predicting and optimising operations by utilising real-time and historical data [81].

Digital twins are developed to run concurrently with the physical systems, generating corresponding data on both platforms [82]. It is important to note that real-time flow of information and data between the physical and digital objects is crucial in digital twins [83]. They allow for bi-directional data flow between the virtual platform and the physical object [84]. Figure 2.4 demonstrates the concept of a digital twin.

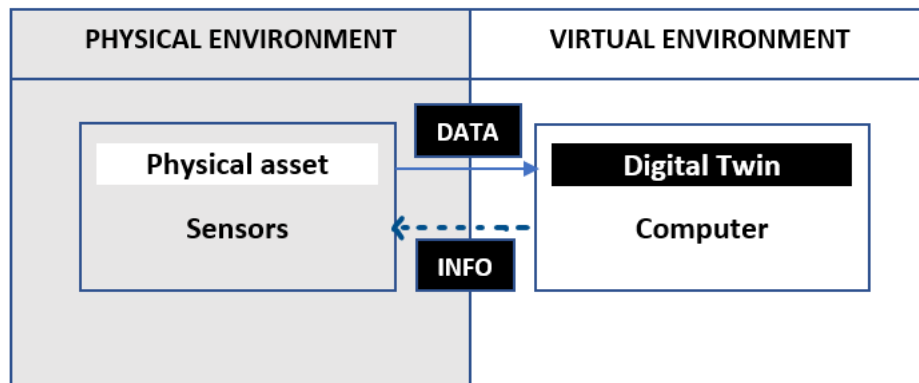


Figure 2.4 Digital twin concept

To effectively represent a physical asset and reflect its behaviour, the digital twin needs to receive real-time feedback on how the asset interacts with its environment, workload, and other factors. To do this, different sensors must be able to be connected to the secured network to be able to send and receive specific kinds of information.

The digital twin must be able to receive, store and process the large volumes of data in real-time. This requires significant computing, storage, and data processing resources. In other words, it must utilise the latest advances in Big Data, data management, and cloud computing. The literature indicates that digital twins are still finding their way in agriculture [85]. When implementing digital twins on livestock farming, there is a possibility to find suitable climate conditions for growth by using simulations based on real datasets collected in the physical world.

The digital twin must be able to make sense of the enormous amounts of data being continuously transmitted. Invariably, this means using AI algorithms to sort out useful information from irrelevant data, since it is beyond the computational abilities of the average human. Additionally, it means using AI algorithms to suggest recommendations and actions.

Implementing a machine learning algorithm on datasets allows for accurate analysis and precise predictions [86]. Machine learning applications integrated with other farming techniques have succeeded in improving production in the farming sector. Machine learning applications based in farming include support vector machines and deep learning [86].

The digital twin needs to be able to adapt to different cause-effect scenarios over time and be able to use these to improve the asset's performance. It involves analysing different scenarios, test cases, and what-if scenarios. As a result, certain conditions need to be met to train machine learning algorithms to learn, experiment, and evolve the best course of action. Figure 2.5 shows AI algorithms and machine learning interacting with the digital twin as a system.

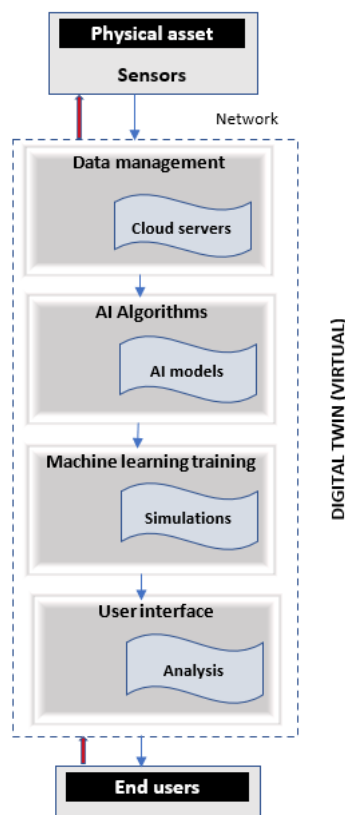


Figure 2.5 AI algorithms and machine learning with digital twins

Digital twins promise to take smart farming to a new level of agricultural productivity and sustainability [23]. This is due to the digital twin's ability to address smart farming challenges. It is easier to map smart farming with digital twins as both concepts base themselves on AI and IoT. Digital twins continuously adapt to operational changes based on real-time data from several IoT sensors and devices to predict the future of the physical system with the aid of AI or machine learning [80].

Digital twins use complex algorithms that allow them to address problems related to smart farming, as stated in section 2.6. Digital twin platforms enable quick analysis and real-time decisions performed based on precise analytics. This pairing of physical and virtual worlds enables real-time monitoring of systems, control and analysis to perform future predictions [87]. Digital twins use models that provide accurate description and behaviour of the object over time [88]. The models can also be tested with what-if scenarios to project unforeseen activities.

Merging of models can be done within digital twins by creating a common model space that allows models to exchange data, defines the correlation between models and sets the link between the digital twin and the physical asset [76]. Digital twins have the potential to tackle the challenge of seamless integration between IoT and data analytics by developing connected physical objects and a digital twin [89].

Digital twins minimise failure occurrences, rather having extended operational pliability and efficiency. The advent of digital twins as primary approach for the farm control has the capability to revolutionise farming [90]. Practically, with digital twin implementation, farming processes no longer require physical proximity, thereby allowing easy remote monitoring, control and strategizing of farm operations. The interplay between the physical and virtual objects is a crucial concept at the back of the IoT technology.

Digital twins are able to predict systems' future behaviours using models that incorporate machine learning and deep learning techniques [91], known as predictive modelling.

2.9.1 Predictive modelling

Predictive modelling is the approach that uses machine learning to predict the future outcome by using historical and current data [92]. Predictive models use algorithms that learn and analyse both the historical and current data to forecast the future outcome. These models make assumptions based on what has occurred in the past and what is happening currently. Thus, new data changes must be fed into the model as it might change the future outcome. Regression and neural models are the most used predictive modelling methods [93].

Predictive analytics can be implemented using machine learning, deep learning and pattern recognition algorithms that help identify the changing trends in operations. The next section looks at different predictive models that were investigated.

2.9.1.1 Regression model

Regression analysis forms an integral part of any forecast or predictive model, thus, it is a common method found in machine learning powered predictive analytics. Regression is the method that determines the correlation among variables and uses these correlations to make predictions [94]. This model estimates the correlations among variables and finds key patterns in massive and diverse data sets and their relationships [95]. The models are trained using regression techniques to forecast or predict trends. The outcomes can then be predicted from new data. Linear regression is the most used type of regression analysis. A model can have one or more independent variables [96]. A simple linear regression model can be represented with:

$$\hat{y} = \mathcal{M}_0 + \mathcal{M}_1 X + \varepsilon \quad (2.1)$$

where:

$\hat{y}$ is the predicted value of y ,

X is the independent variable,

$\mathcal{M}_0 + \mathcal{M}_1$ are the regression coefficients where $\mathcal{M}_0$ is the intercept parameter and $\mathcal{M}_1$ represents the slope and

ε is the vague element that accounts for the variance in the observed values and predicted values.

The analysis generates the predicted value for criterion from linear combination of the predictors [97].

2.9.1.2 Artificial Neural Network model

Artificial neural network (ANN) is non-linear predictive method that has robust pattern classification and pattern recognition ability to perform forecasting [98]. ANN is a data-driven self-adaptive technique which makes it a pliable modelling mechanism for forecasting. They are useful for analysing large data sets and solving complex pattern recognition problems [95]. Neurons are small individual units or nodes through which data and computations flow. ANN is built up by using various artificial neurons where the output of each components is used as the input of the succeeding processing component [99].

The signal between two neurons is controlled by weight. The learning of a neural network is therefore attained by modifying the weights among the neurons with the information passing through them. Typically, neurons are classified into networks at different layers [100]. ANN structure is composed of the input layer, hidden layer and the output layer. The input layer receives the data input, and the output layer produces the ultimate outcome. A hidden layer represents the interactivity among neurons. The mathematical representation of ANN can be expressed as:

$$Y_x = g(\sum_i W_m X_m - \theta_x) \quad (2.2)$$

Where:

Y_x is the output signal,

g is the transfer function,

$\sum_i$ is the summation function,

W_m is the link weight,

X_m is the input signal and

θ_x is the bias.

This is represented by the block diagram in Figure 2.6.

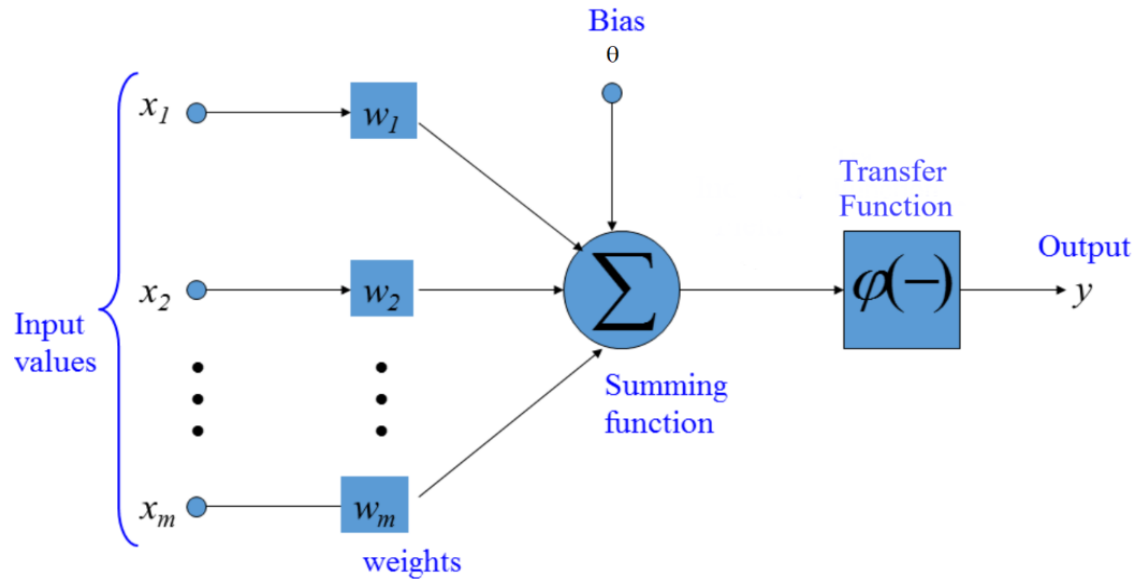


Figure 2. 6 ANN block diagram

ANNs do not follow any specific rules to process data, instead they use the received data to learn the correlation among variables [101]. This makes ANNs useful in solving problems on data that the relationship is not known. The literature reveals that ANN models perform very well in the field of streamflow forecasting [102]. Deep learning is the application of ANNs to learn features by networks in multiple layers [58]. These models can be evaluated and analysed to recognise which one works better on the selected type of data. On the other hand, it is also important to know the type of data to be used to select the appropriate model.

Weather prediction models are common in day-to-day activities, and these models are also helpful in the farming sector. They are commonly known as weather forecast models. One way to minimise the impact of climate change is by providing precise weather forecasts [103]. Weather forecasting helps farmers to perform business decisions and plan better. The literature reveals that there are various weather prediction models used in farming that are developed using machine learning and that work well for multi-timestamp predictions [104]. Various researchers have therefore used several approaches including historical weather data [105], weather generators [106] and climate forecast models [107][108].

Climate forecasts have proved their potential in improving resilience in farming to climate change, but there are still issues which previous models have not yet fully addressed. Firstly, these forecast models focus only on weather data, they do not include soil moisture as one of the parameters that influence crop growth [73]. Secondly, the uncertainty still remains about how farmers would use such information in crop management decisions and whether decisions taken would benefit them [72]. This is where digital twins are of significant use. A digital twin provides an accurate description of objects that change over time. So, using these forecast models in digital twins can extend the use of models to timescale over the object and track its behaviour at a specific moment [88].

The predictive models can also be implemented to the scientific core concept of a digital twin, known as a “digital shadow” [109]. A digital twin starts with a digital shadow to initiate or capture it.

2.9.2 Digital shadow

Digital shadows are the key concept in digital twin development as it is a predecessor to digital twins. A digital shadow is defined as a model with one-way data flow between the physical and digital platforms, compared to the two-way exchange in a digital twin [110]. The model is programmed to act on the data received and modify the parameters according to the changes in the physical object. A change in state of the physical object has a direct effect on the digital object but not vice versa [111].

Digital shadows are used for structuring different kinds of data collected from different data sources that can be stored, analysed and used for various applications [112]. Digital shadows are seen as sufficiently accurate in evaluation on the basis of this data projecting a precise image of processes in production, development and adjacent areas. Digital shadows may contain the historical data [113] of the system that the model can use in identifying patterns that may be helpful in model efficiency.

A digital shadow is seen as the preliminary stage of a digital twin. Digital shadows are developed at the first stage, based on information models. These are represented by various computer-aided design model categories and engineering simulation methods [114]. The experiment outcomes on digital shadows can be recommendations that the simulation models can be of practical use in digital twins. Digital shadows set the basis for the digital twin by first transferring the real production process into the virtual world.

The digital twin can then deliver an absolute image of reality based on the process model and simulation [115].

A digital shadow can predict the behaviour of the real object, but only on the conditions based on data collected [116]. Digital shadows are sure to offer potential in utilising predictive analytics by using complex simulation models [117], which can be predictive models that foretell the future and help to project unplanned scenarios. To design an effective digital shadow, powerful models are derived.

2.9.3 Types of digital twins

After understanding the physical system to twin, the next step may be to choose the suitable type of the digital twin. Generally, there are two types of digital twins: data-driven digital twins and physics-based digital twins.

- A data-driven digital twin is an analytic model developed using historical sensor data from the physical system [118]. Data-driven digital twins use machine learning algorithms to extract hidden relationships between input and output data. These algorithms must first be trained to predict future trends. Data-driven digital twin development consists of three phases which are: data collection, data management and data analysis. These phases are further demonstrated in Table 2.2.

Table 2.2 Phases in developing data-driven digital twin

Data collection	Data Management	Data analysis
Setup of sensors	Data storage	Feature extraction
	Data processing	Section of appropriate use of algorithm

- A physics-based digital twin is constructed from the first principles that define laws of nature of how the physical processes evolve. Physics-based digital twins extract knowledge in the form of conservation and constitutive relations based on theoretical development and experimental validation [119]. The relations can be expressed in differential equations that are solved numerically with high-performance computing [119]. Physics-based digital twins issue predictions that have explanatory power with qualified uncertainties that go beyond the current state and simulate what-if scenarios. Physics-based digital twins are also developed in three steps, as shown in Table 2.3.

Table 2.3 Physics-based digital twin design

Use case	Modelling	Experiments
Identify critical components	Analysis of system parameters	Simulation execution
Investigate physical failures	Creation of a model	Results interpretation
	Results interpretation	Derive initial recommendations

2.9.4 Digital twins in livestock farming

Implementation of digital twins in livestock farming is still in its early phases of development [120]. Thus, the research on digital twin designs in livestock farming is scarce. However, digital twins for farming have been proposed by various authors noting that they have potential in tackling the challenges faced in agriculture. By integrating digital twin models, robotics, sensors, Big Data, three-dimensional (3D) printing, AI and IoT technology, various resources may be linked to have a more complete picture [121] [122]. From this, farmers will be able to recognise numerous elements and variables that impact the farm's functioning, endmost yield production, and resource utilisation; thus, this permits farmers to take appropriate actions to diminish the environmental effects on natural resources.

Although still in their infancy, digital twins' applications in livestock farming are beginning to emerge and are expected to develop rapidly over the next several years. The following promising examples [22] are considered:

- **Observing the movement of grazing animals:** Using GPS and WSN tracking technology, livestock farmers can not only identify the location of specific animals in a large grazing area, but also observe grazing patterns and behaviours.
- **Understanding development and advancement of animals:** Digital twins can be used to better understand the stages of the animals' growth and development from birth to adult. Multi-agent innovation stages combine sensor and longitudinal information to create phenotypic characteristics of animals.
- **To pick up bits of knowledge on animal conditions:** To optimise production, livestock breeders need to keep their animals healthy. A few parameters such as pregnancy hormones, body temperature, quality and quantity of feed intake can act as solid indicators.
- **Early detection of livestock diseases:** Digital twins can help farmers detect various significant diseases in earlier stages and to isolate exposed livestock from further disease spread.
- **To optimise the feed consumed by the animals:** Digital twins can be used to model changes in feed composition and conduct what-if scenarios to determine the best feed intake techniques for a farm.

The key benefit of digital twins is that the digital unit can foresee the operation of its physical twin, thereby predicting possible failures and thus improving the entire system. Digital twins are already being implemented in farm operations; but improved development of proficiency is required [123].

A digital twin is further broadening with the concept of smart farming by developing small services to help understand the information of a certain system, such as an irrigation system, a seeding system, soil probes, weather stations and harvesters [124][125]. The digital platform is developed to visually analyse the information collected using IoT, as well as to send information to the systems based on the decision-making process performed inside this digital platform.

Thus, digital twin technology is set to assist livestock farmers to predict animal behaviours, monitor and prevent diseases, improve breeding operations, as well as tweak management strategies to prevent livestock losses [22].

Implementation of digital twins in livestock farming engages the following [126]:

- **Data gathering:** Collection of data using sensors such as cameras, drones, temperature sensors and humidity sensors. Data can also be gathered by sensors attached to animals or placed in their surroundings.
- **Analysis and modelling:** To develop a precise model, analysis is performed on collected data using algorithms such as AI and machine learning, and the model is continuously updated with more recent data for accurate results.
- **Big Data:** The sensors collect vast amounts of data, and it is important to decide where to safely store it for processing. Data is usually stored on cloud platforms.
- **Data visualisation:** Data and analysis are represented on dashboards for easy understanding.

Even though implementation of digital twins is still in the early stages, clearly there is much to gain from implementing digital twins in livestock farming. Digital twins have the potential to model the livestock farming future by providing better business solutions, enhancing animal health and well-being, and maximising farming resources.

2.10 Limitations of the existing research

This study focuses on implementing digital twins in pasture management to mitigate the impact of climate change. Growth of the pastures is affected by changing weather patterns [17], which results in poor animal feed, in turn, leading to deaths and putting small-scale farmers at risk of losing their businesses.

The impact of climate change in the country is discussed in Section 2.2. To reiterate, South Africa is experiencing drought and extreme temperatures; hence, this makes it difficult for farmers to keep their animals alive. This is due unanticipated weather conditions that influence pasture management, which serves as the primary feed for the animals.

Smart farming, as a technology that is developed to resolve challenges that hinder production in farming, has been helpful in livestock farming as it eases the management processes, control and monitoring of the livestock farms. Even so, smart farming has setbacks that inhibit smooth operations.

Weather forecast models were implemented to assist farmers in predicting climatic conditions. However, these models do not include soil moisture as one of the important parameters influencing pasture growth [73]. Moreover, farmers are not able to use information from these models to make decisions on pasture growth management [72]. Additionally, these systems lack proper detection and tracking of pasture growth to measure pasture production [74]. This brings about a challenge in obtaining an in-depth view of the physical system in real-time, thus hindering monitoring processes [75]. These factors make it difficult for farmers to predict pasture growth.

Another major challenge with smart farming systems is to incorporate the models [76][77], as well as integrating the sensors and their data to form integrated models [78] rather than using different models separately.

The literature shows that digital twins have the capabilities to address the problems of smart farming [127]. Nevertheless, at the time of conducting this study, there was limited research of optimising digital twins in pasture management. This research therefore aims to develop a digital twin that will enhance pasture management strategies at sheep farms to ensure sustainable feed to the animals.

Chapter 3 – Research Methodology

3.1 Introduction

The aim of this chapter is to outline the research methodology used to conduct the study to resolve the challenges described in existing research detailed in Section 2.8. In this study, the digital twin that predicts the height of the pasture will be designed using the MATLAB[®] and SIMULINK[®] platforms. The focus of this chapter will be on the research objectives detailed in section 1.3.2. Hence, the research methodology will be implemented in three phases:

- *Phase A* – Monitoring the conditions on the farm to manage factors that affect the growth of the pasture.
- *Phase B* – Analysing, structuring and processing data to develop predictive algorithms.
- *Phase C* – Developing a digital twin with predictive models that are updated by real-time data to predict pasture height and identify issues beforehand, thus, providing instant solutions for composite problems.

3.2 Phase A – Monitoring

This section first illustrates the farm chosen to carry out the study and why it was selected. Secondly, it explains how the IoT sensors were set up on the farm to develop a physical system. Lastly, this section explains the cloud platform where IoT sensors log their data.

To design a digital twin, a farm must be located, where the study will be conducted. In this study, the farm owned by Central University of Technology (CUT) was utilised.

The next section details why this farm was chosen for this study.

3.2.1 Central University of Technology's farm – A case study

The aim of the research is to design a digital twin that will help in predicting the height of a pasture. This will help farmers to make proper decisions to have sustainable feed for the animals. Hence, it was logical to select the institution's farm to carry out the study. This would benefit the farm in the following ways:

- The farm will benefit from the smart farm management solution as IoT technology will be implemented, thus improving productivity.
- The predictions performed by the system will help in the proper planning and decision making of the animal feed and pasture management.
- Since the farm is used as training centre for students, the study will also be a good reference for educational programmes.

The Agri Training Centre Farm is located 23 kilometres from the Free State province's main city, Bloemfontein. The farm is under the supervision of Mr Jan Jacobs as the operational manager. The main purpose of the farm is to provide experimental training to Agriculture students enrolled at Central University of Technology, Free State. On the other hand, it is a commercial farm, meaning that products from the farm are taken to the markets for sale.

This farm is about 30.74 hectares (ha.) and is sectioned into several fields, where the study was conducted on a field of 0.7 ha. The farm practices mixed farming systems with integrated crops and pasture-based livestock production. This combination increases the sustainability of the farm and environmental benefits are obtained through this system, as this leads to enhanced land use and rising income [128]. Figure 3.1 shows the layout of the farm.

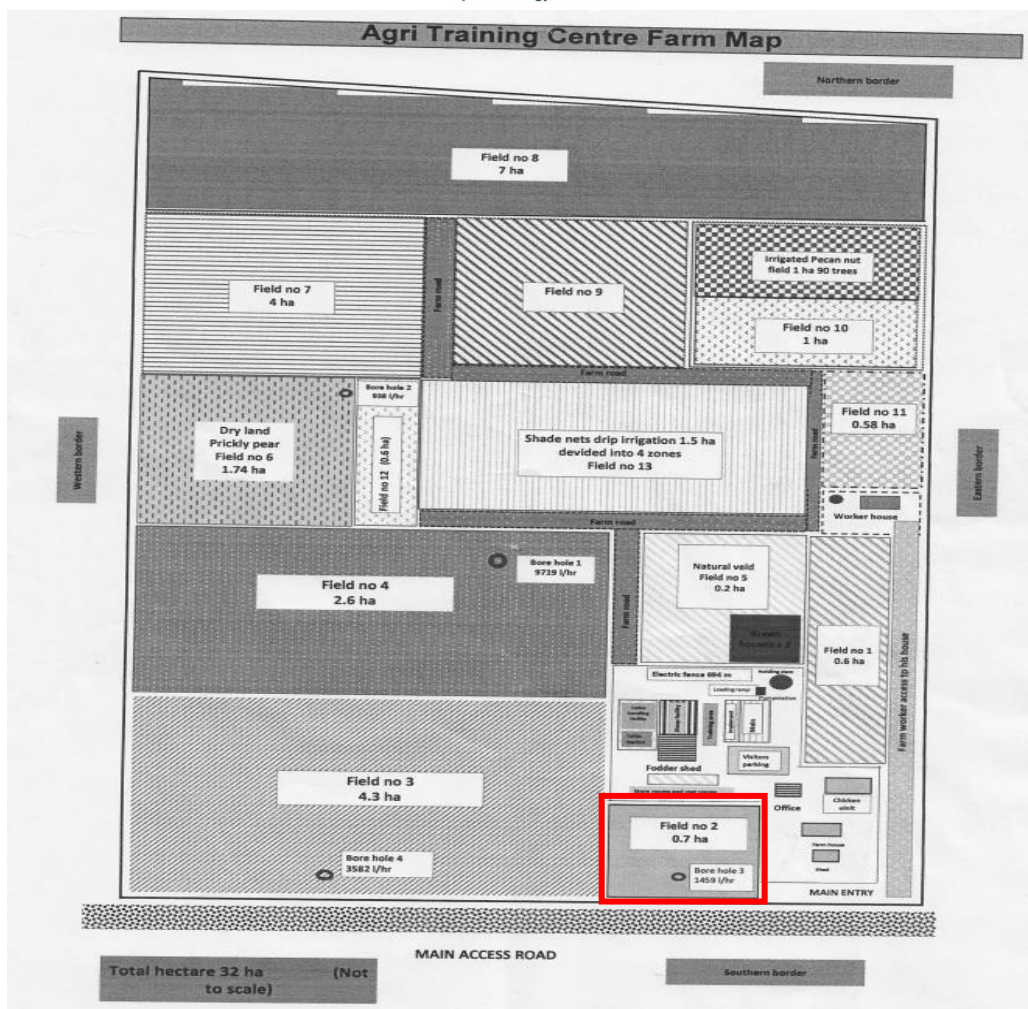


Figure 3.1 Map showing the structure of the Agri Training Centre farm

Figure 3.1 shows the overall structure of the farm, and the study was conducted on the section labelled “Field no. 2”. The farm had 45 Dohne Merino sheep at the time this study was conducted. Dohne Merino is the most common breed in South Africa as it occupies 49.7% of the data set nationwide and the remaining percentage is shared amongst 4 other breeds [129]. According to the farm manager, the Dohne Merino breed was chosen because they are dual-purpose animals, meaning they are raised for both meat and good quality wool production.

On this farm, plantation of the pasture is crucial as 87% of the sheep feed is mainly from the pasture and the remaining 13% makes up the additional supplements given to the animals. The additional feed is only given to the animals on rainy and cold days to give them energy. However, in case of the farm running low on the pasture, additional supplements must be given to animals in greater quantity, which is an expensive way of feeding more than 40 sheep.

At Agri Training Centre, pasture is planted twice year – in Autumn (March to April) and in Spring (September to November). When the pasture is ready to be utilised, the sheep would be allowed to graze and monitored until they are fully developed lambs. The sheep will then be taken to the market when they at a satisfactory weight. Pasture growth on this farm depends on climatic conditions. Thus, because of the changing weather patterns, this farm needed a predictive model that can predict whether there will be enough pasture to feed the sheep. If not, proper decisions would have to be made in time to avoid surprises.

Hence, the aim of this research is to develop a digital twin that can predict the height of the pasture to ensure enough feed to the animals throughout the year. The goal is to use digital twin system to enhance pasture management strategies that will help farmers to limit the impact of climate change on their sheep farms. This chapter covers all the processes carried out in developing the digital twin that includes the tests and simulations.

3.2.2 Developing the physical system

A digital twin is described to be the virtual representation of the physical system [80]. That is, there must be a physical system for a digital twin to exist. In this study, the physical system was represented by the “*smart farm*”. The smart farm was developed by integrating IoT sensors that monitor pasture growth as the link between the physical system and the digital twin. The sensors also play an important role in digital twin development as they collect data that is used to build and update the predictive models. The predictive models are used to project unforeseen scenarios based on the physical systems. The physical system is constructed of IoT sensors, the gateway, and the cloud platform. The architecture of the physical system is demonstrated in Figure 3.2.

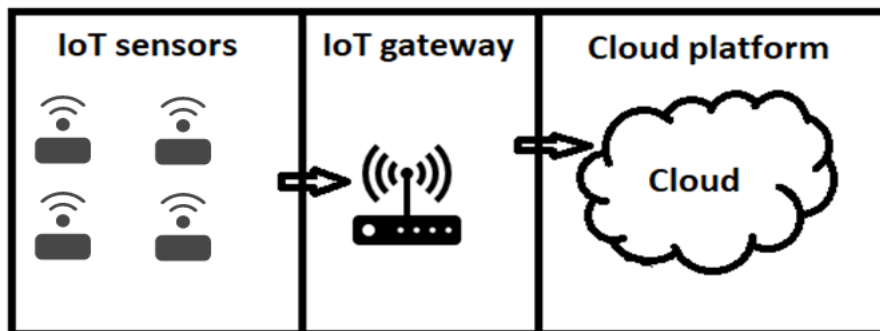


Figure 3.2 Architecture of the physical system

3.2.2.1 *IoT sensors*

Sensors that monitor pasture growth have been identified and they were set up on the farm as part of the physical system. These sensors measure temperature, rainfall, soil moisture and pasture height. While the fertiliser was applied to make sure the nutrients on the pasture were of high quality, they were not accounted as a factor in pasture growth and for this reason no sensors were used to detect fertiliser. The sensors used are as follows:

- **Weather station:** This is a Wi-Fi driven device that monitors weather conditions, including indoor/outdoor temperature, indoor/outdoor humidity, wind speed, wind direction, rainfall, ultraviolet, solar radiation and barometric pressure. Accordingly, the advantage of using the weather station is that this device can collect data on several physical parameters that help in improving crop productivity [130] rather than deploying different sensors to gather data. Nonetheless, the focus of this study is on the temperature and rainfall. Collected data can be easily uploaded on cloud service where it can be analysed and processed.
- **Soil sensor kit:** This is the sensor that reads the amount of moisture present in the soil. The moisture level is measured by reading the resistance on the probes inserted in the soil. This sensor has a benefit of 3.3 – 12V working voltage and digital analogue dual output. This soil moisture sensor is programmed using ESP32 CAM development board to upload measurement and log data to the cloud.
- **ESP32 CAM:** Hardware development platform that embeds hardware, communication interface and software development environment for a complete IoT solution [131]. ESP32 CAM is the mini-board that allows the flexibility to control programmed input-out pins. This device supports data transfer via Wi-Fi and Bluetooth. The ESP32 CAM was used for two purposes in this study – integrated with the soil moisture sensor and measuring pasture height. ESP32 CAM has the OV2640 camera which allows for capturing images with resolution of up 1600x1200 with a maximum refresh rate of 15 frames per second [132]. The captured images were then processed using the Raspberry Pi.

- **Raspberry Pi:** Also a hardware development platform, with more advanced features that runs as computer. Raspberry Pi runs MATLAB[®] software and executes MATLAB[®] scripts as standalone programs. MATLAB[®] is a convertible programming platform for scientific computing. This software has capabilities that are required in this study which include hardware support package, data analysis, problem solving, algorithm development and integration with SIMULINK[®] features to support model-based design. MATLAB[®] connects to ESP32 CAM using the IP address with an *ipcam ()* object. The captured images are processed in MATLAB[®] using an image processing algorithm to calculate the height of the pasture. The calculated height is sent to cloud, and the image is stored in the local storage of the Raspberry Pi.

3.2.2.2 *IoT gateway*

In section 3.2.2.1, it is discussed how the data collected by IoT sensors is transferred to cloud storage. Hence, an IoT gateway is needed to serve as the connection link between the IoT sensors and the cloud. IoT gateways acts as network router that provides internet access and routes data between IoT sensors and the cloud. A 4G LTE modem Wi-Fi router was used as the gateway. The modem delivers 300Mbps and has a stable Wi-Fi experience. Stable internet access is crucial as data is collected in real-time.

3.2.2.3 *Cloud Platform*

IoT sensors collect data and send it to the cloud storage. ThingSpeak[®] was chosen to be used in this study because of its capabilities to live stream sensor data to the cloud [62]. The IoT sensors were configured to send data to ThingSpeak[®] using IoT protocols. Then, ThingSpeak[®] was used to log and visualise data from connected sensors in real-time. Collected data included temperature, rainfall, soil moisture and the pasture height. This platform made monitoring easy as the data could be accessed remotely. The other benefit of using ThingSpeak[®] is that it can be integrated with MATLAB[®] to pre-process and analyse the data [133]. Data analysis is important in performing the predictions.

3.2.3 Structural design of physical system

The IoT sensors, gateway and ThingSpeak® had to be integrated to form a complete physical system. The design of the physical system is important as it forms part of the digital twin. Figure 3.3 shows the structure of the physical system.

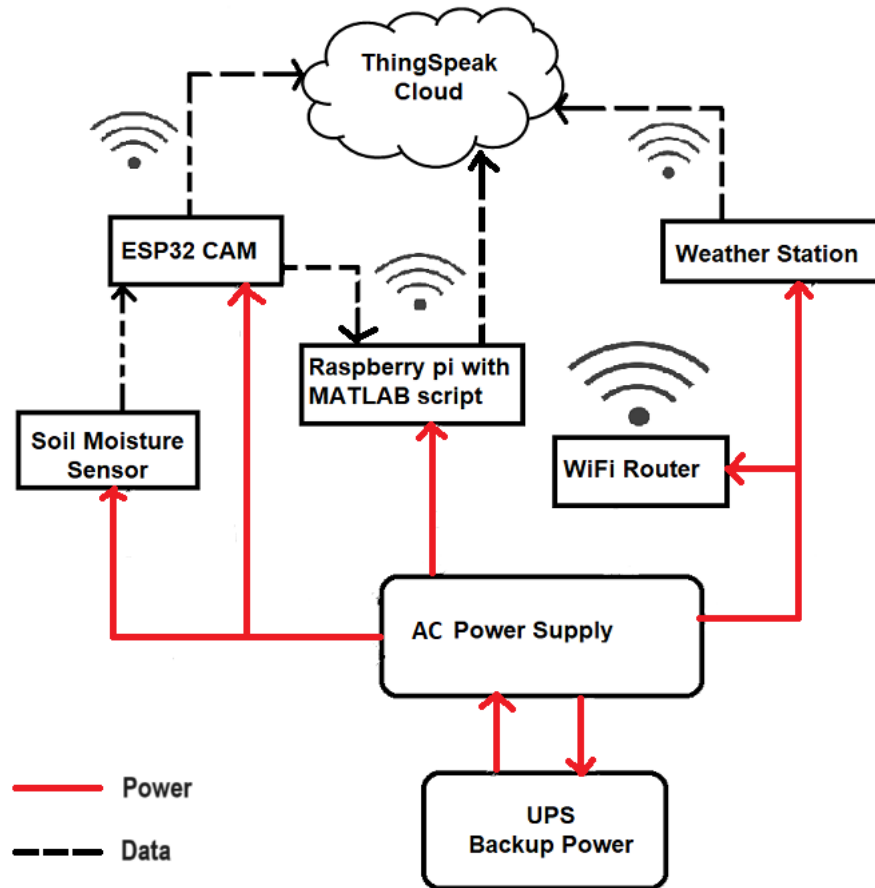


Figure 3.3 IoT sensors setup

Figure 3.3 shows the connection of IoT sensors and the associated devices that help sensors to operate. The next section describes how the system operates.

- A weather station was used to measure daily temperatures and rainfall every three hours and to log the results in ThingSpeak®.
- A soil moisture sensor was used to measure the soil moisture content. It was programmed with ESP32 CAM to take the readings and send the results to ThingSpeak®. The readings were taken twice a day – in the mornings and evenings.

- The ESP32 CAM was also used weekly to capture the image of the pasture, and the image was interpreted by MATLAB[®] script run in Raspberry Pi. The image processing algorithm script was created to calculate the height of the pasture and the result was logged into ThingSpeak[®]. Changes in pasture growth can be noticed after a few days and taking measurements in close points did not show the significant change; hence, the weekly measurements were recorded.
- The Wi-Fi router provides internet access to all IoT devices for a smooth data transfer from the sensors to ThingSpeak[®]. Internet access is important for the entire system as it allows for remote and real-time monitoring.
- All the sensors and other devices on the system are powered from Alternating Current (AC) supply and, in case of power failure, an Uninterruptible Power Supply (UPS) acts as backup power for the system.

3.3 Phase B – Algorithm development

Section 3.2.2.1 demonstrates how data is collected and stored using IoT platforms. Nonetheless, not only the data from sensors was used in the study but the historical data and farm data too. For that reason, the process of developing the algorithm was performed into two steps which are:

- Firstly, the analysis was performed on the historical data combined with the data collected on the farm to develop and select a suitable algorithm for prediction.
- Secondly, the selected algorithm was used to analyse IoT sensors' data to update prediction models on the digital twin. Although, this step will be covered in the next chapter.

MATLAB[®] was used to gain insight into the collected data by performing analysis on the data through algorithm development. This section shows how that data was filtered, prepared and analysed with the goal of developing a digital twin.

The goal of the study is to build a digital twin that will predict the height of the pasture, meaning, the digital twin must have an effective predictive model to accurately predict the height of the pasture. Predictive models use historical data to predict future events, therefore, these models also use current data to keep them updated in order to improve the model's efficiency.

The subsequent sub-sections describe the process carried out in selecting the right algorithm to build a predictive model and use the preferred model in achieving the research goals.

3.3.1 Selecting the right algorithm

Predictive modelling is crucial to the study as it predicts the future outcomes. Climate change has made it difficult for farmers to manage their farms due to unpredicted weather patterns. Hence, this is where predictive models come in handy. Predictive models are created using the historical data and take new data sets to make predictions. Regression and ANN machine learning algorithms were used to develop predictive models in this study.

Regression and ANN models are commonly used for climate prediction [134]. Hence, these are the only models covered in this study. The benefit of using machine learning and deep learning is that these algorithms can automatically learn large volumes of data and discover trends and patterns without any human intervention. They ultimately perform predictions and keep improving their accuracy and efficiency.

The other advantage of using machine learning algorithms for prediction is that there is no need to derive an equation to identify relationships in the set of data. Trying to extract complex relationships by writing an equation to set inputs and outputs can be extremely challenging and does not lead to an efficient solution [135]. Instead, the underlying idea of machine learning is to learn and train data to identify patterns and relationships and perform new predictions.

Both algorithms were used to build predictive models and analysed to determine which one could perform predictions better after learning and training with historical data. Figure 3.10 shows the procedure followed in developing the predictive models.

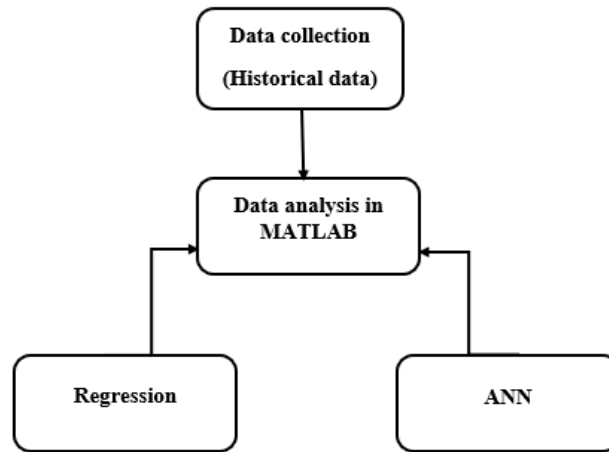


Figure 3.4 Process followed in selecting the suitable predictive algorithm

The models were developed to predict temperature and rainfall. Researchers have demonstrated that a larger sample size leads to better predictive performance [136]. The accuracy and the reliability of the models are therefore determined by the sample size. This makes sample size an important factor in model development.

3.3.1.1 Determining the sample size

Sample size determination is considered an important step in the research methodology [137]. Sample size determination means selecting the number of observations to use in the statistical sample. The sample size of the development dataset should be large enough to develop a prediction model that is reliable when provided with a new dataset [138].

According to Kaur, the larger the sample size, the smaller the sampling error [137]. What constitutes the appropriate sample size for model development can be challenging to determine [138]. Thus, for this study, the design basis of the dataset to be used was identified. Developing a prediction model to track climate change requires a development dataset which contains historical data of weather data.

It is evident that climate change is monitored based on decades of the earth's atmospheric observations [139]. Hence, the ten-year historical data of temperature and rainfall was used to develop the prediction models. The data gathered was from the period of 2011 to 2020 from [140] a source for the area where the farm is located.

3.3.1.2 Developing regression prediction models

Temperature and rainfall models were developed using the regression algorithm. This was to determine how efficiently these models could perform the predictions. Temperature and rainfall are among the factors that influence pasture growth, so being able to closely predict these factors is very important to this study.

- **Regression temperature prediction model**

Historical temperature data was loaded into MATLAB[®] to develop the regression model and perform the predictions. The model was created with the regression learner app in MATLAB[®]. The year and day of year were defined as the inputs of the model and the maximum temperature as the output. In a common year, there are 365 days. Figure 3.5 shows the trained temperature prediction model in the regression learner app.

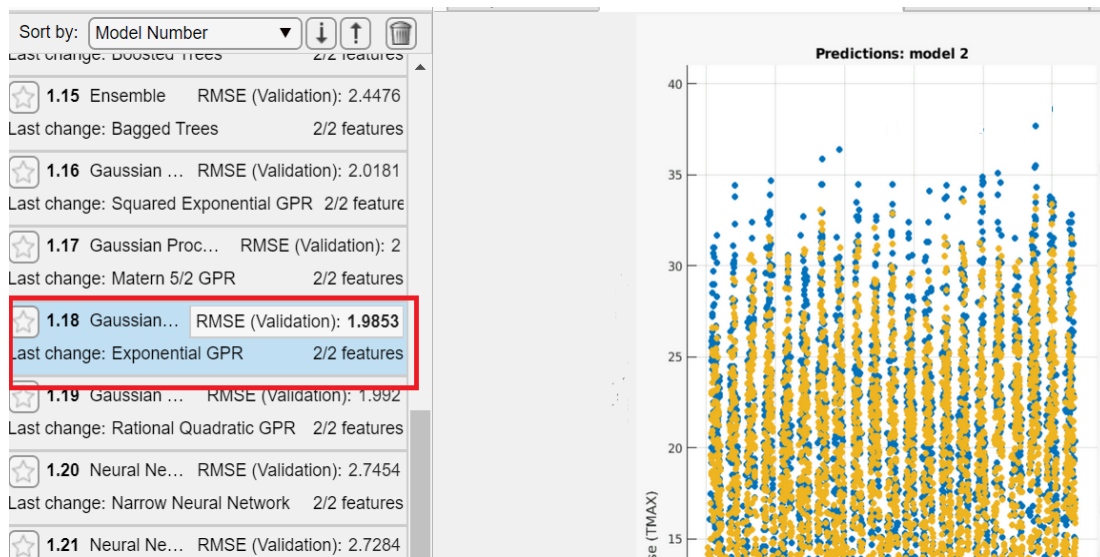


Figure 3.5 Importing and training prediction temperature model using regression learner app

MATLAB[®] has various types of built-in regression types that are used to develop the models. These models differ by their performance in training a specific type of data. Figure 3.5 shows that among all other regression models, exponential GPR was chosen as the recommended model due to lower Root Mean Square Error (RMSE) as compared to the other models. RMSE is a measure of accuracy to compare forecasting errors of different models [141] and is commonly used as an error metric for numeral predictions. The lower the RMSE, the higher the accuracy of the model. The model performance is also determined by comparison of true and predicted response.

After training the model, the predictions were performed for the next 60 days. That is, the predictions were done for the first 60 days in 2021. The 60-day duration was chosen because a model that can predict up to two months is needed. The reason for this is that pasture is ready for grazing at six to eight weeks after sowing. For that reason, having a model that could predict climatic conditions up to the forage life cycle would be ideal. Table 3.1 shows the dataset used for temperature prediction.

Table 3.1 Dataset used for temperature predictions

Year	Day of year
2021	1
2021	2
2021	3
2021	4
2021	5
2021	6
2021	7
2021	8
2021	9
2021	10
2021	11
2021	12
2021	13
2021	14
2021	15
2021	16
2021	17
2021	18
2021	19
2021	20
:	:
:	:
2021	60

Figure 3.6 shows the results obtained.

```
>> T = readtable('test_temp1.xlsx');
>> yfit = trainedModel2.predictFcn(T);
>> yfit = trainedModel2.predictFcn(T)

yfit =

    29.0100    29.4300
    25.0900    28.9900
    23.9300    29.4400
    26.9800    29.4300
    22.7800    29.1200
    28.6700    28.6600
    29.0200    30.2200
    29.5400    29.1100
    28.9800    28.7600
    28.6700    29.2500
    25.6500    27.5600
    29.3200    28.8700
    29.2100    29.2100
    28.8900    29.0300
    28.5400    29.0500
    29.3400    29.4300
    28.9800    29.2300
    30.0100    27.6600
    29.2300    29.5500
    29.4500    27.7700
    29.1100    28.7600
    29.4100    29.6500
    29.4500    28.7600
    28.9800    29.2200
    28.8800    28.9600
    30.0100    31.0200
    27.0300    29.4500
    27.3200    28.8700
    29.2300    29.0100
    29.1100    29.3300
```

Figure 3.6 Predicted temperature values in regression model

- **Regression rainfall prediction model**

A model that predicted rainfall was also developed. Predicting daily rainfall was not feasible and so the weekly rainfall data was predicted instead. The data in Figure 3.11 was structured to train the model using the total weekly rainfall. The historical weekly rainfall data was used to develop the model. Figure 3.7 shows the model with lower RMSE value obtained when training the model.

Models		
Sort by:	Model Number	
ast change: Dagged trees 2/2 features		
1.16	Gaussian ...	RMSE (Validation): 5.8353 ast change: Squared Exponential GPR 2/2 features
1.17	Gaussian ...	RMSE (Validation): 5.6046 ast change: Matern 5/2 GPR 2/2 features
1.18	Gaussian ...	RMSE (Validation): 5.557 ast change: Exponential GPR 2/2 features
1.19	Gaussian ...	RMSE (Validation): 5.7381 ast change: Rational Quadratic GPR 2/2 features
1.20	Neural Ne...	RMSE (Validation): 6.0912 ast change: Narrow Neural Network 2/2 features
1.21	Neural Ne...	RMSE (Validation): 6.2031 ast change: Medium Neural Network 2/2 features
1.22	Neural Ne...	RMSE (Validation): 6.3655 ast change: Wide Neural Network 2/2 features
1.23	Neural Ne...	RMSE (Validation): 6.2453 ast change: Bilayered Neural Network 2/2 features
Current Model Summary		

Figure 3.7 RMSE value obtained while training regression rainfall prediction model

Figure 3.7 shows that the Exponential GPR model was also still outstanding due to lower RMSE value, therefore, it was used to train the model. Rainfall was predicted weekly; hence, the predictions were done for a period of eight weeks for the first weeks of 2021. Figure 3.8 shows total anticipated rainfall values per week.

```
>> T = readtable('test_rainfall.xlsx');
>> yfit = trainedModel3.predictFcn(T)

yfit =

    20.7900
     7.6500
    22.8700
    49.2300
     5.7000
         0
     6.7000
     4.8700
```

Figure 3.8 Predicted weekly rainfall values using regression model

These predicted results were compared with the observed values to determine the efficiency of the models. The evaluation was performed to assess the performance of the model based on the predicted and actual values on both the temperature and rainfall prediction models.

3.3.1.3 Evaluation of regression prediction models

After obtaining the predicted values from the prediction models, these values were compared with the observed values to evaluate the performance of the model. It is important to perform model evaluation because it helps to assess the efficiency of the model during the initial research phases. The model evaluation was therefore conducted using two evaluation metrics, namely: correlation coefficient and estimated error.

- Correlation coefficient measures the relationship between two variables [142]. The values range is between -1 and 1. The closer the calculated value moves to 1, the stronger the relationship between two values and vice versa. The correlation between observed and predicted values was performed in Excel[®] because it can perform correlation on multiple corresponding elements.
- Prediction error is the difference between the observed value and the predicted value [143]. The smaller the difference, the better.

Observed and predicted temperature results were compared in Table 3.2.

Table 3.2 Comparing temperature predicted and observed values on regression model

Day of year	Observed Temperature	Predicted Temperature	Prediction error	Day of year	Observed Temperature	Predicted Temperature	Prediction error
1	28	29,01	-1,01	31	31	29,43	1,57
2	22	25,09	-3,09	32	31	28,99	2,01
3	20	23,93	-3,93	33	25	29,44	-4,44
4	23	26,98	-3,98	34	27	29,43	-2,43
5	20	22,78	-2,78	35	27	29,12	-2,12
6	28	28,67	-0,67	36	30	28,66	1,34
7	31	29,02	1,98	37	28	30,22	-2,22
8	30	29,54	0,46	38	29	29,11	-0,11
9	30	28,98	1,02	39	30	28,76	1,24
10	30	28,67	1,33	40	30	29,25	0,75
11	23	25,65	-2,65	41	32	27,56	4,44
12	27	29,32	-2,32	42	31	28,87	2,13
13	29	29,21	-0,21	43	32	29,21	2,79
14	29	28,89	0,11	44	32	29,03	2,97
15	29	28,54	0,46	45	31	29,05	1,95
16	29	29,34	-0,34	46	30	29,43	0,57
17	30	28,98	1,02	47	28	29,23	-1,23
18	31	30,01	0,99	48	30	27,66	2,34
19	30	29,23	0,77	49	32	29,55	2,45
20	33	29,45	3,55	50	32	27,77	4,23
21	33	29,11	3,89	51	31	28,76	2,24
22	32	29,41	2,59	52	31	29,65	1,35
23	33	29,45	3,55	53	25	28,76	-3,76
24	33	28,98	4,02	54	25	29,22	-4,22
25	28	28,88	-0,88	55	27	28,96	-1,96
26	25	30,01	-5,01	56	29	31,02	-2,02
27	22	27,03	-5,03	57	28	29,45	-1,45
28	24	27,32	-3,32	58	27	28,87	-1,87
29	29	29,23	-0,23	59	27	29,01	-2,01
30	31	29,11	1,89	60	27	29,33	-2,33
				0,6452			

Correlation
Coefficient

The correlation coefficient was calculated in Excel[®] by using the correlation function. Table 3.2 shows the correlation coefficient of 0.6452 between the observed and predicted values. The second method is the estimated error which shows the difference between the predicted values and the actual values of $\pm 5.03^{\circ}\text{C}$.

The comparison of rainfall results is demonstrated in Table 3.3.

Table 3.3 Comparing rainfall predicted and observed values on regression model

Week	Observed rainfall	Predicted rainfall	Prediction Error
1	43	20,79	22,21
2	12,4	7,67	4,75
3	37,3	22,87	14,43
4	65,6	49,23	16,37
5	1,4	5,7	-4,3
6	5,2	0	5,2
7	0	6,7	-6,7
8	14,1	4,87	9,23
0,9447			

Correlation
Coefficient

Table 3.3 shows the calculated correlation value of 0.9447 and the prediction error of $\pm 22.21\text{mm}$. These results from both models were compared with the obtained values in ANN models to determine which algorithm performed better.

3.3.1.4. Developing ANN predictive models

Predictive models based on ANN algorithm were also developed. This was done to perform an analysis between the regression and ANN model to determine which algorithm performs better. Both temperature and rainfall prediction models were developed.

- **ANN temperature prediction model**

This model was developed using the ANN algorithm to predict daily temperatures. To develop the ANN prediction model, the same data was used in temperature prediction using a regression algorithm. The data was imported on the neural net fitting app to develop and train the model. The neural network training architecture is shown in Figure 3.9.

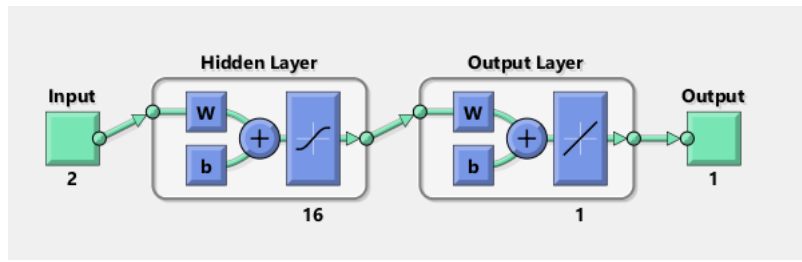


Figure 3.9 neural network training architecture

Figure 3.9 shows that the model is built on 16 hidden neurons, based on two inputs and one output. The number of neurons is altered to increase the performance of the model. The performance of the model is shown in Figure 3.10.

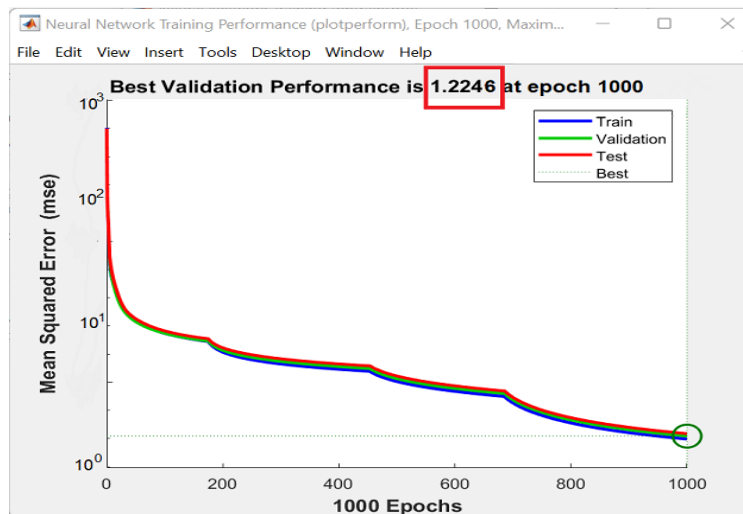


Figure 3.10 Temperature prediction model performance

Figure 3.10 shows that using the ANN algorithm, the obtained RMSE value is 1.2246. However, the analysis of the two algorithms will be performed later in this chapter. The trained ANN model was then deployed in SIMULINK® to perform the predictions. Figure 3.11 shows the ANN model being deployed to the SIMULINK® platform.

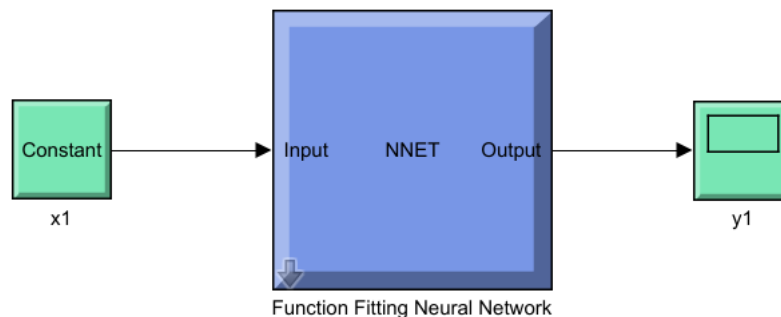


Figure 3.11 Deployed ANN model to SIMULINK®

New data set was fed into the model to perform the predictions for the next 60 days. The same dataset in Table 3.1 was used as new data to perform the predictions. The data was imported into the model using the *from workspace* block and the results were demonstrated in the *display* block. The results are shown in Figure 3.12.

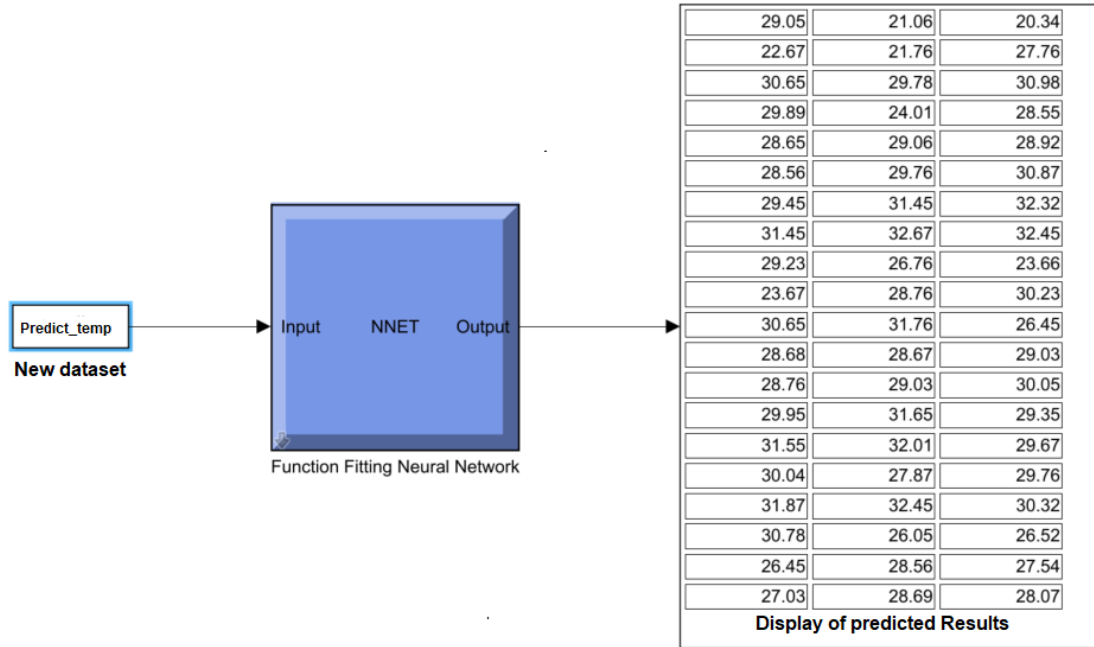


Figure 3.12 Predicted temperature values in ANN model

- **ANN rainfall predictive model**

The model that predicted rainfall based on the ANN algorithm was also developed. The model predicted weekly rainfall, and the performance of the model is shown in Figure 3.13.

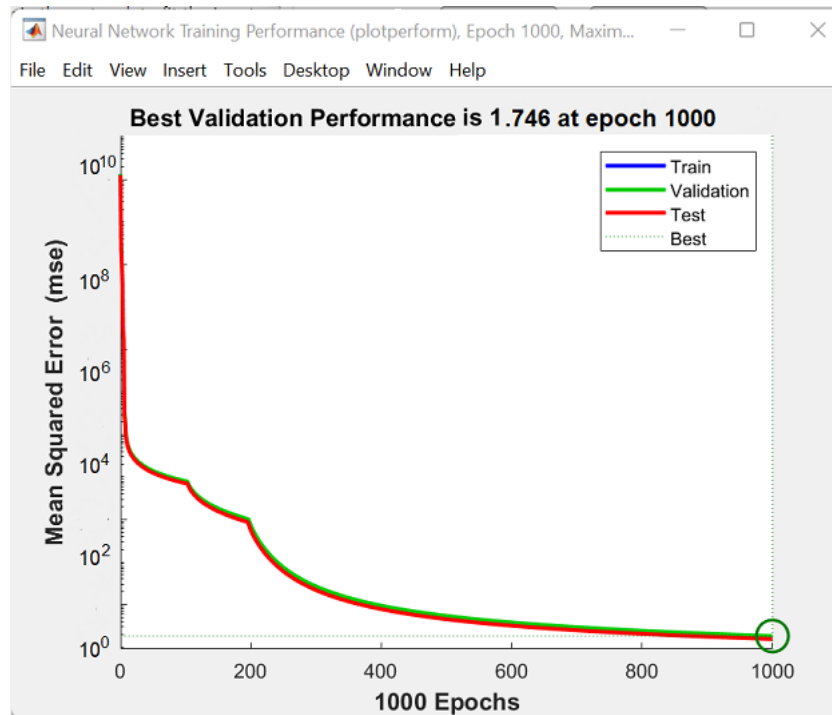


Figure 3.13 ANN rainfall model performance

Rainfall was predicted weekly, and the results were recorded for eight weeks. Figure 3.14 shows the results for predicted rainfall.

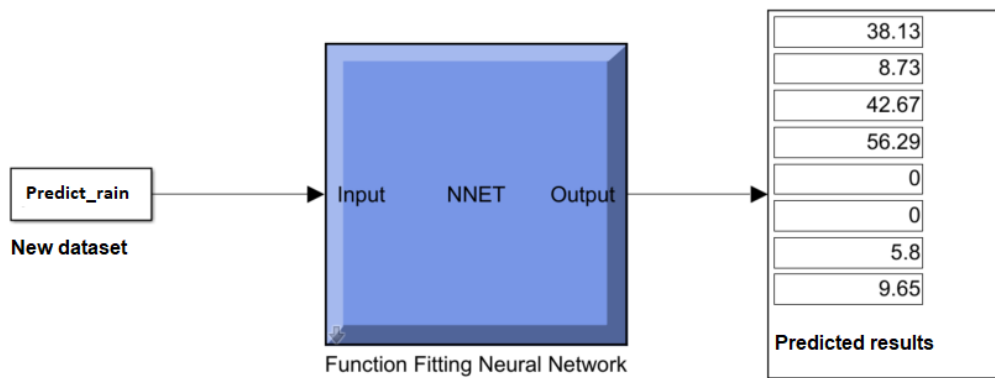


Figure 3.14 Predicted rainfall values in ANN model

3.3.1.5 ANN prediction models evaluation

The performance of the ANN model was evaluated using the two metrics: correlation coefficient and estimated error. Both correlation coefficient and estimated error were calculated based on the observed values compared to the predicted values. The results are displayed in Table 3.4.

Table 3.4 Evaluation of ANN temperature prediction model

Day of year	Observed Temperature	Predicted Temperature	Prediction error	Day of year	Observed Temperature	Predicted Temperature	Prediction error
1	28	29,05	-1,05	31	31	30,65	0,35
2	22	21,06	0,94	32	31	31,76	-0,76
3	20	20,34	-0,34	33	25	26,45	-1,45
4	23	22,67	0,33	34	27	28,68	-1,68
5	20	21,76	-1,76	35	27	28,67	-1,67
6	28	27,76	0,24	36	30	29,03	0,97
7	31	30,65	0,35	37	28	28,76	-0,76
8	30	29,78	0,22	38	29	29,03	-0,03
9	30	30,98	-0,98	39	30	30,05	-0,05
10	30	29,89	0,11	40	30	29,95	0,05
11	23	24,01	-1,01	41	32	31,65	0,35
12	27	28,55	-1,55	42	31	29,35	1,65
13	29	28,65	0,35	43	32	31,55	0,45
14	29	29,06	-0,06	44	32	32,01	-0,01
15	29	28,92	0,08	45	31	29,67	1,33
16	29	28,56	0,44	46	30	30,04	-0,04
17	30	29,76	0,24	47	28	27,87	0,13
18	31	30,87	0,13	48	30	29,76	0,24
19	30	29,45	0,55	49	32	31,87	0,13
20	33	31,45	1,55	50	32	32,45	-0,45
21	33	32,32	0,68	51	31	30,32	0,68
22	32	31,45	0,55	52	31	30,78	0,22
23	33	32,67	0,33	53	25	26,05	-1,05
24	33	32,45	0,55	54	25	26,52	-1,52
25	28	29,23	-1,23	55	27	26,45	0,55
26	25	26,76	-1,76	56	29	28,56	0,44
27	22	23,66	-1,66	57	28	27,54	0,46
28	24	23,67	0,33	58	27	27,03	-0,03
29	29	28,76	0,24	59	27	28,69	-1,69
30	31	30,23	0,77	60	27	28,07	1,07
				0,9657			

Correlation
Coefficient

In Table 3.4, the correlation value is 0.9657 and the estimation error is $\pm 1,76^{\circ}\text{C}$. Table 3.5 displays the evaluation results on the rainfall prediction model.

Table 3.5 Evaluation of ANN rainfall prediction model

Week	Observed rainfall	Predicted rainfall	Predicted Error
1	43	38,13	4,87
2	12,4	8,73	3,67
3	37,3	42,67	-5,37
4	65,6	56,29	9,31
5	1,4	0	1,4
6	5,2	0	5,2
7	0	5,8	-5,8
8	14,1	9,65	4,45
0,9757			

Correlation
Coefficient

The ANN rainfall prediction model shows the correlation value as 0.9757 and the estimation error is $\pm 9.31\text{mm}$. All the models are to be analysed in the next section to determine with models performed better.

3.3.1.6 Analysing ANN and regression prediction models

ANN and regression models are the most commonly used predictive models, and most importantly, they can predict climatic conditions. Even so, the most effective model in this study had to be determined. The analysis of the regression and ANN models was performed based on models' performance to determine their efficiency, thereby choosing the most appropriate.

Firstly, the analysis was performed on temperature prediction models. Table 3.6 demonstrates the comparison of the results from both models.

Table 3.6 Comparison on ANN and Regression predicted temperature results

Metric	Regression	ANN
RMSE	1,985	1,225
Correlation	0,645	0,966
Estimation error	$\pm 5,03$	$\pm 1,76$

Table 3.6 shows that the ANN model had a lower RMSE value as compared to the regression model. A lower RMSE value demonstrates a better performance on the model. The ANN model also had a lower correlation value which is much closer to the value that represents a strong relationship (1) between the actual values and predicted values. The error on predicted values was considerably bigger in the regression model than in the ANN model. With these findings, the ANN model proved to be a better model in predicting temperature.

The second analysis is on rainfall models, of which the comparison of results is demonstrated in Table 3.7.

Table 3.7 Comparison on ANN and Regression predicted rainfall results

Metric	Regression	ANN
RMSE	5,557	1,746
Correlation	0,945	0,976
Estimation error	±22,21	±9,31

Table 3.7 shows the ANN model with a lower RMSE value and a lower estimation error. The correlation value in the ANN model is higher, as compared to regression model. The ANN model also had a better prediction of rainfall, as compared to the regression model.

Thus, the ANN algorithm was chosen to develop the predictive models for this study.

3.3.2 Predictive modelling using an ANN algorithm

Predictive modelling is an important aspect in this study as the main goal is to predict the extent of the available pasture for the future. The results obtained from section 3.3.1 show the ANN algorithm performed better, thus, it was the algorithm chosen to develop predictive models within the digital twin. The ANN algorithm proved to work better and one of its benefits is that it works well with complex and unstructured data [101], which makes it suitable for this research. The next section reveals how ANN prediction models were utilised within the digital twin.

3.4 Component C – Digital twin development

Unstable and unpredictable climatic conditions due to climate change have caused a reduction in sheep production, though predictive analytics is anticipated to address common problems of this nature [127]. Consequently, the study focuses on developing a digital twin based on current trends in pasture management. The main purpose is to have an improved pasture management system with predictive scenarios that can be detected at early stages for better decision making and risk management procedures in livestock husbandry.

The study focuses on developing a digital twin that predicts future pasture growth to help farmers come up with suitable decisions and planning to ensure sustainable feed to the animals. The digital twin is a proposed solution that addresses the problem of unpredictable weather conditions that affect pasture production. Predictive modelling is important in a digital twin, which is why predictive algorithms were discussed in section 3.3. Subsequently, it was discovered that an ANN algorithm can perform predictions better, thus, this section will discuss how this algorithm was used towards digital twin development. The digital twin development occurs in two stages:

First stage: Digital shadow development

Second stage: Digital twin model development

3.4.1 Stage 1 – Developing a digital shadow

Developing a digital shadow is the first step in designing a digital twin. Digital shadow maps all the operating, status or process of data collected while the product is in use or during an ongoing process [144]. The digital shadow then reflects the digital model that contains all the information from development and production that forms an intelligent link to the digital twin.

The digital shadow development sets the foundation for a digital twin. The digital shadow is made of predictive models that perform prediction for the future. The digital shadow prediction models were developed using an ANN algorithm with data collected on the farm. Digital shadow development was the preliminary stage that provided the assurance that when the ANN models are implemented on the digital twin, that digital twin could be trusted.

A digital shadow was therefore developed using farm data collected based on temperature, soil moisture, rainfall and pasture height. The aim was to determine how pasture growth is affected by these factors, which are temperature, soil moisture and rainfall. The data acquired was used to develop a digital shadow.

The next section explains how farm data was collected.

3.4.1.1 Farm data collection

As stated in section 3.2.1., the pasture is planted twice a year at the farm – in Autumn (March to April) and in Spring (September to November). The data collection was conducted on “Field no. 2”, as shown in Figure 3.1.

The data was collected for the duration of one year, in 2021. This was a cultivated pasture with oats forage. Oats is one of the most commonly used forages in South Africa to feed livestock. It grows fast, can survive on low soil moisture, and has good feed value [145]. Oats also has high fibre content, which makes it a safe feed for sheep [146].

Data collected included pasture (oats) height, soil moisture, rainfall, and temperature. As the parameters influencing the pasture growth, temperature, rainfall and soil moisture were measured as the pasture grew.

The height of the pasture was measured by a grazing stick in centimetres (cm). Grazing sticks appear to be a simple measuring devices, and consist of a system of measurements that assist in making quick pasture management decisions, by keeping track of pasture yield, grazing days, and other data that can help evaluate previous efforts [11]. These variables are helpful in assisting the farmer to determine the amount of pasture available.

Soil moisture is also an important parameter in pasture growth. The soil moisture was recorded using the hand soil moisture sensor. Figure 3.15 shows how pasture height and soil moisture were measured.



Figure 3.15 Measuring pasture height and the soil moisture

This study uses historical weather data from [140] the source. The readings were recorded weekly and prepared in spread sheets. Figure 3.16 shows the sample data collected for the month of April.

	PASTURE DATA COLLECTION 2021			
		MONTH:April		
Plantation date: 15/03/2021				
	3rd wk	4th wk	5th wk	6th wk
	week14	week15	week16	week17
Date	2021/04/04	2021/04/11	2021/04/18	2021/04/25
AverageTemperature (°C)	25,86 °C	28,14 °C	26,86 °C	25 °C
Total weekly rainfall (mm)	1,9 mm	0,4 mm	0 mm	0,9 mm
Average soil moisture (SI)	4 SI	3 SI	2 SI	1 SI
Pasture height (cm)	18 cm	25 cm	31 cm	40 cm

Figure 3.16 April farm data in Excel®

3.4.1.2 The findings on the data collected

Data based on pasture growth was collected for two seasons for the total of six months and the following are inferences made based on the data:

- Pasture is normally ready for grazing after eight weeks of plantation but, at Agri Training Centre, it is common practice to extend to the ninth week.
- The height of the pasture was higher in Autumn as compared to the Spring period.
- Pasture height of 50 cm and above is sustainable to feed 45 sheep.

Thus, with the data collected, a digital shadow was then developed. The next section details how the digital shadow was created.

3.4.1.3 Creating a digital shadow model

Data presented in Figure 3.16 was used to develop a digital shadow model. The digital shadow model was developed to predict pasture height for Autumn in 2022. The growth of the pasture is dependent on three parameters, which are: temperature, rainfall and soil moisture. The training of the model will therefore involve those three parameters to determine the height of the pasture. Thus, training a model with those parameters is accomplishable, though the challenge will arise when providing a new dataset to the model because it is unknown. As a result, this digital shadow was composed of four different predictive models. Figure 3.17 shows how the models are structured.

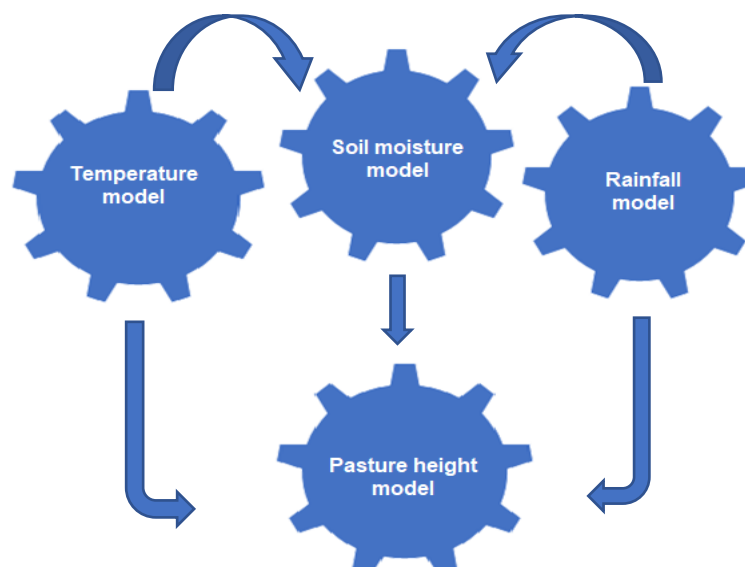


Figure 3.17 Models in digital shadow

Figure 3.17 shows that the pasture height prediction model depends on three models which are temperature, rainfall and soil moisture prediction models. For the pasture height prediction model to perform predictions, it will need a new dataset provided by three prediction models. The soil moisture predictive model also depends on temperature and rainfall predictive models. Nonetheless, the digital shadow was made up of four models to predict the farm status [147]. This section will detail how these predictive models were developed to structure a digital shadow.

The first step was to work on temperature and rainfall prediction models. These are the same models developed in section 3.3.1.4, but they were updated with farm data collected in Figure 3.16. For efficiency of temperature and rainfall predictive models, the historical data is needed for models to identify patterns in weather changes, hence, a decade's worth of data was used to train these models. The soil moisture and pasture height models are dependent on temperature and rainfall to make predictions and the efficiency of these model is important.

The temperature model was restructured to predict average temperature values per week, because overall farm data based on pasture growth was recorded weekly. After training the models, they were deployed in SIMULINK[®] and tested with a new dataset and the results are demonstrated in Chapter 4. The models are demonstrated in Figure 3.18.

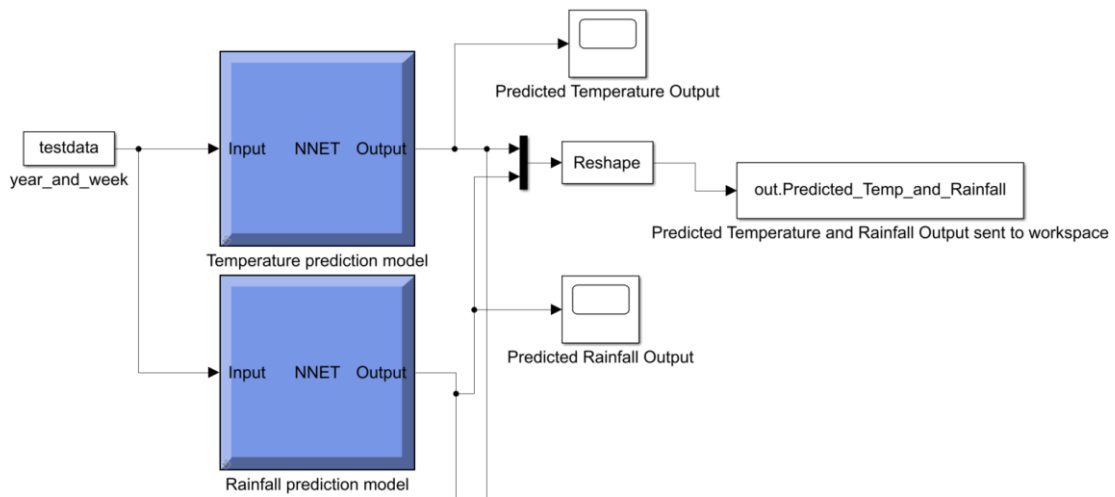


Figure 3.18 Digital shadow temperature and rainfall prediction models

Figure 3.18 shows the temperature and rainfall predictive models deployed to SIMULINK[®] to perform the predictions. The predictions were performed for the Autumn season (March – April) in 2022 and the new dataset was provided as the year and the weeks for that period. The output was stored in the workspace to be used for the soil moisture prediction model.

The next step was to develop the model that predicted soil moisture. Soil moisture is dependent on temperature and rainfall, thus, these were the parameters used as inputs, while the soil moisture was defined as the output to develop the model. Data presented in Figure 3.16 was used to train the model.

A soil moisture predictive model is an advanced feature proposed in this study to add on to the forecast models that aid in pasture management. At the time of conducting the study, there was no historical data available; hence, the model was developed with six months' worth of data collected at the farm. For predictions, the outputs of the temperature and rainfall prediction models were used as the new dataset and the results obtained from this model are shared in Chapter 4. The predicted soil moisture, temperature and rainfall was also sent into the workspace so as to be used in the pasture height prediction model. The soil moisture prediction model is shown in Figure 3.19.

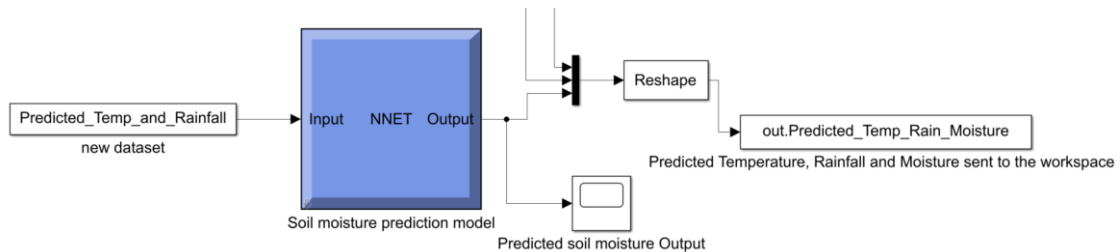


Figure 3.19 Digital shadow soil moisture prediction model

Lastly, the model that predicted pasture height was developed. Data collected on the farm demonstrates the insights on parameters affecting pasture growth. The farm data on temperature, rainfall, soil moisture and pasture height were therefore used to develop and train the pasture height prediction model. The outputs from the temperature, rainfall and soil moisture prediction models were used as the new dataset for predictions and the outcome is shown in Chapter 4. The model is shown in Figure 3.20.

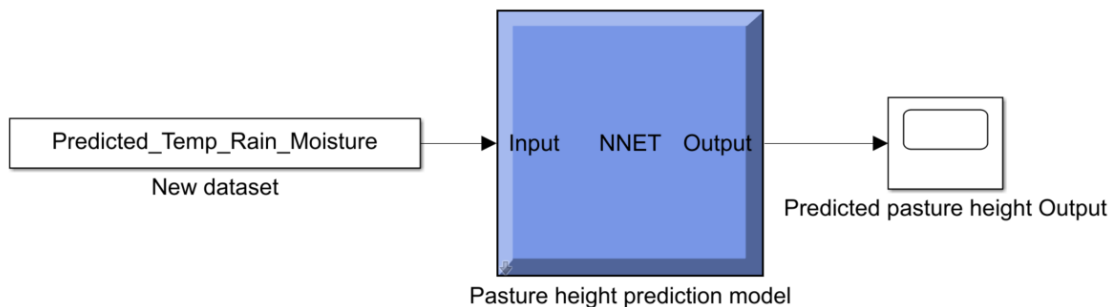


Figure 3.20 Digital shadow pasture height prediction model

3.4.2 Stage 2 – Developing a digital twin

Developing a digital shadow was the first step in developing the digital twin to test the selected algorithm on the physical system and determine if it can be trusted when implemented on the physical systems. The set of models help the researcher to understand the structure and the behaviour of the systems in the physical world as these models are used to create digital twins to perform predictions for the future. The design of the digital twin facilitates the activities, monitoring and digital control of operations in all the connections of the system. Typically, the activities are implemented in stages where each stage processes plans and executes operations.

The digital twin development is comprised of two platforms: A physical system and the digital platform. As shown in section 3.2.2, the physical system is basically the setup of IoT sensors that collect data and store the data on a cloud platform. The digital platform portrays the digital representation of the physical system. It is the digital twin – described as a digital copy of the physical system with additional capabilities, including predictive modelling.

The digital twin receives the real-time data from the physical system so that the two platforms can have corresponding data. Running systems in real-time distinguishes the digital twin from the digital shadow [113]. Digital twins consist of three components, namely: data, model, analytics or algorithms [148]. The next section details how the digital twin was developed.

3.4.2.1 Design of the digital twin

The design of the digital shadow was helpful in understanding the scenarios of the physical system. Getting a clear picture of the physical system was beneficial in guiding which type of digital twin to develop. Predictive models built from historical data were to be created, and a data-driven digital twin was developed. This type of the digital twin was developed in three phases, namely:

- data collection and monitoring;
- data storage, and
- data analytics and predictive modelling.

The digital twin development process is demonstrated in Figure 3.21.

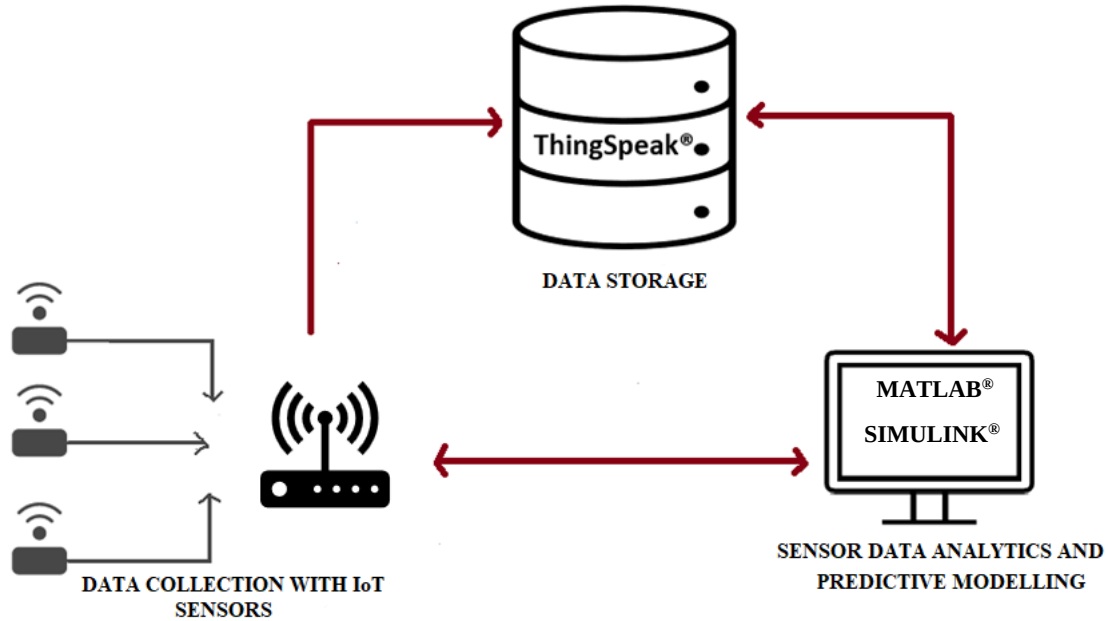


Figure 3.21 Digital twin development process

- **Data collection and monitoring**

This includes the connection of IoT sensors to develop the physical system. The design of the physical system was discussed in section 3.2.3. This enables the real-time monitoring using the sensors, which enables the link between the physical system and digital platform. The structure includes the IoT gateway that allows transfer of data between the two platforms. The structure and setup of the physical system are shown in Chapter 4.

- **Data storage**

Data from the sensors was collected in real-time and stored in ThingSpeak® storage. ThingSpeak® recorded daily temperatures, rainfall and soil moisture. The daily records were then analysed after a week to obtain weekly data, and stored in a different ThingSpeak® channel. Weekly pasture height measurements were also recorded. The collected data is demonstrated in Chapter 4.

- **Data analytics and predictive modelling**

Section 3.4.1 explains the development of the digital shadow using an ANN algorithm. These models are developed in MATLAB® platform on the local computer. The digital shadow consists of predictive models built from historical weather data and farm data. Farm data collection was conducted weekly and data that was used to develop the models was processed and analysed in weekly format. These trained models were used in the digital twin as well.

The digital twin was also made up of four prediction models: temperature, rainfall, soil moisture, and pasture height prediction models. These models are deployed as functions in SIMULINK® and are updated with real-time data from the sensors. Data was collected daily and had to be analysed to obtain weekly data since the prediction models were updated on a weekly basis. Figure 3.22 summarises the process of analysing sensor data and using this data to keep prediction models up to date.

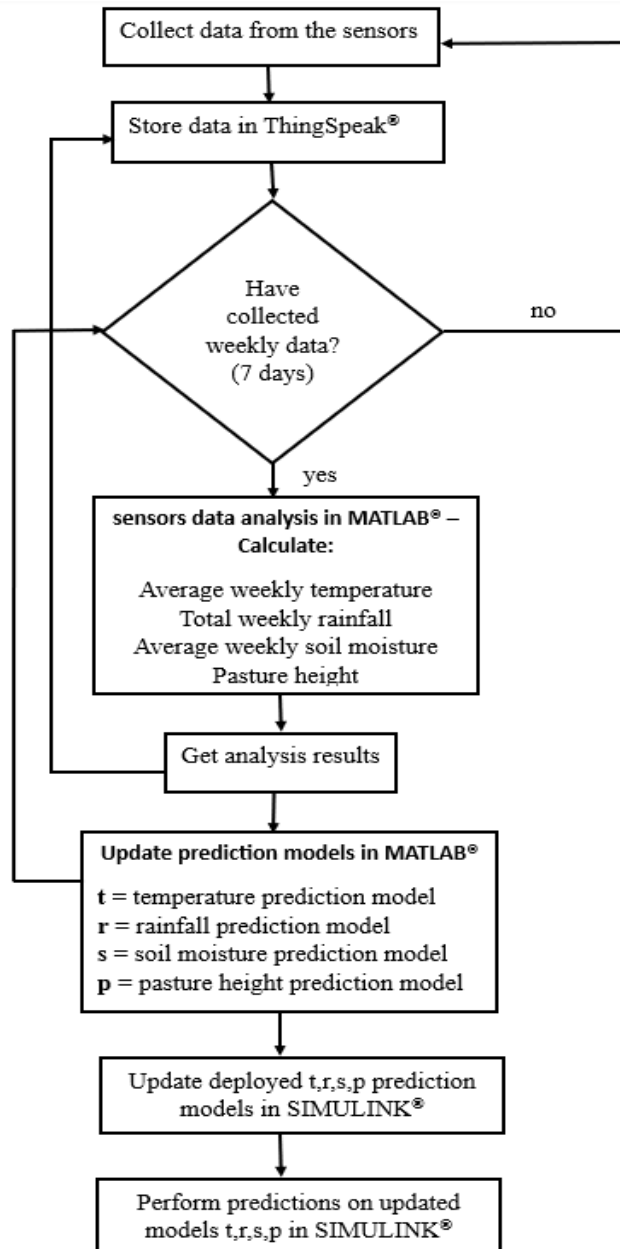


Figure 3.22 Data analysis and predictive modelling in the digital twin

A digital twin model runs in real-time, thus, live data was retrieved from ThingSpeak® to SIMULINK® for easy monitoring. The digital twin model was composed of two sections, which is the current status section and the prediction section. Figure 3.23 shows data retrieved from ThingSpeak® to SIMULINK® in real-time.

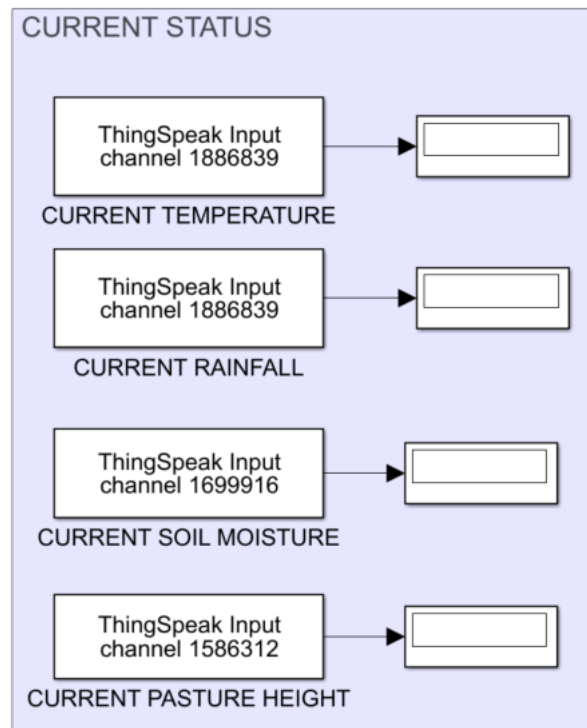


Figure 3.23 Sensor data retrieved from ThingSpeak® to SIMULINK® in real-time

In Figure 3.23, real-time data based on temperature, rainfall, soil moisture, and pasture height are retrieved from ThingSpeak® using *ThingSpeak input* block. This allows for easy monitoring to map the digital twin with the physical system.

Prediction models are updated by sensor data every week. These updated models are deployed in the SIMULINK® platform to enable real-time predictive modelling. Figure 3.24 shows the deploying of predictive models in SIMULINK®.

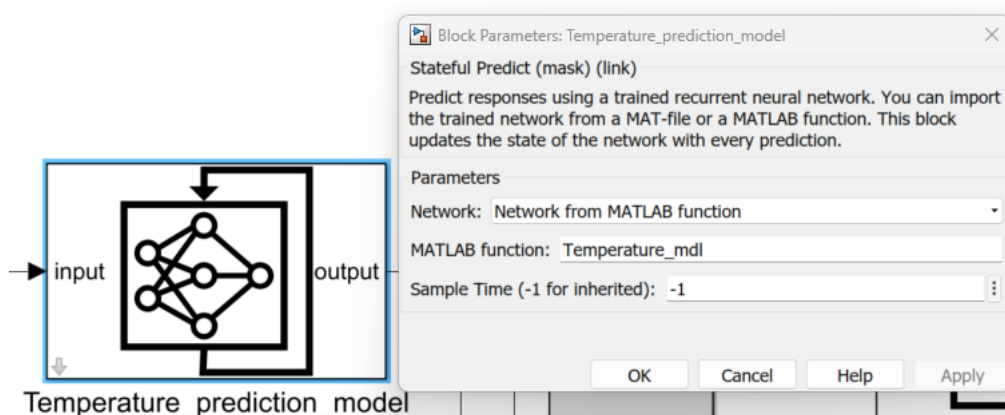


Figure 3.24 Deploying prediction models in SIMULINK®

Figure 3.24 shows a deployed temperature prediction model in SIMULINK®. Predictive models run as function networks in the MATLAB® platform. A stateful block in SIMULINK® accepts these trained neural networks as functions. Thus, when the model updates in MATLAB®, the updated version is automatically sent in SIMULINK®.

All the prediction models were deployed to SIMULINK®. Predictive modelling is an important feature within the digital twin. The prediction models were thus used to forecast the parameters that affect pasture growth, which assisted in predicting the pasture height. Figure 3.25 shows how the predictions were performed within the digital twin model.

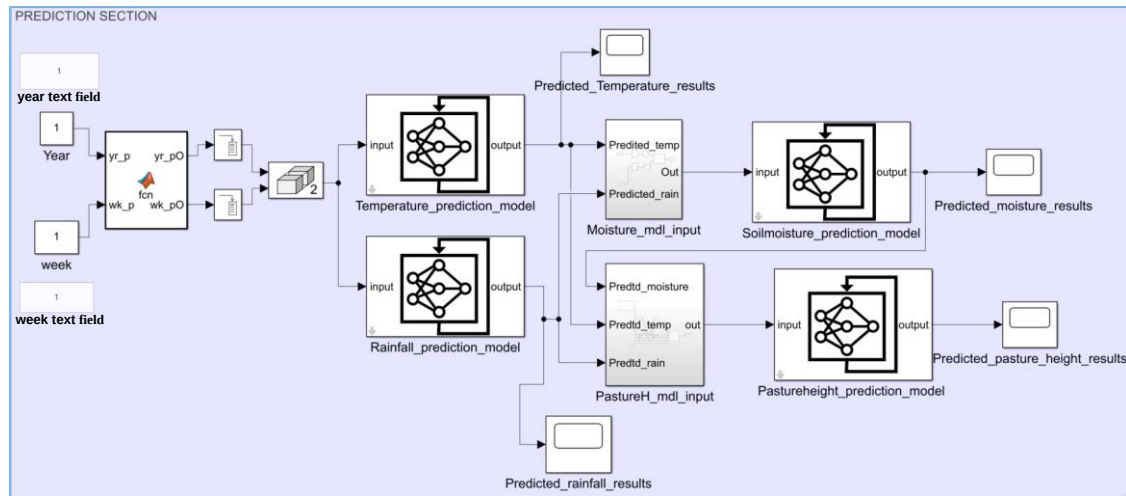


Figure 3.25 Predictions with the Digital model in SIMULINK®

Figure 3.25 shows the prediction section within the digital twin model. To perform the predictions, the period of the prediction has to be provided – that is, the year and the starting week of the prediction. The model counts from the starting week as the first week to the ninth week because the predictions are performed for the period of nine weeks. Pasture growth occurs within nine weeks, and for this reason, predictions are for nine weeks in order to keep track of predicted pasture height. Temperature and rainfall prediction models then receive the year and week's parameters as their inputs to perform the predictions. The outputs of these models will then be the weekly predictions based on the provided inputs.

Figure 3.25 also shows that the soil moisture prediction model depends on the temperature and rainfall prediction models. The predicted results for these models are provided as inputs in the soil moisture prediction model. The pasture height prediction model also depends on the temperature, rainfall, and soil moisture prediction models. The output results from models are provided as a new data set for the pasture height prediction model. The results of these models will be demonstrated in Chapter 4.

3.5 Conclusion

This chapter systematically outlines the research methodology aimed at investigating how to limit the impact of climate change on pasture management in sheep farms. The selection of appropriate methods has been guided by a thorough consideration of the research questions and objectives. Developing a digital twin of a smart farm has been chosen as a proposed solution to predict pasture height. The digital twin consists of four predictive models that depend on each other. These predictive models are constructed using machine learning algorithms employing complex learning methods. ANN and Regression were investigated to determine which one works better.

Historical climate data were used to train the models and identify trends. The digital shadow was developed as the first step in digital twin development. The digital shadow comprises predictive models built using historical data, and these models are updated with current data collected on the farm. The digital twin operates in real-time; therefore, sensors had to be installed to form the physical system. Low-power sensors were chosen, considering that there should be no overload when the backup power kicks in. Sensors measuring rainfall, temperature, soil moisture, and pasture height were installed. Data from the sensors were streamed into the cloud and retrieved by the digital twin to update the models. These models, developed using historical data, become more efficient in prediction when updated with live data.

The research methodology adopted for this study is well-aligned with the research objectives, providing an exploration of the research gap. The next chapter will present the results of our selected algorithm, digital shadow, and the digital twin with predictive models of pasture height based on predicted climatic conditions and soil moisture.

Chapter 4 – Results and Analysis

4.1 Introduction

The aim of this chapter is to lay out the results obtained in the processes of developing a digital twin. An ANN algorithm was selected to develop the prediction models in this study. Thus, this chapter will demonstrate how prediction models were used toward developing a digital twin, including the tests and simulations done, from developing a digital shadow as a predecessor, to digital twin development to predict the pasture height. The results are shared and analysed in the same sequence detailed in Chapter 3.

4.2 Digital shadow model development and results

As discussed in section 3.4, developing a digital shadow is an important stage towards developing a digital twin. The results obtained from the digital shadow determine the efficiency of the digital twin to be developed, as the same algorithm used in the digital shadow will be implemented on the digital twin. The digital shadow consists of predictive models developed out of collected data. The next sub-sections detail the analysis on farm data collected and the results on prediction models.

4.2.1 Results on collected farm data

The data show the results on the pasture growth as well as the parameters influencing growth which are temperature, rainfall and soil moisture. Pasture was planted twice a year – in Autumn and in Spring, thus, data was collected for those two seasons in 2021. In each season, pasture was planted over a period of nine weeks and data collection was conducted weekly. This section will detail the findings on temperature, rainfall and soil moisture, and their effects on pasture growth in two seasons. Figure 4.1 shows the results of temperatures in both seasons.

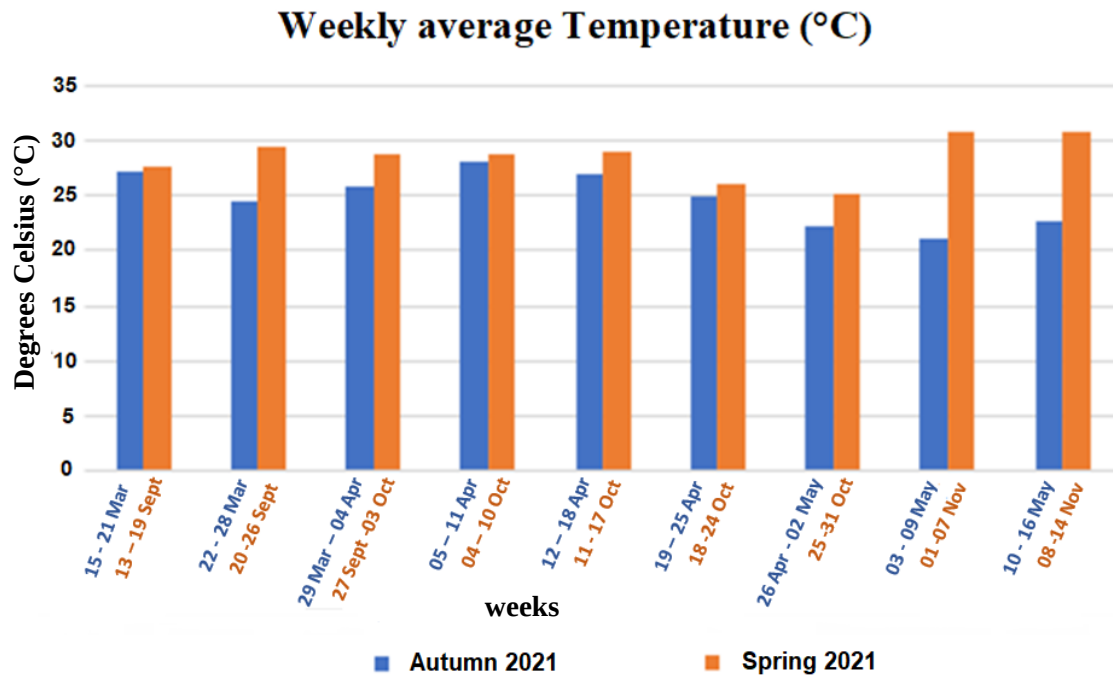


Figure 4.1 Weekly average temperature observed in Autumn 2021 and Spring 2021 while monitoring pasture growth

Figure 4.1 shows the observed average weekly temperatures recorded while the pasture was growing. It was observed that the temperatures were much higher in Spring as compared to Autumn during the period of nine weeks of the pasture growth. Figure 4.2 shows the observations on weekly rainfall.

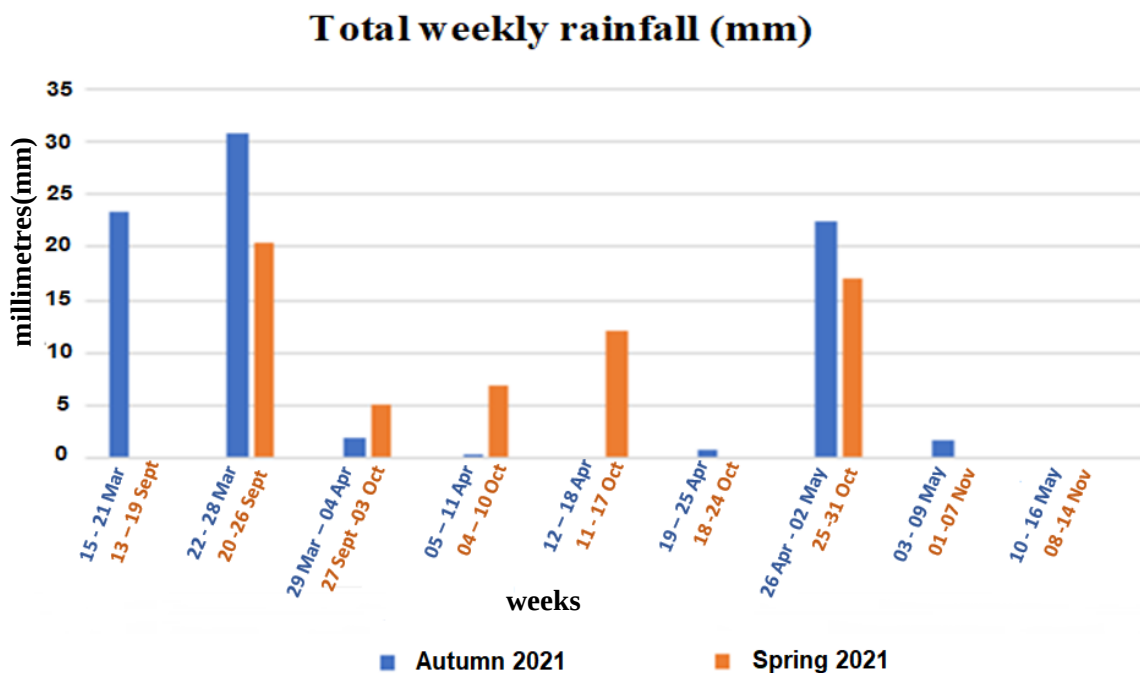


Figure 4.2 Weekly total rainfall recorded in Autumn 2021 and Spring 2021 during pasture growth

Figure 4.2 shows the total weekly rainfall for the two seasons. It was observed that more rainfall was experienced in Autumn than in Spring. Observations on soil moisture are shown in Figure 4.3.

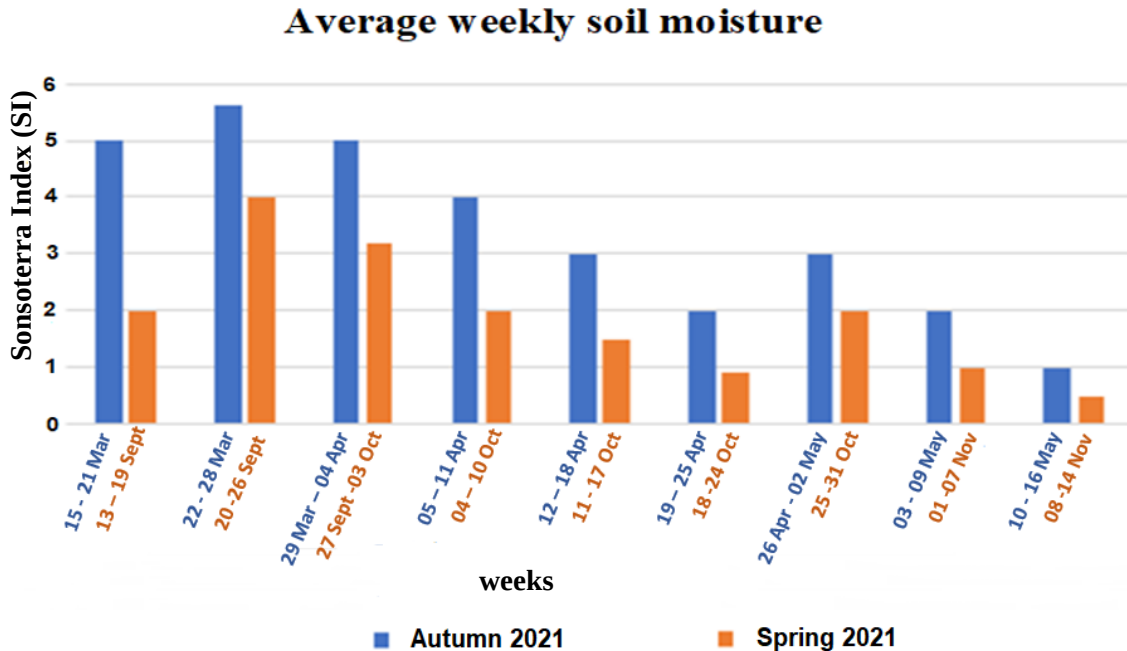


Figure 4.3 Weekly average soil moisture recorded in Autumn and Spring in 2021 while growing the pasture

Figure 4.3 shows the average soil moisture recorded weekly for the monitored Autumn and Spring seasons. The soil moisture measurements were recorded based on the Sensoterra Index (SI). The SI spreads the three zones over a 0 – 10 scale. Any value from 7 – 10 shows a high soil moisture. From 3 – 6.9 is moderate moisture. Between 0 and 2.9 is low soil moisture. Soil moisture is thus dependent on the rainfall and the temperature. Thus, as demonstrated in Figure 4.3, at the weeks where there was rainfall, the soil moisture increased. Nonetheless, in Spring, even when there was rainfall, the soil moisture quickly deteriorated due to high temperatures that caused high evaporation. Figure 4.4 demonstrates pasture height recorded for the two seasons.

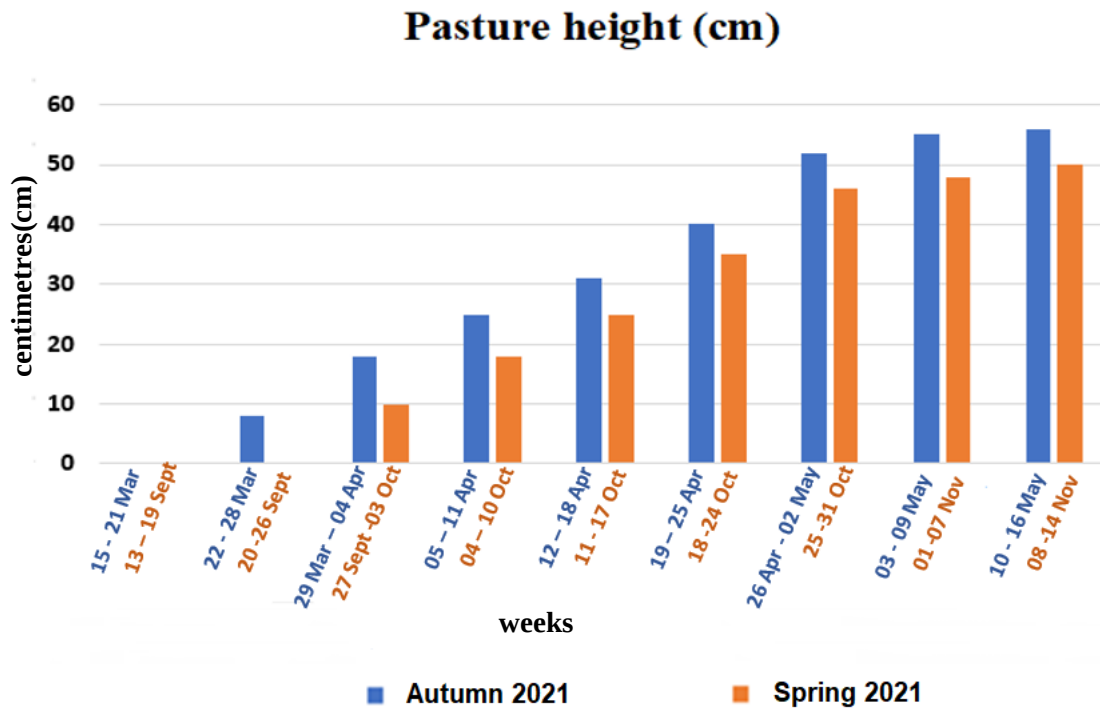


Figure 4.4 Pasture height recorded in Autumn and Spring seasons in 2021

Figure 4.4 shows the growth of the pasture in the two seasons. It was discovered that the pasture height recorded in Autumn was higher than in Spring. The results revealed the mutual relationship between pasture growth, temperature, rainfall and soil moisture. There was more rainfall expected in Autumn than in Spring, thereby increasing the soil moisture content. Temperatures were much lower in Autumn, thereby containing the moisture longer.

In section 3.4.1.2, it was explained that pasture is ready to be utilised after eight weeks of plantation; even so, at the selected farm pasture is kept until the ninth week. This is done to prove that after the eighth week, the rate of the pasture growth decreases. As demonstrated in Figure 4.4, starting from the seventh week, the rate at which the pasture grows deteriorates.

Data collection was conducted weekly, hence, the week number was important as it was used to perform the predictions. The year and the week number in a year was therefore specified in the data. The number of weeks of the collected data in Autumn 2021 and Spring 2021 is presented in Table 4.1.

Table 4.1 Number of weeks in a year in Autumn and Spring seasons in 2021

Autumn season 2021		Spring season 2021	
Week days	Week in a year	Week days	Week in year
15-21 March	12	13 – 19 September	38
22-28 March	13	20 – 26 September	39
29 March – 04 April	14	27 September – 03 October	40
05 – 11 April	15	04 - 10 October	41
12 – 18 April	16	11 - 17 October	42
19 – 25 April	17	18 - 24 October	43
25 Apr – 02 May	18	25 – 31 October	44
03 – 09 May	19	01 – 07 November	45
10 – 16 May	20	08 – 14 November	46

Table 4.1 shows that, in the Autumn season, pasture was planted on the 12th week until the 20th week. In Spring, in the same year, the pasture growth was between the 38th week and the 46th week. Thus, this showed that, in both seasons, pasture was ready for utilisation after nine weeks. For this reason, predictions were performed for the period of nine weeks.

4.2.2 Findings on pasture height for both seasons

In the Autumn season, the recorded pasture height was 56 cm and, in Spring, it was 50 cm. The height of the pasture is important in sheep grazing management. This is because the sheep graze from the bottom up, and the longer the grazing plant, the longer the animals will take to feed on the pasture. It was therefore important to determine whether the available pasture would sustain the sheep by allowing them to feed on the pasture. Figure 4.5 shows the grazing sheep on the pasture.



Figure 4.5 Grazing sheep on the pasture

The maturity of the sheep was measured by their weight. When the pasture was 56 cm, the animals were at the desired weight just before the pasture could be fully grazed out. While at 50 cm, the field was entirely grazed out and in good condition. Consequently, it was concluded that the pasture height of 50 cm or above can sustainably feed 45 sheep on 0.7 ha. of land.

4.2.3 Digital shadow model predictions and results

The digital shadow was made up of four predictive models: temperature, rainfall, soil moisture and, finally, pasture height predictive models. The predictions were done for the next pasture plantation period which was Autumn 2022. The predictions were performed from the 12th to 20th week (14 March to 15 May) of 2022, which was the period when the pasture was planted. The predicted values were compared to the observed values to determine the performance of the models.

- **Predicted temperature results**

Figure 4.6 shows the predicted average weekly temperatures compared to the observed values for the nine-week period of pasture growth in the Autumn season for the year 2022.

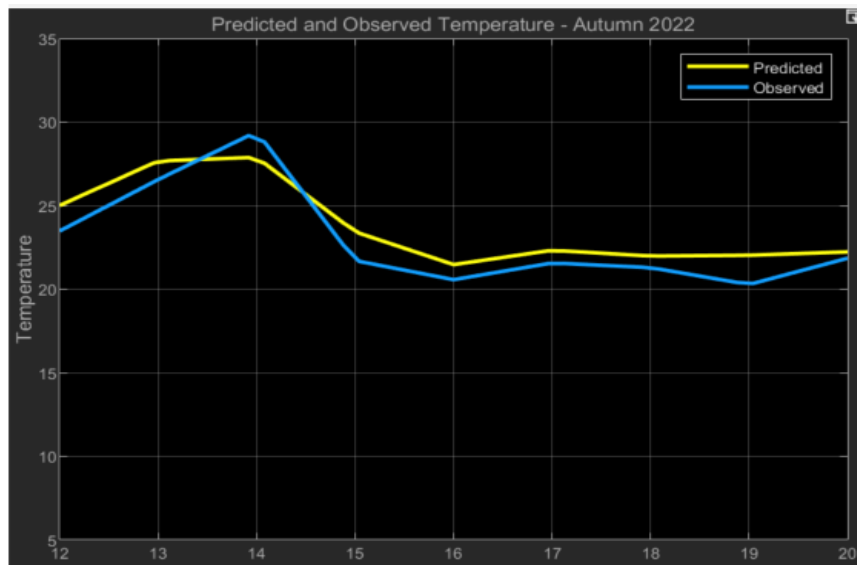


Figure 4.6 Predicted temperature and observed temperature for Autumn 2022

Figure 4.6 shows the average temperatures predicted and the observed values for the period of nine weeks of pasture growth in Autumn 2022. It was determined that the prediction error of the model was ± 1.67 °C which is a relatively good performance.

- **Predicted rainfall results**

The results of the predicted weekly rainfall for the Autumn season in 2022 are demonstrated in Figure 4.7. These results are compared to the observed values.

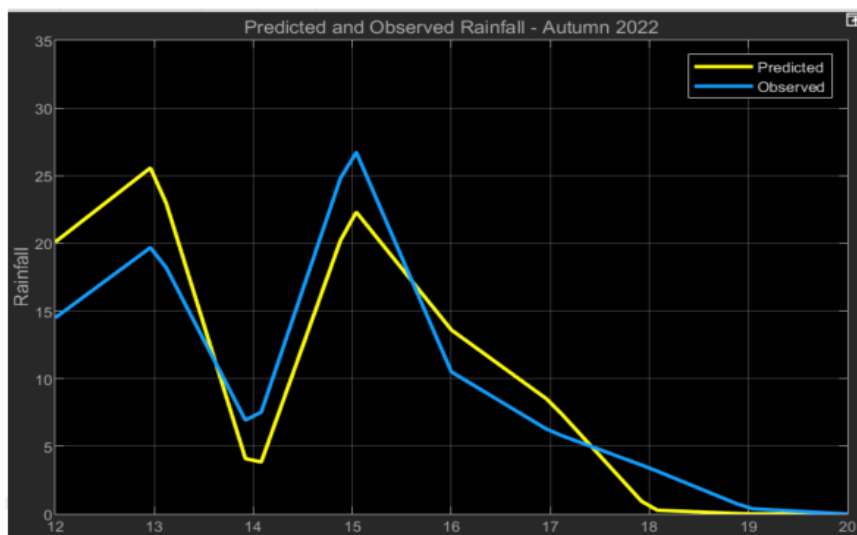


Figure 4.7 Predicted and observed rainfall for Autumn 2022

Figure 4.7 shows the predicted rainfall results compared to the observed values. The comparison shows the prediction error of $\pm 5.9\text{mm}$. Nonetheless, the model was able to predict the weeks where there will be more rainfall, even though the observed values were slightly lower as compared to the predicted values. The rest of the weeks still show the close correlation of the values.

- **Predicted soil moisture results**

Figure 4.8 shows the results on predicted soil moisture of the Autumn period for the pasture plantation period.

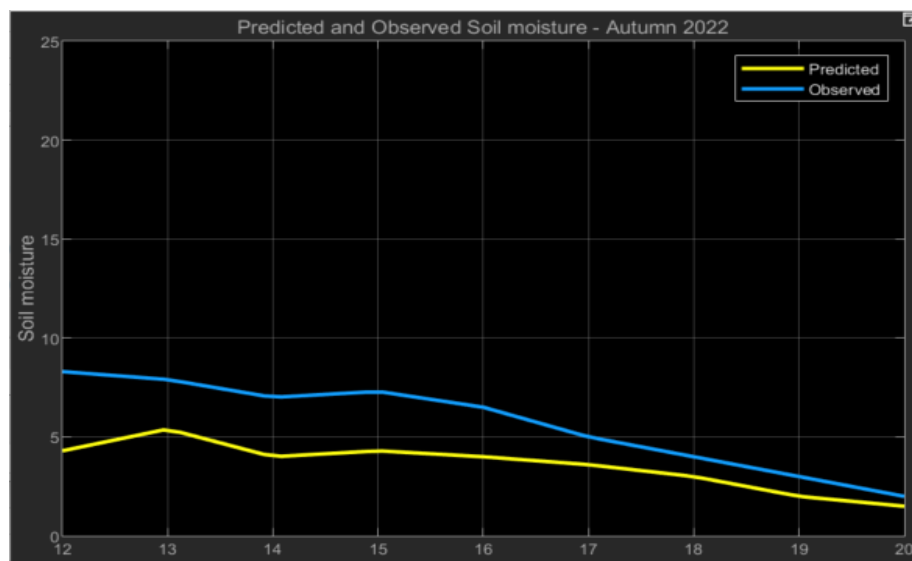


Figure 4.8 Predicted and observed Soil moisture for Autumn 2022

In Figure 4.8, the predicted soil moisture is lower than the observed values with the prediction error maximum of -4. From the first week, the observed values show that there was already good soil moisture. This is because even before the pasture was planted, there was a good rainfall, hence, the improved soil moisture content.

- **Predicted pasture height results**

The predicted pasture height results for the Autumn period in 2022 are presented in Figure 4.9.

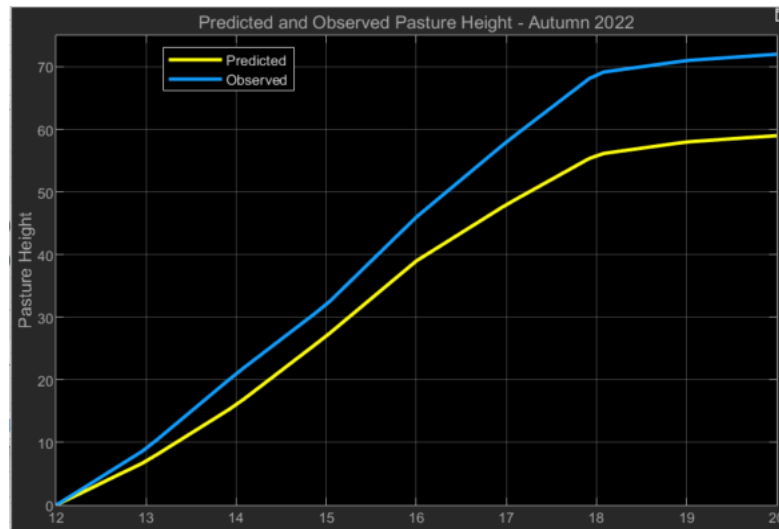


Figure 4.9 Predicted and observed pasture height for Autumn 2022

Figure 4.9 shows the predicted pasture values that are lower than the observed values. The lower pasture height was expected due to lower soil moisture predictions detected in Figure 4.8. There is however a higher prediction error in this model. This is because this model was only trained with two seasons worth of data. More data was needed to improve its efficiency, including the soil moisture prediction model.

The predictions were done for Autumn 2022, and these results were compared to the observed results in Autumn 2021 to get a better understanding of the predicted results and the observed results. The predicted temperature, rainfall and soil moisture results were analysed to determine the expected pasture height results. The first analysis was temperature results, shown in Figure 4.10.

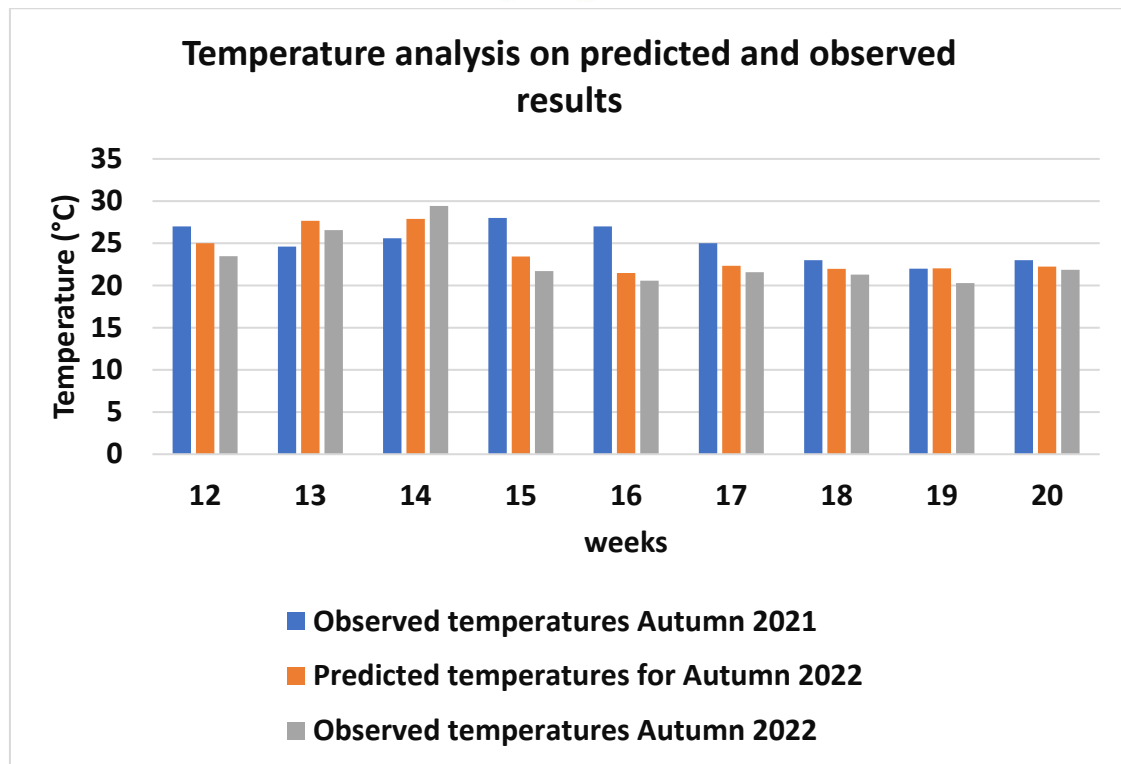


Figure 4.10 Temperature analysis on predicted and observed results

As presented in Figure 4.10, in comparison with the previous results of temperature in Autumn 2021, the model was able to predict that it anticipated lower temperatures in 2022, and indeed, the observed temperatures showed lower temperatures recorded in this period. Lower temperatures would mean a good sign of production since there will be reduced evaporation on the soil, thus keeping good soil moisture.

Figure 4.11 demonstrates the analysis on Rainfall.

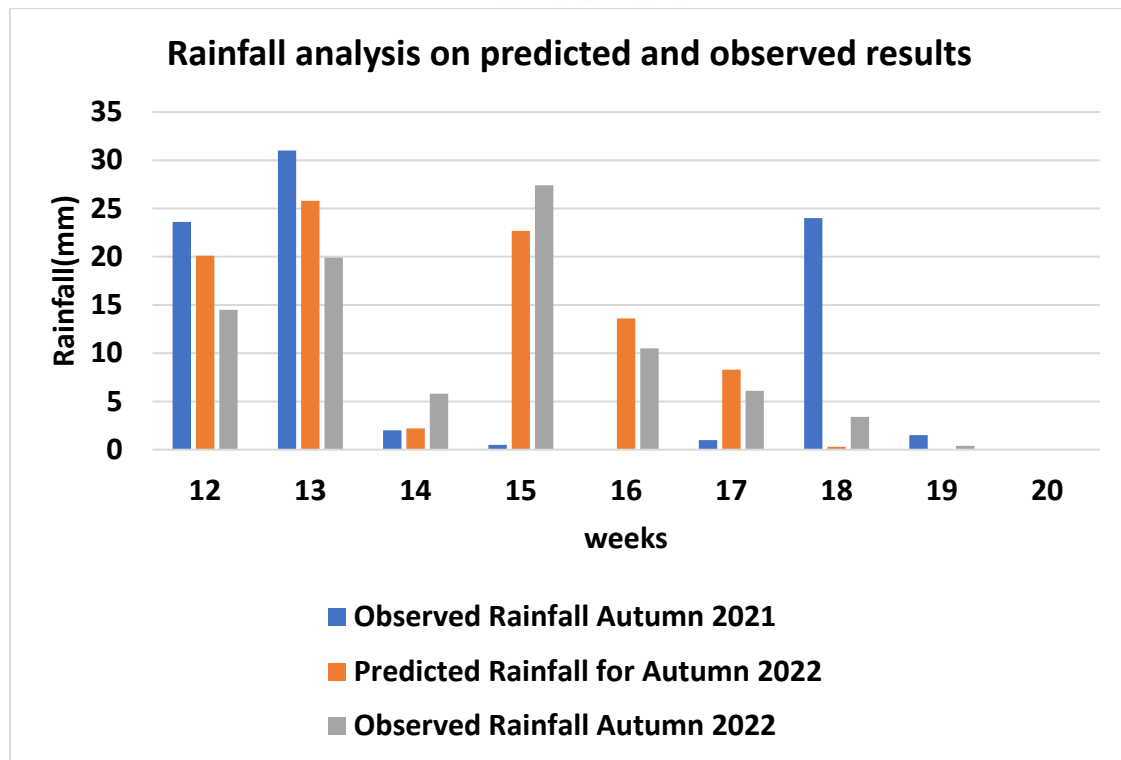


Figure 4.11 Rainfall analysis on predicted and observed results

In Figure 4.11, it was observed that there was more rainfall predicted for Autumn 2022 as compared to Autumn 2021. Even though the observed rainfall results were lower than the predicted values, the observed rainfall was higher in Autumn 2022, as compared to Autumn 2021. Already, this was a positive observation because good rain results in enhanced soil moisture that leads to good pasture growth.

Figure 4.12 shows the analysis on soil moisture results.

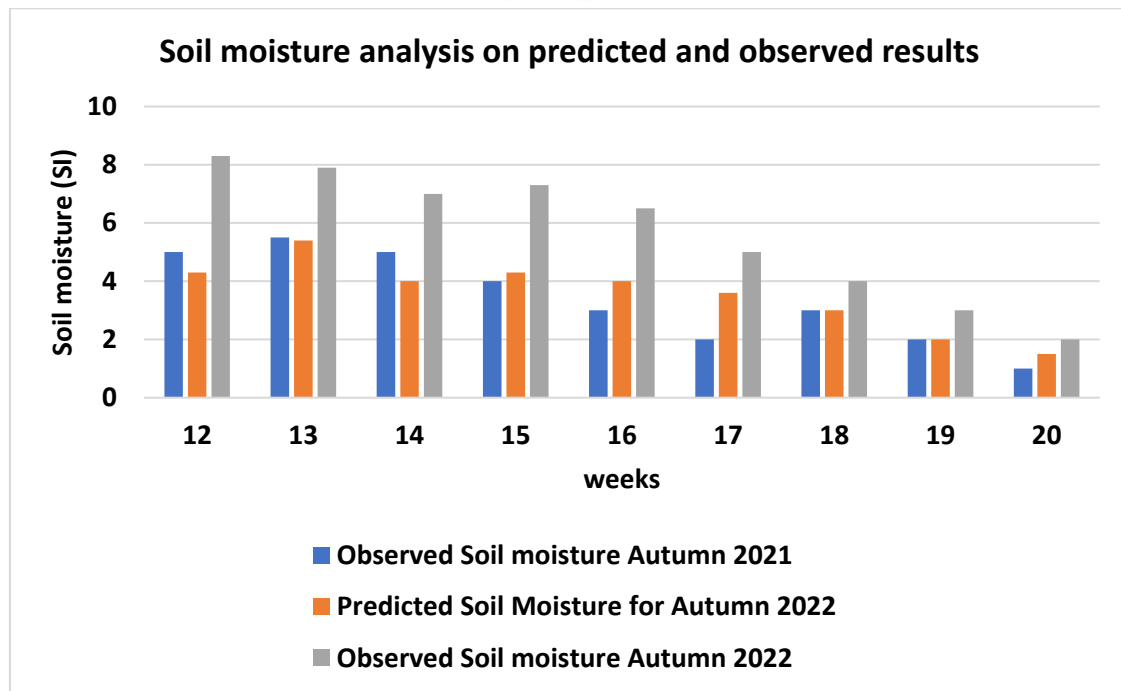


Figure 4.12 Soil moisture analysis on predicted and observed results

Figure 4.12 shows that the predicted soil moisture for the first and third week were lower than Autumn 2021. However, what was important on the predicted values was that the soil will take longer to lose moisture content until the last week, as compared to the Autumn season results. The observed results, however, demonstrated good soil moisture from the start of the experiment.

As a result, based on the predicted results on temperature, rainfall and soil moisture, the pasture height prediction model predicted the final pasture height of 59 cm. The observed pasture height was 72 cm, and the highest prediction error was -13 cm. Nonetheless, what was important was that the model was able to predict that the anticipated pasture height would be higher than in Autumn 2021. The pasture height in Autumn 2021 was 56 cm and anything higher than that would still be a good production, which was the positive outcome. Hence, this proved that the prediction models in the digital shadow could be trusted and set the basis of the digital twin.

4.3 Digital twin development and results

Section 3.4.2.1 discussed the process of developing the digital twin. The digital twin development was composed of three phases which are: data collection, data storage, and data analysis. This section demonstrates the procedures carried out toward digital twin development and the results obtained.

- **Data collection and monitoring**

The physical system made up of IoT sensors was set up on the farm to gather data. Data was collected for the Autumn season in 2022. Figure 4.13 shows the structure of the physical system.



Figure 4.13 Structure of the physical system on the farm

Figure 4.13 presents the physical system made up of IoT sensors that build a smart farm. *Label 1* is the weather station which is responsible for collecting temperature and rainfall data. *Label 2* is the ESP32 CAM which captures pasture images for height calculations. *Label 3* is the soil moisture sensor that measures the moisture content. *Label 4* is the pole which is helpful in image processing script that interprets image properties for pasture height calculations. The pole had a fixed height of 90 cm. As the pasture grows, the portion of red pole was covered by green pasture from the ground. On the captured image, the height of the red portion that was not covered by the pasture was calculated (Y coordinate), and the result was subtracted from the fixed height of the pole (90 cm) to get the actual height of the pasture. The captured image was processed in MATLAB® run on the Raspberry Pi. The Wi-Fi modem acted as IoT gateway to enable data transfer and connection on the devices. The modem and the Raspberry Pi were placed in the container on *label 5*.

Results of data stored in ThingSpeak®

Live data was retrieved and stored in ThingSpeak® cloud.



Figure 4.14 Data collected daily from the sensors and stored in ThingSpeak®

Figure 4.14 shows that temperature and rainfall data was recorded daily at 3-hour intervals while soil moisture was measured after every 12 hours. Daily data was collected for a week and analysed to obtain weekly data and stored on a different channel in ThingSpeak®. The weekly data is shown in Figure 4.15.

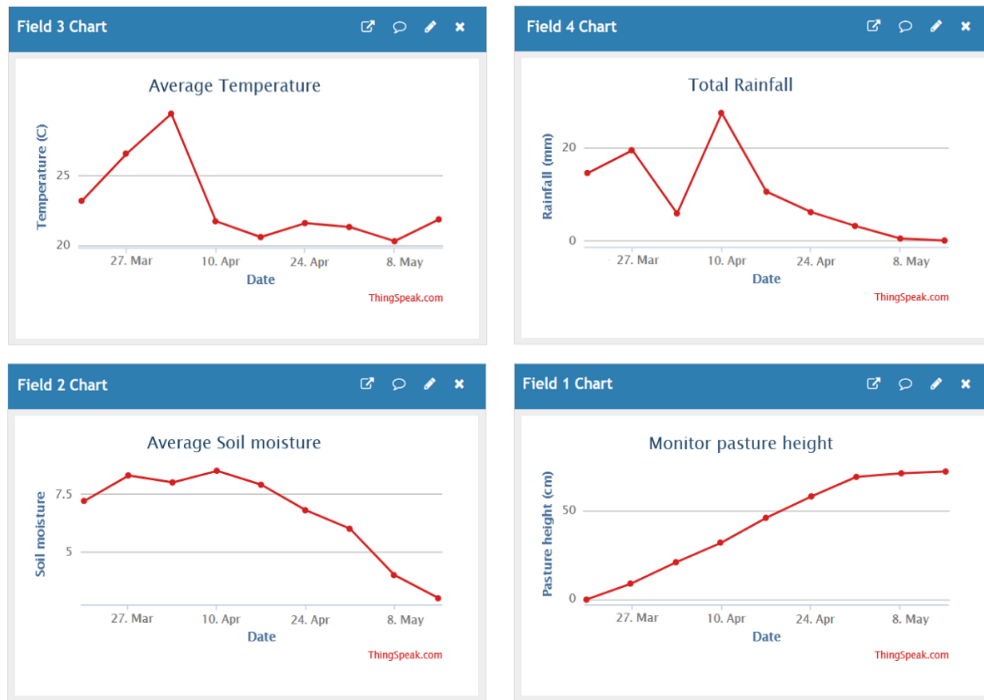


Figure 4.15 The sensors' weekly data

Temperature, rainfall and soil moisture daily data had to be analysed to obtain weekly data. Figure 4.15 also shows the pasture height data. Pasture height was only obtained weekly. Weekly data was important in the study as it was used to update the prediction models.

- Predictive modelling results**

The digital twin was composed of four predictive models which were updated by sensor data. The predictions were performed for the Spring season in 2022. That is, from the 38th week to 46th week of 2022. Figure 4.16 shows the provided input as the prediction period from the 38th week of 2022. The edit text field was used as the input text field to automatically update the constant field because the model was run in real-time.

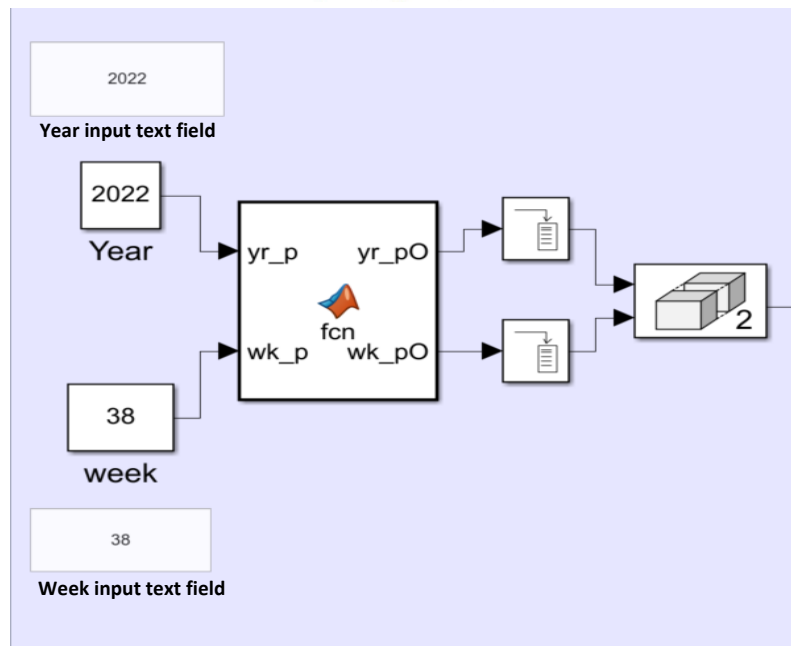


Figure 4.16 Prediction period within the digital twin

Figure 4.16 shows the provided period in which the predictions were to be performed. It shows the year and the starting week of the prediction. These were the inputs provided to the temperature and rainfall prediction models. The prediction started from the 38th week and the function looped through until the 46th week.

Figure 4.17 demonstrates the predicted temperature results compared to the observed values.

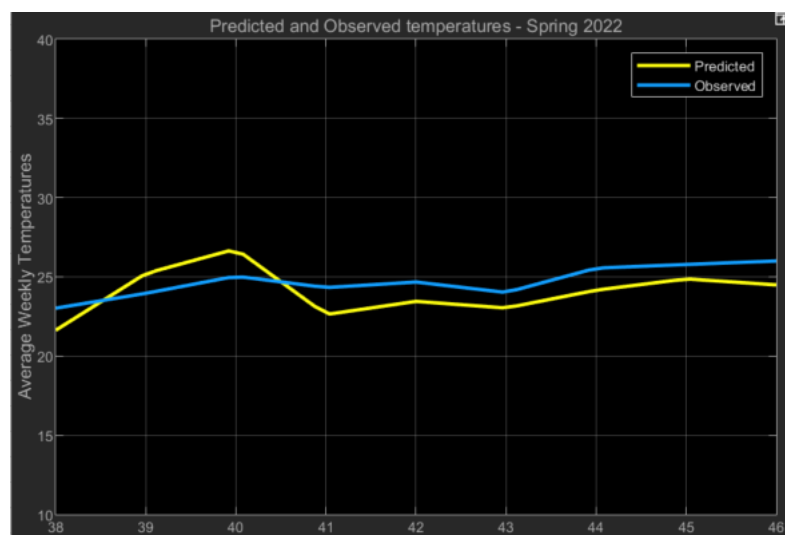


Figure 4.17 Digital twin temperature predicted results compared with the observed results

Figure 4.17 demonstrates the predicted average temperatures for the period of nine weeks when growing the pasture. Table 4.2 summarises the results.

Table 4.2 Analysis of predicted average temperatures by the digital twin

Week	Predicted Average Temperature (°C)	Observed Average Temperature (°C)	Prediction error
38	21,63	23,02	-1,39
39	25,21	23,96	1,25
40	26,66	25,04	1,62
41	22,72	24,32	-1,6
42	23,45	24,67	-1,22
43	23,03	24,01	-0,98
44	24,16	25,55	-1,39
45	24,87	25,78	-0,91
46	24,49	26	-1,51
			0,5835

Correlation
value

Table 4.2 demonstrates the model predicted that the average temperatures expected would range between 21.65 °C to 26.66 °C. The observed temperature results ranged between 23.02 °C and 26 °C, which is within the predicted range. The prediction error between the predicted and observed results is of ± 1.62 °C with the correlation value of 0.5835.

The predicted weekly rainfall results are shown in Figure 4.18

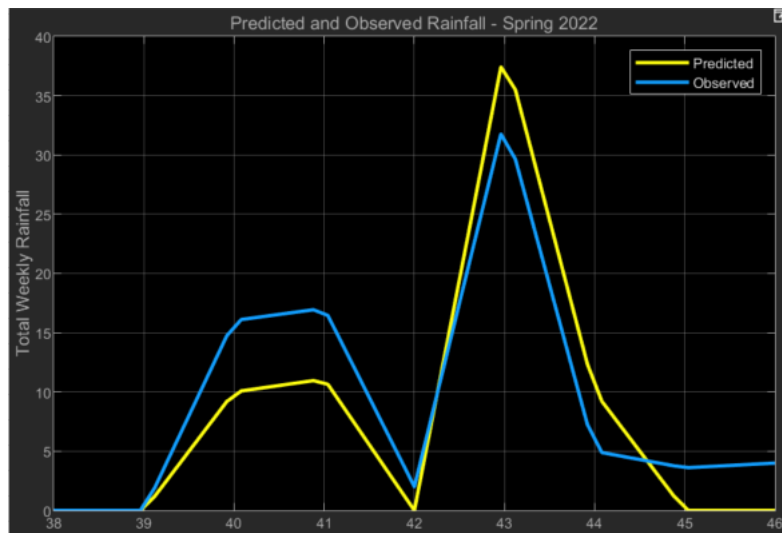


Figure 4.18 Digital twin predicted rainfall results compared with the observed rainfall results

The analysis of Figure 4.18's results is presented in Table 4.3.

Table 4.3 Analysis on digital twin predicted rainfall results

Week	Predicted weekly rainfall (mm)	Observed weekly rainfall (mm)	Prediction error
38	0	0	0
39	0	0	0
40	10	16,03	-6,03
41	11,09	17,06	-5,97
42	0	2	-2
43	38,98	33	5,98
44	10,01	5	5,01
45	0	3,6	-3,6
46	0	4	-4
SUM = 70,08		SUM = 80,69	
		0,9422	

Correlation
value

Table 4.3 shows that the predicted total rainfall for the entire period of experiment was lower than the observed rainfall results. The results display the prediction error of ± 6.03 mm between the predicted and observed values. Still, the model was able to predict the weeks in which it was most expected to rain and there is a relatively close correlation between results.

The predicted results of average temperatures and total rainfall were the inputs on the soil moisture prediction model. Figure 4.19 shows the predicted average soil moisture results based on the predicted temperatures and rainfall results.

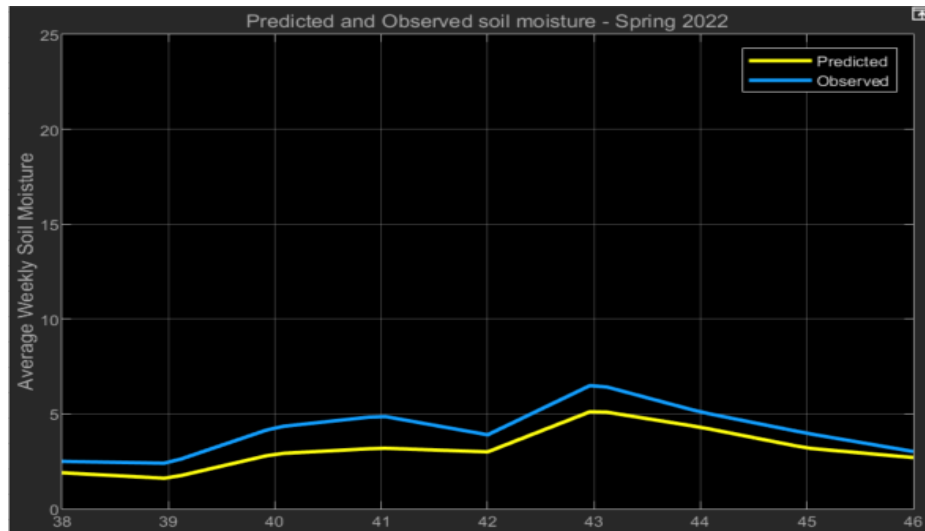


Figure 4.19 Digital twin predicted average soil moisture compared with the observed rainfall results

Table 4.4 presents the analysis of the results obtained in Figure 4.19.

Table 4.4 Predicted soil moisture results analysis

Week	Predicted average soil moisture (SI)	Observed average soil moisture (SI)	Prediction error
38	1,9	2,5	-0,6
39	1,6	2,4	-0,8
40	2,9	4,3	-1,4
41	3,2	4,9	-1,7
42	3	3,9	-0,9
43	5,2	6,6	-1,4
44	4,3	5,01	-0,71
45	3,2	3,98	-0,78
46	2,7	3,02	-0,32
		0,9517	

Correlation
value

The analysis presented in Table 4.4 shows that the average soil moisture predicted was lower than the observed rainfall results. This was due to lower predicted rainfall, as shown in Table 4.3, and it demonstrates the relationship between the rainfall and the soil moisture. The results show the maximum prediction error of -1.7 and the correlation value of 0.9517.

The last prediction model was the pasture height prediction model. This model depends on three parameters which are temperature, rainfall and soil moisture. Thus, the pasture height prediction model was provided with new data of predicted average temperatures, predicted total rainfall, and predicted average soil moisture to perform the predictions. The results are demonstrated in Figure 4.20.

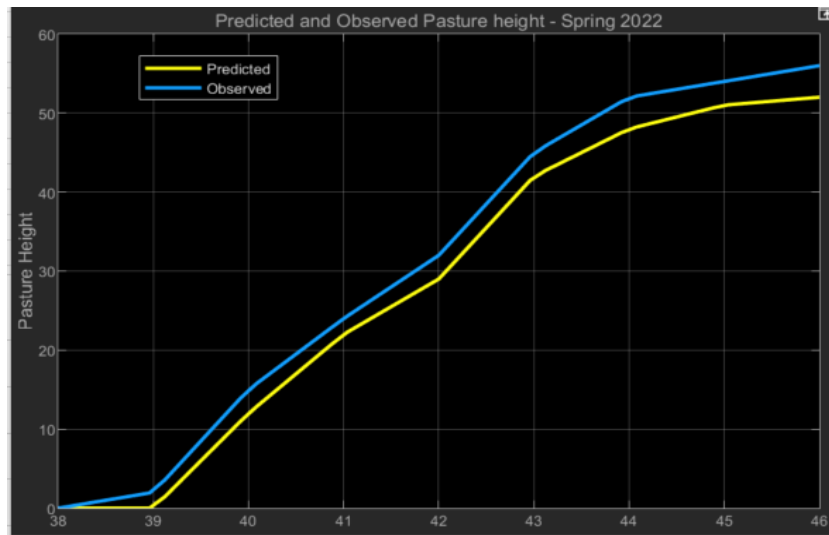


Figure 4.20 Digital twin predicted pasture height compared with the observed results

The analysis of the results obtained in Figure 4.20 are presented in Table 4.5.

Table 4.5 Analysis on predicted pasture height results

Week	Predicted pasture height (cm)	Observed pasture height (cm)	Prediction error
38	0	0	0
39	0	2	-2
40	12	15	-3
41	22	24	-2
42	29	32	-3
43	42	45	-3
44	48	52	-4
45	51	54	-3
46	52	56	-4
		0,9994	

Correlation
value

Table 4.5 shows the final predicted pasture height of 52 cm and the observed value of 56 cm. The maximum prediction error between the values is -4 cm and with the close correlation value of 0.9994.

4.4 Analysis of the digital twin results

The aim of the digital twin development was to predict pasture height for the future to determine if there will be enough feed for the sheep. The digital twin model was proposed after determining that sheep farmers struggle to keep their animals alive due to improper pasture management caused by changing farming seasons due to climate change.

Thus, pasture management is affected due to changing weather patterns. As a result, pasture growth is dependent on three factors, which are: temperature, rainfall and soil moisture. Therefore, to predict pasture growth, predictions on temperature, rainfall and soil moisture are needed. Hence, the digital twin was made up of four models: temperature, rainfall, soil moisture and pasture height prediction models.

In the presented outcomes, temperature and soil moisture prediction models showed good performance with a prediction error of ± 1.62 and -1.7 , respectively. Rainfall prediction model had a prediction error of ± 6.03 , which was slightly higher as compared to other prediction models. The results on the rainfall prediction model signify the impact of changing weather patterns. However, the results of this model demonstrated a good outcome as predicted values and observed results showed a close correlation.

Based on the predicted temperature, rainfall, and soil moisture, the predicted pasture height was 52 cm and observed pasture height was 56 cm. Even though the observed pasture height value was higher than the predicted value, the predicted pasture height represents a good outcome, meaning there will be enough feed for the sheep. It was discussed in section 4.2.2 that the pasture height of 50 cm and above represents a sustainable feed. Thus, the digital twin model successfully predicted the pasture height anticipated for the next plantation season which was Spring 2022.

The digital twin did not only help in predicting pasture height but was also helpful in grazing management, which is also an important aspect in pasture management. The digital twin kept track of how much of the pasture animals feed on per week and how long the animals take to feed on the length measured until they are ready for the market. This was done by measuring the height of the pasture as animals were grazing and results were recorded weekly. The results were only obtained to monitor the grazing of the sheep and were not part of any prediction model within the digital twin. The monitoring of sheep grazing is demonstrated in Figure 4.21.



Figure 4.21 Monitor pasture height as animals graze

Chapter 5 – Research contributions and conclusions

5.1 Introduction

This chapter highlights how the objectives and the research goals of the research were obtained, discussing the researcher's own field of knowledge contributions modelled towards the research. This chapter also summarises the results achieved and draws the conclusions to the research.

5.2 Summary

In the first chapter, the research project was introduced and the problem to be solved was also stated. The hypothesis was recognised, and the objectives were outlined. The objectives were utilised to map out the research methodology of the study. This chapter was concluded by formulating the layout of the research.

The second chapter focused on the literature review, stating the findings about climate change impact on pastures. It further explored smart farming technologies implemented in pastures and their benefits. The concept of a digital twin was also introduced, how it is beneficial in livestock farming, and how a digital twin can be used to solve a stated problem. This chapter was concluded by discussing the limitations of the existing research in the field which are of great importance in this study.

The basis of the third chapter was the research methodology used to solve the stated problem. This chapter showcased the procedures undertaken in designing a digital twin. Firstly, an algorithm to develop a predictive model was identified. Secondly a digital shadow was developed using historical data as the first step in developing a digital twin. Lastly, a digital twin was modelled in SIMULINK[®], integrating historical and live data from the sensors to predict the height of the pasture for the next plantation season. A digital twin reflected a digital copy of the physical smart farm set with IoT sensors.

The fourth chapter focused on the analysis and obtained results of the research. This was done by development of the digital shadow model as the first step in digital development. Thereafter, a digital twin was developed to make predictions. The comparisons in measured values and predicted values were performed to determine the performance of the model and whether the goal of the research was achieved.

5.3 Discussions

The main goal of the research was to develop a digital twin that could be used to predict the height of the pasture to ensure sustainable feed to the animals and allow farmers to make good decisions on time. This was after the problem was identified that climate change has resulted in unpredictable weather patterns which have a huge impact on pasture management, which hinders sheep production.

In section 2.8, the limitations of existing research that necessitated this study were discussed. One of the concerns were that pasture growth is negatively impacted by changing weather patterns [17] and the existing IoT systems lack proper detection and tracking of pasture growth [74]. This brought up the issue while obtaining an in-depth view of the physical system in real-time, thus making the monitoring process difficult [75]. Through this research, using IoT sensors and an interacting image processing mechanism, the growth of the pasture was monitored in real-time and the results were stored in ThingSpeak[®]. Factors affecting pasture growth, which include temperature, rainfall and soil moisture, were also monitored.

Consequently, the first research objective of monitoring the conditions on the farm to manage factors that affect pasture growth was achieved. Monitoring pasture height and factors affecting the growth in real-time helped to log live data in the digital twin to have corresponding data on the two platforms, otherwise, the digital twin could not be trusted. The live data also helped to update the models of the digital twin to improve the model performance and run the system in real-time.

The other challenge was that the weather forecast models did not include the soil moisture factor as one of the main parameters influencing pasture growth [73]. Through this project, a means of including soil moisture through the sensors and ThingSpeak[®] was introduced to develop a soil moisture forecast model. This model was used in conjunction with temperature and rainfall forecast models to predict anticipated conditions that shaped the predicted growth of the pasture, thus meeting the second research objective of developing predictive models. The predictive models were developed using historical data that was analysed and processed using an ANN machine learning algorithm.

Additionally, another challenge was that farmers are unable to use information from these forecast models to implement proper decisions on pasture management [72], consequently farmers still lose their animals due to poor quality pasture which they could not identify on time and plan accordingly.

In this study, a digital twin was developed, and through its predictive models that were updated in real-time, the farmer was informed whether the expected weather conditions would be conducive or not for pasture production. As a result, a farmer is guided in taking appropriate decisions at early stages in pasture management. This helps farmers to plan beforehand to avoid issues that may cause poor animal production. Hence, the last research objective was achieved – *‘developing a digital twin with predictive models that are updated by real-time data to predict pasture height and identify issues beforehand, hence, providing instant solutions for composite problems’*.

Incorporating the models and sensor data in smart farming systems still stands as a challenge [78][76][77]. In this project, the digital twin is demonstrated as one model comprising four different models that are integrated. It further shows the smooth interaction of sensor data through ThingSpeak® to the models. As a results, by interacting the four models, the digital twin was able to successfully predict the expected pasture height for the next plantation season, based on the predicted temperatures, rainfall and soil moisture.

5.4 Research Contributions

A digital twin model was developed to predict the pasture height for the next three months to ensure sustainable animal feed. The following contributions were made by the study.

5.4.1 Contributions to the literature

To get a descriptive background on current pasture management systems, several written journal articles were explored. Further findings were on digital twins and their applications in farming. As a form of contributing to new knowledge, a review journal article [89] ‘*A Review on Current IoT-Based Pasture Management Systems and Applications of Digital Twins in Farming*’ was published. This paper reveals the current IoT pasture management systems implemented for better management of farm operations and the applications of digital twins in farming to address the problems created by smart farming technology.

Section 4.5 showed the development of a digital shadow as the first step in creating a digital twin. The results of this model were shared in the second article ‘*Designing a Digital Shadow for Pasture Management to Mitigate the Impact of Climate Change*’ [147], which demonstrated how the digital shadow could be used for prediction using farm data.

5.4.2 Contribution to farming

Measuring the height of the pasture was crucial in this study as it monitored the growth of the pasture which was helpful in the predictions. The height of the pasture was measured using image processing techniques which allowed the process of automation. The measurement was also done in real-time which made remote monitoring simpler. The entire system proved helpful to the farmers as it can show how the predicted weather conditions will affect the pasture growth by revealing the predicted lifecycle of the pasture. This helps farmers to improve their management strategies and decision making, thus enhancing production.

5.4.3 Development of a digital twin model

The uncertainty of farmers in not being able to use predicted weather data for management of pasture growth drove a need to develop a digital twin model. This model was the digital copy of the physical system set up on the pasture with integrated sensors. Using historical and live data, this model was able to predict the pasture height for the next plantation season.

The prediction was based on the predicted temperature, rainfall and soil moisture. Farmers were aware of the weather forecast but they did not know the exact impact of those predictions on the pasture growth. Thus, the digital twin was able to display the projections of the pasture growth with correlating accuracy by showing its predicted height based of the predicted weather forecast. The information obtained from the digital twin assists in appropriate decision making.

5.4.4 Contributions to the Fourth Industrial Revolution

The fourth industrial revolution (4IR) includes a range of technologies that have the potential to make a positive impact on the productivity and profitability of the agricultural sector. These emerging technologies include AI, IoT, Big Data and drones, to name but a few. These technologies drive smart farming that allows devices to collect data that can help farmers to efficiently manage their farms. The digital twin model developed in this project incorporated IoT technology that increased the value of collected data by analysing it and performing predictions that supported farm management decision-making.

5.5 Future work

Climate change is an ongoing process, and a lot still has to be done to limit its impact in livestock farming. Pastures are substantially affected by climate change because they depend on climatic conditions for growth. This study only focused on monitoring the pasture growth by measuring its height, but many aspects can be studied further.

Farmers practice what is called ‘rotational grazing’ in their pastures and this practice helps to maintain the pastures in many ways. The sensors connected in this study can already measure the height of the pasture while animals are grazing, as stated in section 4.6.2. Accordingly, the first aspect to further the study will be, based on the predicted pasture height, predicting how long the animals will graze on one section before being moved to the other. This can help to identify how long the animals will feed on the pasture. This can also be extended by predicting the sheep’s weight while they are feeding on the pasture.

The second possible extension on this study would be to implement drones into pasture management. Some factors can slow down pasture growth, including weeds, diseases and pests. Using drones to monitor the presence of these factors can aid in quick decision making. Animals also need water while they graze, and drones could be used to monitor the amount of water available for animals so that farmers can know when to fill the containers.

5.6 Scientific outcomes

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N. J. Lemphane, B. Kotze, and R. B. Kuriakose, “Designing a Digital Shadow for Pasture Management to Mitigate the Impact of Climate Change,” *Inf. Commun. Technol. Compet. Strateg.*, vol. 400, pp. 367–376, 2022, doi: 10.1007/978-981-19-0095-2_35.

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