Mapping Cattle Transportation Movements in New Zealand: Application of Spatial Techniques on Cattle Transportation Flows

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Abstract

The livestock transport movement is the representative movement driven by humans, the environment, and livestock in livestock study. The main body of this movement is livestock, and humans and the environment are the driving factors. This movement can reflect the dependence and influence of livestock on external factors. Therefore, in areas with large numbers of livestock farming, it is crucial to study the possibility and consequences of external factors on livestock transport movements. This paper focuses on the two main islands of New Zealand, the North and South Islands, and will cover the transportation movement of dairy cattle and beef cattle in sixty-six territorial authorities (TAs) of sixteen regions. A series of statistical and geographic information systems (GIS) were used to obtain density maps for the human-dominated and environmental variables, as well as the peak movement of dairy and beef cattle, indicating that the peak movement for dairy and beef cattle was around May and that infrastructure and climate conditions in the North Island were more suitable for cattle farming. This study used modelling techniques to model the explanatory variables and flows of dairy cattle and beef cattle transportation movements between sixty-six TAs. Subsequently, Geographically Weighted Regression (GWR) was used to assess the spatial distribution of the relationship between independent and dependent variables to examine the influence of external factors on the outflow and inflow of dairy and beef cattle across regions. Spatial Interaction (SI) modelling showed that the flow of dairy and beef cattle was positively or negatively affected by population occupation, port distance, rainfall, insolation duration, and vapour pressure, but at the same time changed with time. In addition, GWR modelling showed that the spatial distribution of the relationship between the inflow and outflow of dairy and beef cattle and explanatory variables was dominated by the number of dairy and beef cattle. The more the number of dairy and beef cattle,

the explanatory variables would have a more noticeable impact on dairy and beef cattle inflow and outflow. Therefore, exploring SI and GWR modelling to cattle transport movement flows in the New Zealand region demonstrates the potential of spatial technology as an accurate and robust mapping and assessment tool.

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1 Introduction

1.1 Research Rational

Livestock movement, whether it is a self-willed movement within the confines of human captivity or movement to a specific destination under the influence of the human will, has a persistent impact on the natural environment and potential disease control problems for both human and animal communities. In New Zealand, agriculture has always been an essential source of economic growth and an essential part of its cultural and aesthetic landscape, but at the same time, livestock-led New Zealand agriculture contributes more than 50% of the country's total greenhouse gas emissions (Ministry for the Environment and Stats NZ, 2018). Livestock produced 85.8% of total methane emissions in 2018, while 92.5% of nitrous oxide emissions came from agricultural soils affected by urine and faeces deposited by grazing animals (Ministry for the environment, 2021). Nevertheless, in the same way, greenhouse gas emissions can lead to climate change, leading to higher temperatures and problems that destabilise ecosystems and feedback on human society and livestock production. In addition, infectious diseases are a fatal problem for domestic animals. In New Zealand, where bovine tuberculosis was controlled for many years, its spread was often attributed to the presence of possums (Warburton and Livingstone, 2015). A country focusing on the export trade of agricultural and livestock products poses a risk to the overseas trade market when the disease level exceeds a certain level. The economic consequences of this are severe. A Regulatory Impact Statement from the Ministry for Primary (Collins, 2016) mentioned that implementing the Bovine Tuberculosis Control Plan at that time cost about 80 million dollars annually. Thus, it is crucial to understand the pros and cons of moving livestock and the potential disease control risks to ensure that the proper management programmes are in place to minimise environmental damage and reduce financial costs.

This thesis will focus on the second research direction, investigating the influence of external factors on the livestock transportation movement. The goal is to assess New Zealand dairy, and beef cattle transportation flows using various GIS techniques and computational models. As a prominent exporter of dairy and meat products, New Zealand has high numbers of beef and dairy cattle, potentially vulnerable to various external factors, possibly resulting in the Mycoplasma Bovis outbreak between 2015 and 2019 (Jordan et al., 2020). However, no studies have examined the impact and implications of external factors on cattle transport movements in New Zealand.

1.2 Research Aims and Objectives

The main objectives of this study are:

I. To perform a preliminary assessment of the movement of dairy and beef cattle within sixty-six TAs in the North and South Islands of New Zealand between 2015 and 2020, using Geographic Information System (GIS) techniques.

II. To visualise cattle transportation movements across New Zealand's sixty-six TAs

III. To explore the external factor variables within sixty-six TAs using exploratory spatial data analysis.

IV. To evaluate the influence of external factors on the transportation movement of dairy and beef cattle and predict the transportation movement flow under the influence of external factor variables by using the destination-constrained model.

V. To draw parameter estimates maps to evaluate the spatial relationship between external variables and the transportation movement inflows and outflows of dairy and beef cattle using GWR.

The main aims of this research are:

I. To review the current literature on livestock movement and interaction of human and environmental factors and the application of SI models and GWR in various aspects.

II. Discover the peak of cattle movements and the potential risks associated with them.

III. To use the obtained results to analyse the different influences of external factors on the transportation and movement of cattle within New Zealand.

1.3 Thesis Structure

Apart from the introduction, this thesis consists of five chapters. Chapter 2 reviews the appropriate literature and explains the causes of climate change and the interrelationship between livestock and climate change. In addition, emphasis is placed on defining the relationship between livestock and human factors, explaining the significance of research on livestock for human society and disease control. Finally, the literature on the application of spatial analysis, SI models and GWR is reviewed to help us understand how to apply them to this study.

Chapter 3 introduces the research area of this study, New Zealand, including the geographical factors, administrative units, and cattle farming status in New Zealand. Then, the original and secondary datasets used in this study and their sources were introduced, including the cattle movement data set and various external factors. In addition, the methods used to assess herd movements in New Zealand and their relationship to external factors are introduced, and the use of exploratory data and exploratory spatial data analysis is explained, as well as the process of visualisation of temporal patterns of herd movements and spatial distribution patterns of external factor variables. Finally, the method of preparation and evaluation of the SI model and GWR is explained.

Chapter 4 summarises the results of different methods used to assess the impact of explanatory variables on cattle transport movement flows. The results of exploratory data analysis revealed a peak movement in dairy and beef cattle transport.

Chapter 5 explains the critical results of different approaches to evaluating the impact of explanatory variables on cattle movement flow, additionally discussing the risks of time patterns of cattle movement and the external factors and potential causes of cattle movement through the results. Finally, Chapter 6 summarises the main findings of this study and points out the study's limitations to propose hypotheses for future research to improve the assessment of external factors affecting cattle movement in New Zealand.

2 Literature Review

2.1 Introduction

With the development of human society and the improvement of people's living standards, the demand for animal husbandry products is also on the rise, which leads to the rapid development of livestock-related industries, such as dairy products, meat, and leather. Such rapid growth has also exposed problems related to livestock. The Food and Agriculture Organisation (FAO) report (2006) says that the meat industry contributes to the marked consumption of the environment and has a significant impact on global warming (Steinfeld et al., 2006; Dopelt et al., 2019). Dalibard (1995) points out that livestock's harmful effects are mostly related to management methods and are not sustainable. The harmful effects of livestock feedback on the livestock themselves lead to the occurrence and spread of infectious diseases (Altizer et al., 2013; Fletcher and Schaefer, 2019). Thus, we need practical management tools to help us track and manage livestock. This chapter provides management insights and fills gaps in livestock transport and movement by reviewing climate change conditions, infectious disease hazards and control, livestock management practices, and discussing the application of methods to be used in this study.

2.2 Climate change

The impacts of climate change are multi-layered and multi-scale, with both positive and negative impacts in which the adverse effects are more concerning than the former (Hodgson, 2001). An Intergovernmental Panel on Climate Change (IPCC) report (2018) shows that climate change has become a significant problem in the world (Masson-Delmotte et al., 2018). In New Zealand, this report indicates that climate change has impacted various aspects of ecosystems, such as rainfall, slope stability and plant biomass (Nottage et al., 2012).

Climate change usually can be seen through temperature rise, sea level rise and increased precipitation, of which temperature rise is the most pressing environmental issue (Feulner, 2017). The environmental impact of temperature rise is directly reflected in natural ecosystems, such as glacier retreat, lake water level decline, lake area reduction and biodiversity change (Chen et al., 2012). Natural ecosystems are vulnerable to climate change due to their limited capacity to adapt (Malhi et al., 2020). As the frequency and intensity of climate change increase, the number of natural ecosystems damaged will increase, and the animals and plants in the ecosystems will also be affected (Pedrono et al., 2016)

Solar irradiance is a term associated with the topic of the relationship between the sun and climate change (Lean, 2010; Lockwood, 2010). It stands for the level of solar energy received by the Earth, usually electromagnetic radiation, as measured by instruments. The sun does not always shine at a constant brightness. It takes 11 years to complete a solar brightness cycle, during which the sun's radiation levels also change (Lean, 2010; Broomhall et al., 2014). These changes affect the Earth's atmosphere and surface. However, the Earth received solar radiation following the sun's 11-year natural cycle with no net increase since the 1950s (Lean, 2010). Over the same period, global temperature has risen significantly (Kweku et al., 2017). The evidence suggests that solar energy cannot explain climate change (Mountford et al., 2021).

The change in climate conditions comes from two aspects: the sun (Bard and Frank, 2006) and the other is the existence of some gases in the atmosphere (Manabe, 2019). Greenhouse gases as the other cause of climate change. It is mainly any gaseous compound in the atmosphere that can trap heat, prevent it from escaping, and absorb infrared radiation (Manabe, 2019). Heat in the atmosphere can accumulate because there is no practical way to escape it, leading to the greenhouse effect and climate change (Kweku et al., 2017). Four common natural gaseous compounds are responsible for the greenhouse effect: water vapour, carbon dioxide, methane, and nitric oxide (Kweku et al., 2017). In addition, artificial greenhouse gases include various compounds containing chlorine and bromine, such as chlorofluorocarbons (CFC) (Ramanathan and Feng, 2009).

Water vapour is the most abundant greenhouse gas and has an important feedback mechanism in climate change (Schneider et al., 2010). It will increase as the temperature gets higher, which will lead to more water vapour and further increase the temperature, which is positive feedback (Held and Soden, 2000; Cess, 2005); Negative feedback is when water vapour condenses into clouds that reflect sunlight and reduce the amount of energy that reaches the Earth's surface, lowering the temperature (Cess, 2005). Thus, water vapour complicates matters because possible positive and negative feedbacks cancel each other out.

Carbon dioxide is the main greenhouse gas caused by human activity. It is part of the Earth's carbon cycle, the natural circulation of carbon between the atmosphere, oceans, soil, plants, and animals (Keller et al., 2018). However, human activity alters the carbon cycle by producing more carbon dioxide and reducing nature's ability to store and remove it from the atmosphere (Schmitz et al., 2014). Reducing fossil fuel consumption is an effective way to control carbon dioxide emissions.

Methane is a hydrocarbon gas. It comes from the production and transportation of fossil fuels, the decomposition of organic matter in landfills, and the digestion and manure management of livestock and ruminants (Bakkaloglu et al., 2021). Methane emissions can be controlled in various ways, from upgrading fossil energy production and transportation facilities to reducing methane leaks to rationally managing animal waste to reduce and capture methane (Vo et al., 2018).

Approximately 40% of nitrous oxide emissions globally come from human activities (Stocker et al., 2014). It occurs when agricultural and industrial activities, such as commercial and organic fertiliser use, accelerate agricultural productivity, leading to structural damage, nutrient imbalance, deterioration of soil physical and chemical properties, and ultimately reduced yield (Reay et al., 2012). In addition, nitrous oxide can be obtained by combustion in industrial activities. Reducing nitrous oxide emissions would require reducing nitrogen fertiliser and industrial fossil fuel burning (Li et al., 2014), or it could be reduced through catalytic converters (Viswanathan, 2018).

Fluorinated gases, by contrast, have no natural source and come only from human activities. Fluorinated gases are emitted during the manufacture of refrigerants and industrial manufacturing processes (Sovacool et al., 2021). Fluorinated gases have a very high global warming potential (GWP) compared to other greenhouse gases, and low concentrations of fluorinated gases can significantly impact temperature (Sovacool et al., 2021). Controlling the emission of fluorinated gases requires managing the activities that produce the gas, using products with low GWP or improved technologies to reduce emissions and leakage of the gas (Ramanathan and Feng, 2009).

2.3 Interaction between Livestock and Environment

In New Zealand, agriculture accounts for a large proportion (17%) of greenhouse gas emissions (de Klein and Ledgard, 2005), which mainly come from methane, also known as CH4 in the chemical field, produced by the digestive system of livestock (Lassey, 2008). It breaks down into carbon dioxide when it reacts, which is also responsible for climate change (Guan et al., 2018). In addition, livestock itself is an essential factor in destroying the environment. As herbivores reduce the number of pastures that have the function of carbon sequestration in the ecosystem, this leads to conditions no longer balancing and impacting climate change (Soussana et al., 2010). Also, cattle faeces contain carbon and nitrogen; after being broken down by microbes, they will also form carbon dioxide and nitrous oxide (Thomsen et al., 2013). In order to reduce methane emissions from livestock, Roque et al. (2021) studied the significant reduction in methane emissions from cattle when A.taxiformis was added to the diet of cattle.

Furthermore, livestock's impact on the environment is reflected in climate change and directly impacts the water quality, such as water eutrophication (Leip et al., 2015). It means that the increase of organic and metal elements in water causes the rapid reproduction of algae and plankton, resulting in the decrease of oxygen supply in water and eventually leading to the decay or even extinction of plants, aquatic organisms, and fish (Aure and Stigebrandt, 1990).

Crop production systems typically rely on fossil fuels and herbicides for production, and livestock production systems, require less fossil energy (Dalibard, 1995). Cattle get energy from crops and provide traction for farming, and their faeces improve soil fertility, resulting in a sustainable integrated livestock and agricultural production system (Dalibard, 1995). In China, the integration of livestock farming, fish-pond production and crop production has successfully increased fish production (Dalibard, 1995). Also, livestock is effective for weed control (Dalibard, 1995). In addition, through the influence of livestock production systems, most crop production can maintain seasonal income, while livestock production also generates regular income for farmers due to milk and meat sale (Dalibard, 1995). Therefore, considering livestock's different impacts on the environment, it can be seen that livestock plays a vital role in human society.

2.4 Infectious diseases

Infectious diseases are essential in livestock management and pose a global threat to animal health and welfare. Infectious diseases can be divided into diseases between animals and infections between animals and humans. For example, common infections among animals are foot and mouth, bovine tuberculosis, and brucellosis. Zoonoses are commonly rabies and fungal skin infections (Wang et al., 2014; Tomley and Shirley, 2009; Meng et al., 2009). The study of Tomley and Shirley (2009) pointed out that the number of emergence or re-emergence of animal and human infectious diseases was significantly increasing, with an average of three new diseases reported every two years and one new infected organism released every week. RNA viruses cause a higher risk of zoonosis because of their rapid emergence and transmission (Pulliam and Dushoff, 2009). According to Pulliam and Dushoff (2009), the ability of a virus to replicate in the cytoplasm is the strongest single predictor of its ability to spread across species and infect humans. Megacities in the world provide melting-pot environments for mixed human and animal infectious diseases, such as Mexico City, which in 2009 had a population of about 23 million and became the focus of the transmission of influenza virus A/H1N1 (Tomley and Shirley,2009). Also, an outbreak of the foot-and-mouth disease in the United Kingdom in 2001 and an outbreak of Mycoplasma Bovis in New Zealand in later 2015 reflect this (Ferguson et al., 2001; Jordan et al., 2021).

In addition, the transmission of COVID-19 in the last two years provides evidence of this. Since it was discovered in Wuhan, Hubei, China, in December 2019, it has spread rapidly to the whole world (Mackenzie and Smith, 2020). By January 10, 2022, the virus had mutated multiple times, and 298,915,721 COVID-19 cases had been confirmed worldwide (WHO, 2022). The global economy has also taken an unprecedented hit. Infectious diseases can significantly affect national and international trade and have devastating consequences for human society if they are not managed. Infectious diseases are challenging to eliminate, so more research is needed to improve livestock management and disease control management.

2.5 Livestock and Disease Control

Infectious diseases significantly affect the biosphere, and uncontrolled infectious diseases should be treated as a threat to any living creature's population. As a result, controlling infectious diseases is of interest to the health of people, livestock and wildlife (Chaters et al., 2019). However, the challenge also varies according to the change in spatial scale, where disease control and management on a larger scale become more challenging (Coleman et al., 2006) because, in a vast space, the carrier of the virus is difficult to track. In contrast, controlling local infectious diseases is easy to achieve (Gortazar et al., 2007).

Bovine TB is a common infectious disease among animals, and eliminating Bovine TB in New Zealand is complicated because of the large number of wildlife of Mycobacterium Bovis infection (Livingstone et al., 2015b; Anderson et al., 2017). Possums are the primary hosts of Mycobacterium Bovis, and the disease infects most animals in the presence of possums (Anderson et al., 2017). Therefore, possums are a crucial target for eliminating Mycobacterium Bovis (Anderson et al., 2017), and some areas have shown remissions of infection through pest control (Livingstone et al., 2015a).

In New Zealand, ruminants raised outdoors are highly vulnerable to infectious diseases. Due to various reasons, the movement of livestock increases the scale of disease control, which increases the challenge of management (Anderson et al., 2017). Studies have shown that using social networks to analyse livestock movement on a small scale can effectively help people understand the risk of infectious disease transmission caused by livestock movement and implement complementary strategies to reduce the risk of inter-farm transmission (Marquetoux et al., 2016; Noopataya, Thongratsakul, & Poolkhet, 2015).

Climate change also plays a role in livestock and infectious disease control research. In previous studies, the impact of climate change on the distribution and severity of infectious diseases has been recognised (Altizer et al., 2013; Fletcher and Schaefer, 2019), but how infectious sources lead to climate change has rarely been considered. The COVID-19 pandemic in the last two years has shown that pathogens indirectly regulate the global climate by influencing host physiological behaviour (Ezenwa et al., 2020). For example, restrictive policies implemented by various countries have resulted in a significant reduction in global CO2 emissions in 2020 compared to 2019 (IEA,2021). However, methane produced by livestock can exacerbate climate change, which leads to the prevalence of infectious diseases, which in turn leads to increased methane emissions from livestock, creating a potential positive feedback loop or vicious cycles between climate, contagious diseases, and methane (Ezenwa et al., 2020). For example, studies of parasitic infections in sheep and mastitis in dairy cattle show that sheep infected with the parasite take longer to reach slaughter weight and increase methane production (Gulazari et al., 2018; Fox et al., 2018; Ezenwa et al., 2020). Enteric and manure methane emissions from dairy cattle infected with subclinical mastitis increased by up to 8% compared to uninfected dairy cattle (Ezenwa et al., 2020). Therefore, the impact of climate change should also be considered in control plans to mitigate infectious diseases.

2.6 Livestock Management Practices

In order to reduce the external influence on livestock and improve livestock production, it is essential to manage livestock. Scientific and sound livestock management practices can improve farm efficiency and public health. Gomiero (2021) pointed out that livestock under organic agriculture management have a lower density of animals, and antibiotics and growth hormones are strictly regulated, thus reducing the chance of antibiotic-resistant microbial strains. Emerging technologies, such as nanotechnology, also manage farm animals. The use of nanotechnology can help provide better treatments, diagnostics, vaccines and adjuvants, animal feeds and additives to improve animal health and production for sustainable animal production practices (Poddar and Kishore et al., 2022; Selokar et al., 2020). For example, using magnetic resonance imaging to track iron oxide-based nanoparticles (NPs) can determine drug distribution in vivo (Soenen et al., 2010; Selokar et al., 2020). Innovative NP-based applications can also address livestock diseases, such as an NP-based sensor array (NA-nose) to detect volatile organic compounds associated with bovine tuberculosis in cattle breathing (Peled et al., 2012). Nevertheless, widespread use of the technology will require cost reductions.

The literature review on livestock management above aims to reduce the risk of livestock through technology and management methods that can be used to prevent the risk of livestock getting infected with infectious diseases. While management, through the identification and traceability of animals, can meet production management, disease outbreak control, ownership establishment, export requirements, and consumer demand requirements to maintain production (Bowling et al., 2008). This management method requires marking livestock to record their movements from birth to market chain (Bowling et al., 2008). Animal ID indicates livestock ownership, includes information about the origin, prevents theft and allows tracking livestock with potential infection risk (Greene, 2010). By recording this information, diseases can be tracked and traced back. The scheme can be adjusted to suit individual countries.

National Animal Identification and Tracing (NAIT) Programme is the name of the New Zealand animal identification and traceability system. In the beginning, the Animal Identification and Traceability Working Group started in 2004 as a program to improve Animal Traceability in the country. The development of the program was implemented in 2006 (Greene, 2010). NAIT requires cattle and deer on farms to carry NAIT tags and be registered with the NAIT system. The system records the location and movement of individual animals and works to protect livestock from disease and injury, protecting farmers' livelihoods and New Zealand's reputation and economy.

In addition, the management of livestock also involves the management of farms. A complete cattle-farm operation covers the life of the cattle and is adjusted for external factors. In New Zealand, the operation structure of traditional dairy and beef cattle is slightly different, mainly reflected in the description of dairy farmers, which can be divided into owner-operator, sharemilker, or contract milker (Back, 2017). Generally, the owner-operator owns the farm and is responsible for the maintenance of the farm, while the sharemilker is responsible for the affairs related to dairy cattle and milk, and the profits obtained negotiate dividends with the owner, while a contract milker is employed by an owner (Back, 2017). In farming operations, dairy cattle are different in that it needs to be milked, and the rest of the operations, such as calving, calf management, mating, and pasture management, are much the same (Back, 2017; Morris, 2017). Also, cattle are transported away from the farm each season, involving trading, leasing, cattle mating and the annual 'Gypsy Day' (Table 2.1). When these events occur, cattle are transported to the corresponding places, leading to a disease transmission risk (Mycoplasma Bovis Programme, 2022). Therefore, it is necessary to analyse the movement of cattle and understand its implications for future management.

Table 2.1. The calendar describes the cattle movements by months in seasons

Cattle Movement Seasonal Calendar

Season	Month	Activity on cattle movement
Spring	September	1. being sold on or new calves coming onto the farm. 2. pre-mating, bulls arrive on the farm. 3. leasing or purchasing bulls, bulls arrive on the farm
	October	1. same events as September
	November	1. Weaning calves may move to another property, such as calf rearer
Summer	December	1. same events as November. 2. bulls leave after mating, sending to slaughter (North Island). 3. Send weaned calves to sales.
	January	1. bulls leave after mating, sending to slaughter (South Island). 2. moving stock due to drought
	February	1. moving cull cattle to slaughter
Autumn	March	1. moving cull cattle to slaughter
	April	1. moving cull cattle to slaughter 2. sending weaned calves to sales

	May	1. moving cull cattle to slaughter 2. sending sold cattle away. 3. purchasing replacement cows/heifers and transporting
Winter	June	1. Moving day, most farmers transfer cattle and equipment to winter grazing pasture.
	July	1. transporting stock
	August	1. transporting stock

2.7 Livestock and Social Economy

The livestock industry in New Zealand has brought significant development to the country, especially the dairy industry, which has not only made significant contributions to the national economy (Clark et al., 2007) but also accounted for 30% of the free trade of dairy products in the world (Jay, 2007). This shows that New Zealand's social and economic system greatly depends on the dairy industry. Even before the 1980s, the New Zealand government had implemented a subsidy policy on agriculture, leading to serious resource misallocation (Vitalis, 2007). However, after abolishing the subsidy policy, the impact on the economy and the environment was positive, and the short-term negative social impact was small (Vitalis, 2007). Boyazoglu (1998) mentioned that animal husbandry is a factor of environmental, social and economic stability, and the sustainable development of livestock farming requires interdisciplinary research.

Also, the impact of livestock on the New Zealand economy is related to disease control management. Foot-and-mouth disease is another disease with high infectious risk. Several related disease outbreaks worldwide, such as the UK Foot-and-mouth outbreak in 2001 and the Bluetongue virus outbreak in Northern Europe in 2006, have caused severe economic losses (Tildesley et al., 2019). The foot-and-mouth disease is an example to illustrate that economic losses can be divided into direct losses and indirect losses (Knight-Jones and Rushton, 2013). Direct loss can cause direct damage to fauna, causing production declines (Knight-Jones and Rushton, 2013). Indirect losses refer to the cost of control measures of implementing foot and mouth disease (Knight-Jones and Rushton, 2013); for example, implementing a movement ban can cause damage to tourism and the rural economy (Tildesley et al., 2019). Therefore, based on the impact of livestock on the economy, there is a significant potential for New Zealand's economy to be affected by infectious diseases.

2.8 Spatial Analysis of Livestock Movements

Understanding how and why animals move and migrate can help manage and protect animal populations (Jacoby et al., 2012). Spatial analysis methods can help researchers better understand changes and patterns in animal movement, providing new perspectives for decision-makers (Wittemyer et al., 2019). When using spatial analysis methods to study movement patterns, it is necessary to use spatial and temporal data to identify periodic trend changes in movement and analyse their implications through the relationship between site characteristics and animals (Jacoby et al., 2012; Wittemyer et al., 2019). Therefore, using spatial analysis methods to detect the interrelation between humans, animals, and the environment is conducive to finding hidden connections and helping decision-makers make reasonable and practical plans to protect better the individual interests of humans, animals, and the environment (Miller et al., 2019).

Research on spatial analysis of livestock movement can be classified into two categories. Livestock movement can be voluntary (grazing) or non-voluntary (transportation). In the autonomous movement of livestock, spatial analysis is used to investigate the movement, and the data is recorded by GPS positioning equipment carried by the livestock (Feldt and Schlecht, 2016; Bailey et al., 2021). The data will have a detailed temporal (minute-second) and spatial (coordinates) structure so that spatial analysis methods can be used to understand the behaviour patterns of grazing livestock movement (Feldt and Schlecht, 2016; Roberts et al., 2010; Zhao and Jurdak, 2016). The spatial statistical methods used to analyse the relevant data variables, such as environmental factors, can determine whether there is a statistical relationship between the behaviour pattern of livestock movement and these variables (Homburger et al., 2015; Roberts et al., 2010). Research done by Homburger et al. (2015) showed responses to spatial autocorrelation, environment, and management from the pattern of livestock activity by using the spatial statistical method. They obtained the correlations between covariate effects such as elevation, terrain slope and insolation, and characteristics of the six study areas from spatial regressions using Spearman's rank correlation coefficients to indicate the strength of association (Homburger et al., 2015). It is concluded that the determining factors for grazing are terrain gradient, forage quality, and the stocking rate of a paddock (Homburger et al., 2015). The same covariate determined the rest intensity as grazing intensity, but there were some differences. Sparse forage in a study area affected the rest intensity, while grazing intensity had a positive effect (Homburger et al., 2015). The covariate effect of walking intensity is close to that of grazing, but with the changing terrain characteristics of study areas, the terrain slope variable will have a different impact (Homburger et al., 2015).

On the other hand, when the movement of livestock is based on human will, the information in the data and the way it is recorded are different. In comparison to voluntary animal movements, the time (year, month, and day) and space (place) information in the collected data are different (Noremark et al., 2009; Tratalos et al., 2020). When using spatial analysis of such data, the scope of the research will be more comprehensive, the scale will be broader, and the purpose of the research will be different. For instance, research done by Noremark et al. (2009) spatially and temporally investigated the reported movements, births and deaths of cattle and pigs in Sweden by using the data period from 2005 to 2006. Noremark et al. (2009) showed cattle and pigs' transport-related movements, trade between holdings, geographical distribution, and birth and death. These results can be used for contingency planning, and disease spread control. Briefly, the movement of livestock data with a broader scale of space and time can be related to human society, such as the impact on markets, the impact of infectious disease on the economy or the impact of movement on the disease spread (Noremark et al., 2009; Tratalos et al., 2020).

There are two main reasons for livestock research. First, due to the development of new technologies such as real-time global positioning systems, accelerometers and other sensor applications, accurate livestock management can be carried out to remotely monitor livestock diseases, livestock welfare, and livestock grazing trajectory distribution (Bailey et al., 2021). At the beginning of a problem, livestock managers can be notified to respond if issues arise (Bailey et al., 2021) immediately. For instance, Bailey et al. (2021) found in their study that cattle would leave the water source at least 100 meters after drinking water. When the water source was cut off, cattle would stay within 100 meters of the water source and react more actively. Bailey et al. (2021) also mentioned that implementing accurate livestock management methods could improve the welfare of pasture and forest land, reduce labour costs, and improve the sustainable development of the ranch.

Moreover, as mentioned in the previous paragraph, large-scale movement of livestock based on human will has the potential to spread disease. Research on disease transmission in livestock could help people respond to another outbreak or prevent potential disease transmission through regulations. For example, the current OSPRI guidelines for moving animals in New Zealand include TB surveillance and submission of a declaration of the animal's status. In the study by Kiss et al. (2006), they established a direct contact network for sheep during foot-and-mouth disease in the United Kingdom in 2001. They analysed the characteristics of the network and found that biosecurity monitoring of highly connected nodes can effectively prevent large-scale epidemics. However, the research also has limitations (Kiss et al., 2006). Due to the different policies of livestock management in various countries, it is impossible to guarantee the effectiveness and unity of the method (Chaters et al., 2019).

Considering humans' role in studying these animals' movement data helps develop integrated trajectory science. The research of Miller et al. (2019) discusses concepts and methods of independent development in animal and human movement. Still, geospatial technology breaks down limitations, allowing parallel revolution in both fields. At the same time, the study also found that human trajectories have similar movement characteristics to animals. Therefore, in understanding the purpose and needs of animal movement, it is of great significance to consider the role played by humans in understanding the comprehensive science of movement trajectory (Miller et al., 2019; Demsar et al., 2021).

2.9 Spatial Interaction Modelling Application

Spatial interaction (SI) is a fundamental concept that estimates the flow between locations by considering the interaction of people, goods, services, energy, and information related to the movement of places. There are various flow forms, such as immigration, shopping, commuting information transmission and freight distribution, but each flow state will have different friction states. For example, in immigration, the flow form is dominated by people attracted by the attractiveness in the input place and tired of propulsiveness in the output place. Because the income of interaction is higher than the cost of interaction, the movement flow between the starting point and endpoint is finally generated.

Morrison and O 'Brien (2001) used the SI model to study the decision-making problem of branch closure of New Zealand banks. They point out that the banking industry was changing to reduce costs (Morrison and O 'Brien, 2001). Many bank branches in New Zealand were also reduced to 988 by 1998 (Morrison and O 'Brien, 2001). To this end, they modelled the flow of people going to the bank using a SI model to evaluate the expected change in the call after the selected site was closed (Morrison and O 'Brien, 2001). By taking into account the presence of competition, the location of each person, the attractiveness of each site and the travel events of each person to each site, the estimated number of people transacting at each site was obtained (Morrison and O 'Brien, 2001). The results show that there is a high correlation between the predicted number of customers and the actual number of transactions at each branch, with an R2 of 0.8, and the predicted number of customers must make 9.8 transactions every three months to match the actual number of transactions (Morrison and O 'Brien, 2001). It can be seen that the use of the SI model can provide us with some potential information and provide more systematic information for strategic decision-making.

In addition, Patuelli et al. (2016) studied the impact of Italian World Heritage sites on domestic tourism using SI models and spatial sensitivity analysis. Patuelli et al. (2016) chose the bilateral tourist flow between each pair of Italian regions as the dependent variable in this study. While in terms of explanatory variables, the attractiveness of destinations such as climate and temperature, environmental quality, culture and history, the availability of tourist accommodation, and public transportation infrastructure were considered to conduct SI modelling (Patuelli et al., 2016; Marrocu and Paci, 2013). Their results confirmed their hypothesis, for example, that regional inflow is positively influenced by the quality of the museum and the dissemination of cultural activities; that is, the higher the quality, the more visitors come in (Patuelli et al., 2016; Marrocu and Paci, 2013). In order to demonstrate the robustness of different assumptions about the nature and geographic extent of spatial interactions, Patuelli et al. (2016) also confirmed the results using spatial sensitivity analysis. This can indicate that the conclusions obtained using the SI model are reliable when the data of explanatory variables are reliable, and different combinations of explanatory variables will also bring about different interpretations (O 'Kelly, 2009). The above research provides a reference for using the SI model. However, there is little literature on livestock modelling, which also triggers our interest in using the SI model to model the flow of livestock.

2.10 Geographically Weighted Regression Application

GWR can explore the research object's spatial changes and related explanatory factors at a particular scale by establishing local regression equations at each point in the spatial range (Ballard and Bone, 2021). In spatial analysis, observation data are generally sampled according to a given geographical location as a sampling unit (Fotheringham and Charlton, 2009). With the change of geographical location, the relationship or structure of variables will change, that is, "spatial non-stationarity (Windle, Rose, and Devillers, 2010). Spatial non-stationarity is prevalent in spatial data, such as regional housing prices or disease rates. If the traditional linear regression model is used to analyse the spatial data, the result is only a kind of average within the study area. Nevertheless, the local analysis can be summarised by embedding the spatial position of the data into the linear regression equation.

Applying GWR models can be used to understand the spatial relationship between human society and environment, human and animal, and animal and environment. For example, Wang et al. (2019) used a GWR model to investigate the spatial impact of urbanisation quality on CO2 emissions. They established a quality evaluation system for urbanisation, including population urbanisation, land urbanisation, economic urbanisation, and social urbanisation quality, and calculated the quality value that can represent urbanisation development using the entropy weight method. In this case, they choose carbon emissions as a dependent variable and the quality of urbanisation as the independent variable to establish the GWR model. They found that improving urbanisation quality will reduce carbon emissions with the change in time and the change in geographical areas. That is because the regions have developed infrastructure construction, and environmental regulations slow down carbon emissions. In this case, it can be seen that the local analysis of the GWR model helps to understand the Spatio-temporal changes of dependent and independent variables and is conducive to drawing reasonable conclusions related to reality.

Applying GWR can also help understand spatial variations concerning animal relationships. With the development and improvement of data, the GWR model can be used to explore more variable relationships. Velado-alonso et al. (2020) used a GWR model to study the spatial relationship between wild vertebrates' distribution and environmental and agricultural biodiversity distribution. By establishing a GWR model with species richness of mammals, nesting birds, amphibians, and reptiles as dependent variables, climate, human disturbance, and agricultural livestock richness as independent variables, Velado-alonso et al. (2020) found spatial correlations between wildlife and livestock in geographic locations. For example, the positive correlation between wild artiodactyls and cattle may reflect similar habitat requirements. In addition, GWR can also be applied to the exploration of animal habitats. For example, to prevent people from being bitten by snakes in Sikkim, India, Rai et al. (2021) used GWR to model the relationship between snake bites and explanatory variables such as population record, snake occurrence probability, forest area and net arable land area. Their results found four areas of high risk. Therefore, it can be seen that the value of GWR is in exploring the relationship between variables at different positions through case review.

2.11 Conclusion

Domestic animals play an essential role in human society and the environment, and domesticated animals are associated with human migration and activities (Hall, 2004; Tarazona, Ceballos, and Broom, 2019). Current studies usually only emphasize one or several aspects of the impact of livestock on the environment and human society but ignore the potential impact and implications behind the movement of livestock. Livestock movement is a process that involves not only the geographical displacement of economic activities, social structure, mode of production and environmental changes but also resources and environment are required as supporting conditions. In addition, the risk of movement of livestock, i.e., the risk of disease transmission, directly or indirectly affects people's dietary health, disease control, and economic activity. Therefore, further research is needed to explore the livestock movement and involve social and environmental explanations. In general, SI modelling was conducted to predict the effect of explanatory variables on cattle movement numbers by collecting dairy and beef movement numbers (mainly animal numbers) and human-related and environment-related explanatory variables from sixty-six TAs in New Zealand during 2015-2021. GWR model was used to estimate the effect of explanatory variables on the number of cattle moving into and out of TAs.

3 Methodology

3.1 Introduction

This study aims to explore factors that affect livestock movements across New Zealand. It will hopefully bring understanding about the effect of these external factors on the level of flows (SI modelling), as well as the effect of these factors on the numbers of incoming or outgoing cattle into each of the regions in NZ (GWR modelling). This chapter will cover the case study, data and methods used in this study. *Figure 3.1* shows the boundaries and names for sixty-six TAs and sixteen regions.

Northland
Far North
Whangarei
Kaipara
AUCKLAND
Auckland
Bay of
Plenty
Thames-Coromandel
TAURANGA
Western Bay of Plenty
Rotorua
Hauraki
Waikato
Waikato
HAMILTON
Matamata-Piako
Waipa
Otorohanga
South Waikato
Kawerau
Whakatane
Opotiki
Gisborne
Waitomo
Taupo
Wairoa
Gisborne
New Plymouth
Taranaki
Ruapehu
Stratford
South Taranaki
NAPIER
Hastings
Rangitikei
Hawke's
Wanganui
Manawatu-Wanganui
Mana-watu
Central Hawke's Bay
PALMERSTON NORTH
Tararua
Horowhenua
Kapiti Coast
Masterton
Wellington
PORIRUA
Carterton
South Wairarapa
UPPER HUTT
LOWER HUTT
WELLINGTON

Figure 3.1. Boundaries of 16 regions and 66 territorial authorities in NZ for this study.

3.2 Case Study

This research uses New Zealand, the Aotearoa, as a case study. New Zealand is divided into 16 regions, comprising 67 territorial authorities, with 268,021 square kilometres. New Zealand's animal husbandry products occupy an important position globally, where its dairy products account for 3% of the world's output. According to Statistics New Zealand, in September 2020, agriculture contributed about 5% of GDP (12.653billion) to the country's economy. Also, New Zealand is a perfect case study for this research as there are apparent climate and topographic differences between the North and South Islands. The North Island is warmer and the South Island steeper, making it easier to deal with common environmental factors that affect livestock movement. In addition, dairy products and meat accounted for 35% (6.57 billion) of the total export of 18.64 billion in the year to December 2020, with dairy products being ranked first in total export value (Stats NZ, 2021). It can be seen that livestock-related industries play a crucial role in New Zealand. As of 2020, the total number of dairy and beef cattle is 6.2 million and 3.8 million, respectively. This study's original livestock movement data corresponds to the total number of animals transported between TAs from 2015 to 2020 and have more than 100 thousand observations yearly. As Figure 3.2 shows, dairy cattle have distributed around New Zealand.

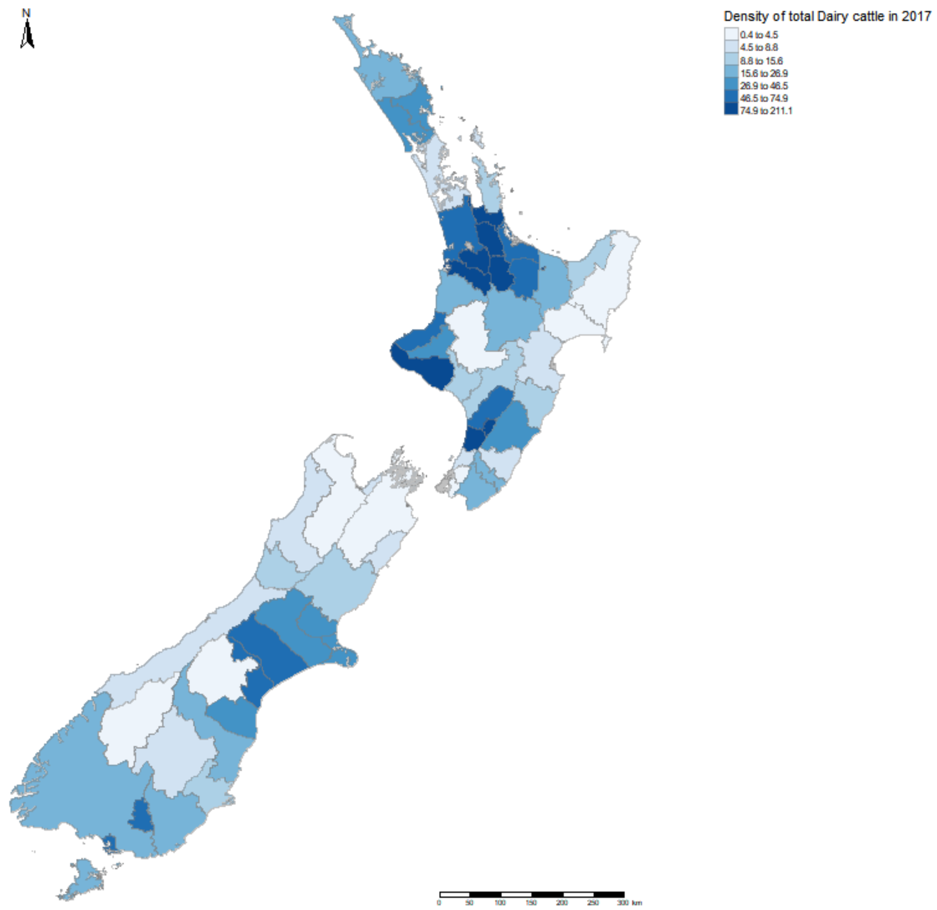


Figure 3.2. number of dairy cattle per km2 (total land area), by territorial authorities, 2017.

3.3 Raw Data

The data required for this research can be categorised into three groups. The first is the livestock movement data set, which is the basis of this study and contains the livestock types and movement information (time, place, and quantity. The second and third groups correspond to external spatial data—the second group being the spatial boundaries of regions and territorial authorities. The third group covers spatial data representing mainly environmental, topographical, and socio-economical statistical data linked to the territorial authorities and is divided into two subcategories: human-based and environmental variables. This dataset is then combined with information from livestock movement data (flows of outgoing and incoming animals) to perform spatial analysis designed for this study: Spatial Interaction (SI) and Geographically Weighted Regression (GWR) modelling.

3.3.1 NAIT movement data

Livestock movement data were obtained from the National Animal Identification and Tracing Programme (NAIT) with permission from the OSPRI company via the NAIT data access panel. The panel reviewed the request for research appropriateness, privacy included in any released data, applicability to policy development and impact on livestock-related industries. The panel agreed to release the data.

The parameters of the data requested were:

- 2015 to 2021 data
- Movement date
- Sending region
- Sending territorial authorities
- Receiving region
- Receiving territorial authorities
- Type of livestock

- The number of animals moved

This dataset's primary goal is to track the livestock in case of a severe biosecurity outbreak (OSPRI, 2022). Locations must be recorded when livestock moves between areas. The time scale of this research is bound to the data availability (2015-2021).

Figure 3.3. A flow map of total dairy cattle transportation movement in 2015

The OSPRI company provides the data in comma-separated values (CSV) file. Each year has information about around 100 thousand observations (number of animals moved between regions), with information about the recorded date of transfer, week of the year, sending region and TAs, receiving region and TAs, type of livestock (e.g., Cattle), type of production, number of movements, and number of animals (Table 3.1). A flow map can be shown with the data (Figure 3.3).

Table 3.1. An example of 2015 raw movement data from NAIT.

YEAR	MONTH	WEEK	FromNAITLocationRegion	FromNAITLocationSubRegion	ToNAITLocationRegion	ToNAITLocationSubRegion	Animal Type	Production Type	Total Number of Movements	Total Number of Animals
2015	1	1	NULL	NULL	West Coast Region	Buller District	Cattle	NULL	1	4
2015	1	1	NULL	NULL	West Coast Region	Grey District	Cattle	Beef	1	2
2015	1	1	NULL	Ashburton District	NULL	Hurunui District	Cattle	Beef	1	1
2015	1	1	NULL	Ashburton District	NULL	Hurunui District	Cattle	Dairy	1	38
2015	1	1	NULL	Ashburton District	Canterbury Region	Ashburton District	Cattle	NULL	1	3
2015	1	1	NULL	Ashburton District	Canterbury Region	Ashburton District	Cattle	Beef	1	30
2015	1	1	NULL	Ashburton District	Canterbury Region	Ashburton District	Cattle	Dairy	1	5

The data required some pre-processing and cleaning. The names of territorial authorities had to be amended to correspond to those in spatial data files. Records that had Null values in them were deleted. Also, we decided not to include data from the Chatham Territory because of its long distance from the two main islands of New Zealand and the low volume of livestock movement, which would not be suitable for complete mapping and analysis later. It requires data to be filtered, sorted and cleaned.

3.3.2 Other datasets

Boundaries of territorial authorities

We downloaded a spatial dataset of TAs in New Zealand from the Stats NZ open database. It is a spatial polygon data frame which shows the shape of each TAs in New Zealand with a World Geodetic System 1984 (WGS84) spatial reference system. The data consisted of sixty-eight TAs, where Area Outside Territorial Authorities and Chatham Islands Territory, which were not relevant to this study, were excluded.

Additional variables for modelling

The input data required by both SI modelling and GWR modelling require additional data on factors potentially affecting livestock movement. The descriptive data can be substituted to predict potential cattle flows and examine the correlation between these factors and the cattle. The explanatory variables for the modelling were divided into two groups, human-based factors and environment-based factors.

Human-based variables

In this study, variables such as distance to the nearest port, number of ports within 200km, total road length, number of slaughterers, number of dairy and beef cattle farmers, and number of veterinarians were classified as human-based variables (*Table 3.2*). Some were directly collected from authorised databases (*Table 3.2,* section 3.2.2), and some were derived using other datasets with proximity analysis (e.g., distance to the nearest port and number of ports within 200km).

Table 3.2. Description of human-based variables

Variable	Description	Source
Distance to the nearest port	The distance from the centroids of territorial authorities to its nearest port.	Own calculation by Proximity analysis
Number of ports within 200km	Number of ports within 200 km of a territorial authority centroid	Own calculation by Proximity analysis
Number of slaughterers	Number of slaughterers in a territorial authority	Stats NZ
Number of veterinarians	Number of veterinarians in a territorial authority	Stats NZ
Number of dairy/beef farmers	Number of dairy or beef farmers in a territorial authority	Stats NZ
Road length	Length of urban roads in a territorial authority	Ministry of Transport

Data such as the number of slaughterers, the number of veterinarians, and the number of dairy and beef cattle farmers were all obtained from the 2018 Census (Stats NZ). NZ Census mainly records information on the usual residence's occupation. These variables are categorised by territorial authorities, occupation, sex, income, and the number of people at the occupation in 2018 (Table 3.3). Data related to this research are filtered (Section 3.4.1).

Table 3.3. Example of Census data.

Census year	Territorial authority	Territorial authority Code	Occupation	Occupation Code	Sex	Measure	Value	Value Unit	Value Label
2018	Far North	Far North District	Chief executive or managing director	111111	Male	Median Income	63400	nzd	NZD
2018	Far North	Far North District	Chief executive or managing director	111111	Male	Mean Income	82900	nzd	NZD
2018	Far North	Far North District	Chief executive or managing director	111111	Male	Total people employed	330	number	Number of people

Data such as distance to the port and number of ports within 200km were calculated using proximity analysis, and road length data were obtained directly from the New Zealand Ministry of Transport. Primary ports' original spatial point data was obtained from the Ministry for Primary Industries (MPI) ArcGIS map serverfor the distance to ports. The Euclidean distance was calculated between port locations and the centroid of each TA. The number of ports corresponding to the number of ports counted within 200km from a centroid of each territorial authority (Figure 3.4). Road length was obtained from the New Zealand Ministry of Transport dataset that also had information on territorial authorities, road type and urban type of the surrounding areas in kilometres. The reason behind looking at the road lengths and distances to and the number of ports lies in how livestock is transported: via road or ship.

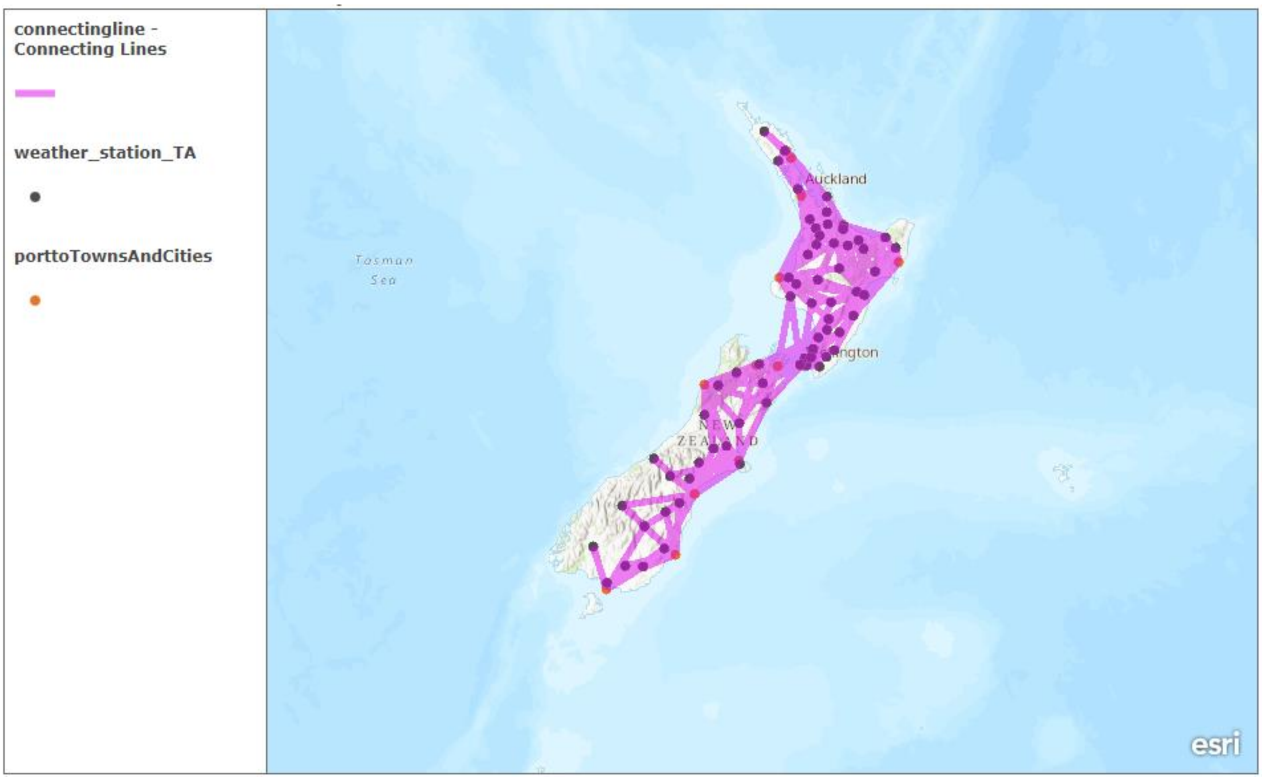


Figure 3.4. Centroids of TAs to the nearest primary ports

Environmental data

Based on the literature review, we selected eight variables related to environmental conditions from the National Climate Database managed by the

National Institute of Water and Atmospheric Research (NIWA) of New Zealand (Table 3.4). Eight climate variables include total rainfall, mean air temperature, mean maximum air temperature, mean minimum air temperature, mean daily grass minimum temperature, extreme grass minimum temperature, total sunshine hours, and mean vapour pressure (Table 3.4). Because the information is not directly recorded at the territorial authorities' level, we used the data of the meteorological station within 100km of the centroid of each TA and assigned it to the corresponding TA. Also, the abovementioned data changes frequently, so it is important to link them to TA at defined temporal scales (intervals). At the same time, to obtain eight climate data, we must include the condition that eight climate data exist in the same station.

However, we found that weather stations which met the screening conditions had data missing in some periods. In order to ensure data integrity, we filled the missing data in these periods. The details of this procedure are available in the following section.

Table 3.4. Description of Climate variables

Description	**Units**
Total Rainfall	Mm
Mean Air Temperature	Celsius
Mean Daily Maximum Air Temperature	Celsius
Mean Daily Minimum Air Temperature	Celsius
Mean Daily Grass Minimum Temperature	Celsius
Extreme Grass Minimum Temperature	Celsius
Total Sunshine	Hours
Mean Vapour Pressure	Hpa

3.4 Data Processing

The data collected in this study were recorded differently, so they needed to be cleaned, screened, and merged with other datasets to become valuable sources of information. As some meteorological data were missing, we had to fill in the missing values (Section 3.4.3). In creating variables related to ports, proximity analysis was used (Section 3.4.4).

3.4.1 Data Filtering and Cleansing

Data filtering is about setting conditions on raw data to get a precise subset. Data cleansing is detecting and correcting inaccurate records in the acquired data set. As mentioned above, we must conduct data filtering or cleansing on irrelevant information, unexpected information, and null values in the data. This research mainly discusses the movement of dairy and beef cattle, so we set a condition on livestock type in the raw movement data to distinguish dairy cattle and beef cattle.

We used this method to process data mainly to distinguish information about different production types of cattle and unify the spelling of TAs in different datasets. We also excluded irrelevant information from each dataset. It facilitates the subsequent merging of data sets to produce more helpful information.

3.4.2 Data Merging

Data merging is combining two or more datasets into one dataset, and two different dataset types can be merged. In this case, data merging involves pre-step for exploratory spatial data analysis, SI modelling, and GWR modelling. After completing the above steps, the variable data is ready to merge.

The purpose of merging based on territorial authority between datasets is to explore the performance of different variables in different spaces in subsequent spatial data analysis, SI and GWR modelling. This method can transform statistical data into spatial statistics for visual analysis.

3.4.3 Fill Missing Value

Fill Missing Value is a method of filling null values calculated with spatial Neighbours, space-time Neighbours, time-series, or global statistic values. It reduces the influence of the null value on subsequent analysis. If the analysis is performed with an incomplete dataset, bias may be introduced, and the adequacy of the results may be affected. When using this method, the input data types that need to be populated can be dots, polygons, or individual tables. The data can be spatial or spatiotemporal, and the missing values can be estimated using spatial or temporal neighbourhood values. The estimated value can then be substituted for the null value while preserving the existing value.

We used Average and Contiguity Edges Only for the fill method and spatial relationship, respectively. Using these two is basically replacing the null value by calculating the average value of the null value polygon's edge neighbour. It ensures the integrity of the dataset but does not guarantee that the data represents authenticity.

3.4.4 Proximity analysis

Proximity analysis is a spatial analysis tool mainly based on geographical distance, which can use a series of corresponding tools according to the type of input data vector or Raster feature for analysing. For example, the Euclidean distance tool can calculate the cells in Raster Features to get the shortest distance from the specified feature. We will use the Find Nearest tool in the spatial analysis tool to calculate the nearest linear distance between a vector feature (point, line, polygons) and another vector feature.

In this research, the data involved in using this method include TAs' centroid points and primary port points. We set the number of nearest locations to 8 and the search range to 200km to make each centroid point find its nearest primary port point so that the data can be used as static data in the subsequent SI modelling. In addition, we obtained the number of major ports that could be reached within 200km by limiting the search area to 200km.

3.5 Exploring Temporal and Spatial Pattern of Cattle Movements

The filtered and merged movement data has Spatio-temporal attributes. Exploratory data analysis (Section 3.5.1) and exploratory spatial data analysis (Section 3.5.2) can be used to analyse the data set to explore the Spatio-temporal patterns in the data, thus paving the way for analysing cattle movements to help us further analyse the movement pattern.

3.5.1 Exploratory Data Analysis

Exploratory data analysis summarises the main features of a data set through statistical graphics and other data visualisation means. It helps us find patterns in the data set, test hypotheses with exceptions, and better manipulate the data set to get the necessary answers. Insights derived from EDA can then be used for more complex data analysis or modelling.

Exploratory data analysis mainly has four data analysis forms, univariate non-graph, univariate non-graph, multivariate non-graph and multivariate graph. The four analysis forms can be used to analyse univariate and multivariate datasets or applied to datasets containing multiple variables simultaneously. The non-graphic analysis mainly uses tables or statistics to understand existing patterns and relationships between variables in the data, but it cannot provide a complete picture of the data. Graph analysis methods can be used by visualising data in different graph types to draw a complete picture of the data.

Standard graph analysis methods include stem and leaf plots, histograms, boxplot plots, bar plots, and scatter plots, from which information can be obtained is also different. The stem and leaf diagram shows the values of all data and the distribution of those values. The histogram uses a bar to show the frequency or proportion of cases. The boxplot depicts the data's minimum, first quartile, median, third quartile, and maximum values. Bar charts can explore the levels of different variables in a data set. Scatter plots explore the influence of dependent and independent variables by plotting data points along the horizontal and vertical axes.

This study used two common graph types, histogram and boxplot. We mainly used RStudio to perform the exploratory data analysis on the filtered cattle movement datasets and variable datasets, using boxplots for the cattle movement datasets and histograms for the variable datasets. In the analysis of moving data by boxplot, we plotted the months and the number of moving cattle for two types each year and explored the differences between movement levels each month in all the years. Using the histogram, we looked at the frequency distribution of the data to check whether it was normal.

To show the standardised data distribution, we used boxplots when selecting an exploratory data analysis graph type for movement data. It can show the outliers of the data, how symmetrical the data is, how tightly the data is grouped, and whether the data is skewed. However, box graphs fail to recognise averages and hide multimodal characteristics of data distribution. Using histograms for variable datasets allows us to examine the distribution of sample data to assess whether the data follows a particular theoretical distribution, such as a normal distribution. However, histograms are only used for continuous data, multiple data sets cannot be compared simultaneously, and exact values cannot be read.

3.5.2 Exploratory Spatial Data Analysis

Exploratory spatial data analysis (ESDA) is usually performed after exploratory data analysis and is an extension of exploratory data analysis, allowing users to visualize spatial distributions, identify spatial outliers, and discover patterns of spatial associations, clusters, or hot spots.

The choropleth map can be used to explore and visualize the data. The choropleth map is a statistical thematic map that gathers two data sets. One is the spatial data that divides geographical space into regions. The other is the statistical data set representing the regions' variables. There are two standard conceptual models to illustrate this. One is "district dominated", where the district is the focus, which collects various attributes, including mapped variables. The other is "variable-dominated", which is dominated by the variables of a geographical phenomenon and shows its distribution in the district. The choropleth map can be displayed on the map in different colours, symbols, and symbol sizes for different information.

In this study, we mainly used the choropleth maps for variable datasets to explore the distribution characteristics in New Zealand territorial authorities. We aggregated/disaggregated the data into values per TAs and mapped them using R. We mainly used the fixed classification rules for climate and census variables in the choropleth maps from different months/years. For variables related to road and port, we used quantile classification.

3.6 Cattle Movement Analysis

For the analysis of cattle movement, we first used the attraction-constrained model to model the number of cattle movements and explanatory variables of sixty-six territorial authorities from 2015 to 2021. The first objective of this research was to calibrate the SI model and verify which of the selected explanatory variables had the most substantial effect on the volume of the studied flows. In addition, GWR was used to evaluate the spatial relationship between the dependent and independent variables. In this case, the number of cattle flowing out and in is the dependent variable, and the environmental and human-based variables are the explanatory variables to analyse the implications of cattle movement.

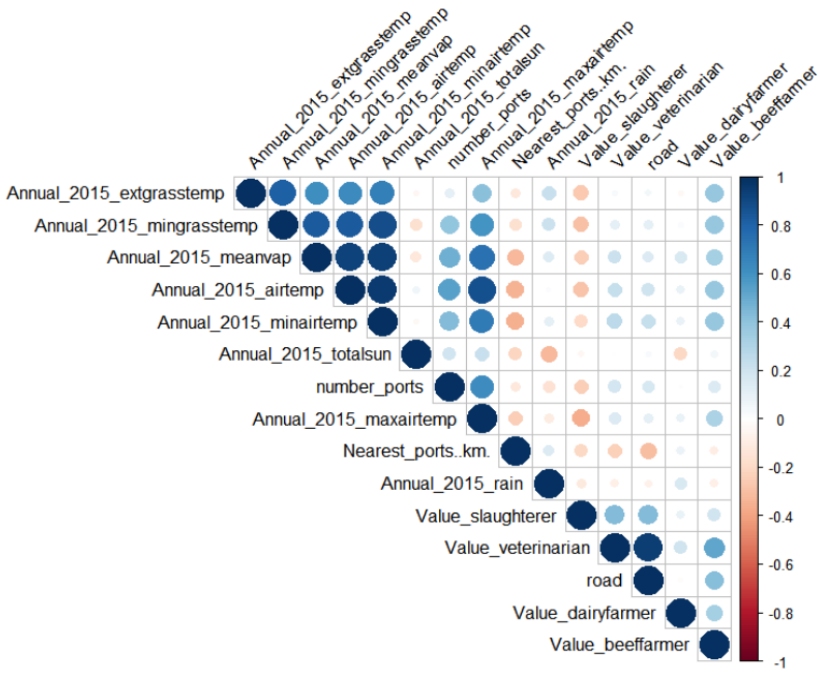
Before modelling the spatial interaction of dairy and beef cattle, we used the correlation matrix to arrange the relations among explanatory variables. Combinations with high correlation coefficients were eliminated to avoid the situation when two variables explain the same phenomena. Then we created origin-destination matrices for each studied month for beef and dairy cattle movements.

3.6.1 Correlation Matrix

A correlation matrix will be used to test the statistical relationship between two random variables. Correlation usually refers to the degree of linear correlation between variables and is expressed by the Pearson correlation coefficient (Pearson, 1909). The correlation coefficient ranges from -1 to 1. The closer to 1, the positive correlation is, and the closer to -1, the negative correlation is.

The correlation matrix summarizes the correlation coefficients between different variables in the data set. A cell in the table represents the correlation between two variables, the relationship of which can be indicated by a number or colour. In our case, we created a correlation matrix for 15 explanatory variables in all datasets, including eight environmental and seven human-based variables, an example as Figure 3.5 shows.

Figure 3.5. A correlation matrix for annual explanatory variables in 2015



3.6.2 Origin-Destination (OD) matrix

In order to calibrate SIM, we need to transform our data into the Origin-Destination (OD) matrix (Table 3.5). The OD matrix is a matrix which consists of information about the total number of cattle moved from a starting point to a destination. Each cell in the matrix represents the total number of cattle moved from the start point (row) to their journey's endpoint (column).

Table 3.5 shows an OD matrix for interactions between the number of origins i and destination *j*. In the OD matrix, the element O_i is the Origin *i* (sum of a row), which represents the total outputs of origin *i* (flows from). In contrast, the element D_j is the destination *j* (sum of a column), and it indicates the total inputs of a destination *j* (flows bound to), and the sum of outputs and inputs is given by T. The OD matrix cannot provide complete planning and allocation information through spatial interaction. Therefore, especially in the absence of empirical data, SI models can be used for further investigation to support planning and allocation purposes.

Table 3.5. An example of the Origin-Destination matrix shows flows (number of cattle) of dairy cattle between territorial authorities in February 2015.

Destination (Dj) / Origin (Oi)	Ashburton District	Auckland	Buller District	Carterton District	Central Hawke's Bay District	Central Otago District	Christchurch City	Clutha District	Dunedin City	j	Total
Ashburton District	0	0	0	0	0	0	98	35	0	.	133
Auckland	0	0	0	0	0	0	0	0	0	.	0
Buller District	0	0	0	0	0	0	2	0	0	.	2
Carterton District	0	0	0	0	0	0	0	0	0	.	0
Central Hawke's Bay District	0	0	0	0	0	0	0	0	0	.	0
Central Otago District	1	0	0	0	0	0	3	224	0	.	228
Christchurch City	0	0	1	0	0	6	0	44	0	.	51
Clutha District	34	0	3	0	0	85	30	0	16	.	168
Dunedin City	0	0	0	0	0	2	19	12	0	.	33
i	.	.	.	.	.	.	.	.	.	T_{ij}	O_j
Total	35	0	4	0	0	93	152	315	16	D_j	T

3.6.3 Spatial Interaction Modelling (SIM)

A Spatial interaction model is a mathematical model that predicts the movement of people, information, objects or animals between origin and destination by examining the distance between them, usually measured in aggregate terms (Fotheringham and O'Kelly, 1989). However, many possible needs and decisions cause movements behind the total flow, such as shopping and medical conditions. Ultimately, movement is related to many background factors, not only distance.

The unconstrained, production-constrained, attraction-constrained, and doubly constrained models constitute a family of SI models (Wilson, 1971). Different models can be employed depending on what type of movement purposes (Table 3.6). The alternative name for these SI models is "gravity models".

Table 3.6. Types of spatial interaction models in different applications.

Want to know	**Spatial interaction models**	**Example**
• Future flow matrix • Total inflows • Total outflows	Unconstrained	Migration
• Future flow matrix • Total inflows	Production constrained	Shopping
• Future flow matrix • Total Outflows	Attraction constrained	Journey-to-work
• Future flow matrix	Doubly constrained	Traffic analysis

The gravity model is from Newton's law of gravity, in which the gravitational force between two objects is directly proportional to the object's mass and inversely proportional to the square of the distance between them (Haynes and Fotheringham, 1985; Peterson, 2007). It can be expressed in a simple form:

$$F_{12} = G\frac{M_1 M_2}{d_{12}^2}$$

Where F is the force between objects 1 and 2, G is the gravitational constant, M_1 and M_2 are the mass of objects 1 and 2, and d represents the distance between centres of the masses.

The gravity model is the most common formulation of the spatial interaction method. Gravity-like representations have been applied in various contexts, such as migration, commodity flows, traffic flows, commuting, and evaluating boundaries between market areas. Consequently, the general formulation of spatial interactions can be adapted to reflect this basic assumption to form the elementary formulation of the gravity model:

$$T_{ij} = k\frac{P_i P_j}{d_{ij}}$$

Where Tij specifies any pair of interactions, Pi and Pj are the populations of origin i and destination j, and dij is the distance between any i and j. From this formation of the gravity model, the other family models are transformed based on it.

3.6.4 Attraction-Constrained Model and Its Calibration

This dissertation mainly uses destination-constrained spatial interaction models to assess New Zealand cattle movement. As shown in Table 3.2, the model is mainly to understand the total outflow of cattle and predict the flow. The reason why we choose this model is also to explore what factors lead to the patterns of transporting cattle in NZ. The model uses the known inputs and explanatory variables of the destination to represent the total number of trips from the starting point, in the form of:

$$T_{ij} = \frac{D_j V_i^{\alpha} d_{ij}^{\beta}}{\sum_i V_i^{\alpha} d_{ij}^{\beta}}$$

Where T_{ij} again specifies any pair of interactions, D_j represents the known total inflow from origin i, α indicates the sensitivity of the flow from i to j to the propulsiveness of origin i as measured by V_i, and β is the sensitivity of the flow between *i* and *j* to the spatial separation between *i* and *j*.

In this research, D_j represents the known total inflow from origin territorial authority, α indicates the environmental and human-based variables of the flow from *i* to *j* to the propulsiveness of origin i as measured by V_i, and β is the sensitivity of the flow between territorial authority origin i and j to the spatial separation between territorial authority *i* and *j*.

Also, to improve the model's fit, we need to calibrate the cattle transport movement flow data parameters. An accurate calibration model is essential for description and prediction (Rodrigue, Comtois, and Slack, 2009; Yue et al., 2012). Model calibration requires a large amount of interactive spatial data to ensure that the parameters' values best fit the observed data (Yue et al., 2012). We calibrated the SIM using Poisson regression (Flowerdew and Aitkin, 1982); thus, our destination-constrained model becomes:

$$\lambda_{ij} = exp(\mu lnV_i + \alpha_i - \beta lnd_{ij})$$

Where λ_{ij} is modelled by a linear combination of the logged independent variables in the model, and μ is modelled as a categorical predictor, the territorial authority's name. Finally, to find the goodness of fit for the modelling, an R^2 value is involved in testing the fits, where the value closer to 1, the better the model fit.

3.6.5 Geographically Weighted Regression modelling and Akaike Information Criterion (AIC) Optimisation

GWR is a spatial analysis technique for spatial non-stationarity (Brunsdon, Fotheringham, and Charlton, 1998; Wheeler and Paez, 2010). It evaluates local models between explanatory and dependent variables by fitting ordinary least squares regression equations to each feature in the dataset (Wang, Ni, and Tenhunen, 2005; Fotheringham and Charlton, 2009). In other words, GWR constructs separate regression equations for dependent and explanatory variables within the bandwidth of each location in the dataset, allowing the relationship between independent and dependent variables to vary from region to region, which means it considers the spatial autocorrelation of variables (Fotheringham, Brunsdon, and Charlton, 2003). Bandwidth can be user-determined or software-determined, with default or "adaptive" bandwidth selected in most cases. Before proceeding with GWR, we need to run the OLS model to determine the global coefficient (β) of the independent variable (X), which is transformed by the following form:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots \beta_n x_n + \varepsilon$$

Furthermore, we get the estimator:

$$\beta' = (X^T X)^{-1} X^T Y$$

GWR can be the next step when we decide on the independent variables to keep in the model, and we have a theoretical basis for believing that these variables are spatially varied. The weight matrix of position *i* was added based on OLS regression so that the observed values close to *i* had more significant weight than those far away from *i*:

$$y = \beta_0(i) + \beta_1(i) x_1 + \beta_2(i) x_2 + \ldots \beta_n(i) x_n + \varepsilon$$

and the estimator depends on location:

$$\beta'(i) = (X^T W(i) X)^{-1} X^T W(i) Y$$

However, when using the GWR model, we should choose the type of model for analysis based on the measurement of dependent variables and the range of their values. In this study, the data is discrete and represents the number of events. The general form of the Poisson model type is:

$$Y_i = N_i \, e^{\beta_0 + \beta_1 X_{i1} + \ldots + \beta_n X_{in}}$$

or

$$ln(Y_i) = ln(N_i) + \beta_0 + \beta_1 X_{i1} + \cdots + \beta_n X_{in}$$

Where Y_i is the expected count of the parameter given conditions at location *i*, and N_i is the offset value which, if not specified, defaulted to $N_i = 1$ for all location *i*.

Furthermore, we also need to select variables before calibrating the GWR model. To select a set of variables, we select them based on common sense and literature review, then check multicollinearity amongst these variables and reject other variables if necessary (Fotheringham, Kelly, and Charlton, 2012). Afterwards, a stepwise-AIC procedure eliminates redundant variables (An and Gu, 1989; Yamashita, Yamshita, and Kamimura, 2007; Burnham, Anderson, and Huyvaert, 2011). A stepwise-AIC method shares similar procedures as stepwise regression, where explanatory variables are added through the following:

$$Y = \beta_0 + \beta_1 X_{i1} + \beta_n X_{in}$$

and keep adding one variable per round until there are no more variables that would be the one set with the most significance, following by taking the variable out of the set and calculating the AIC value, where the set with the most negligible AIC value is counted as the best model set to use in GWR modelling. Finally, the AICc and Pseudo R^2 values will be given in the output to evaluate the model strength. The AICc is the information score of the model; the smaller the value, the better the model fit (Cavanaugh and Neath, 2019). The Pseudo R^2 value explains the wellness of observed data explained by a model, whereas a higher Pseudo R^2 value indicates a better explanation by a model (Laitila, 1993; Walker and Smith, 2016).

3.7 Summary

This chapter discusses the methods used to assess the relationship between New Zealand dairy and beef cattle transport movement and external factors. In order to make the data expression accurate and feasible, we processed the data and created variables related to ports for the external factor variable set. To assess the time patterns of transport movement flows for dairy and beef cattle in New Zealand, exploratory data analysis was used, and exploratory spatial data analysis was performed using external factor variables to explore areas suitable for cattle farming. In order to predict the cattle transportation outflow under the influence of the obtained variables by the destination-constrained model, we used a correlation matrix to identify highly correlated variables and eliminate them and finally created an OD matrix for the model to use. The spatial relationships between explanatory variables and incoming and outgoing cattle transport moving flows were assessed using GWR, and stepwise-AIC Optimisation was used to select the set of variables for the best fitting model.

4 Results

4.1 Introduction

This chapter summarises the results from the methods used to assess cattle movement within New Zealand. The results include visualisations of spatial and temporal variations in dependent and independent variables, parameter estimates from calibration of SI models, and parameter estimates explaining the spatial relationship between explanatory variables and the outflow and inflow of cattle derived using GWR models.

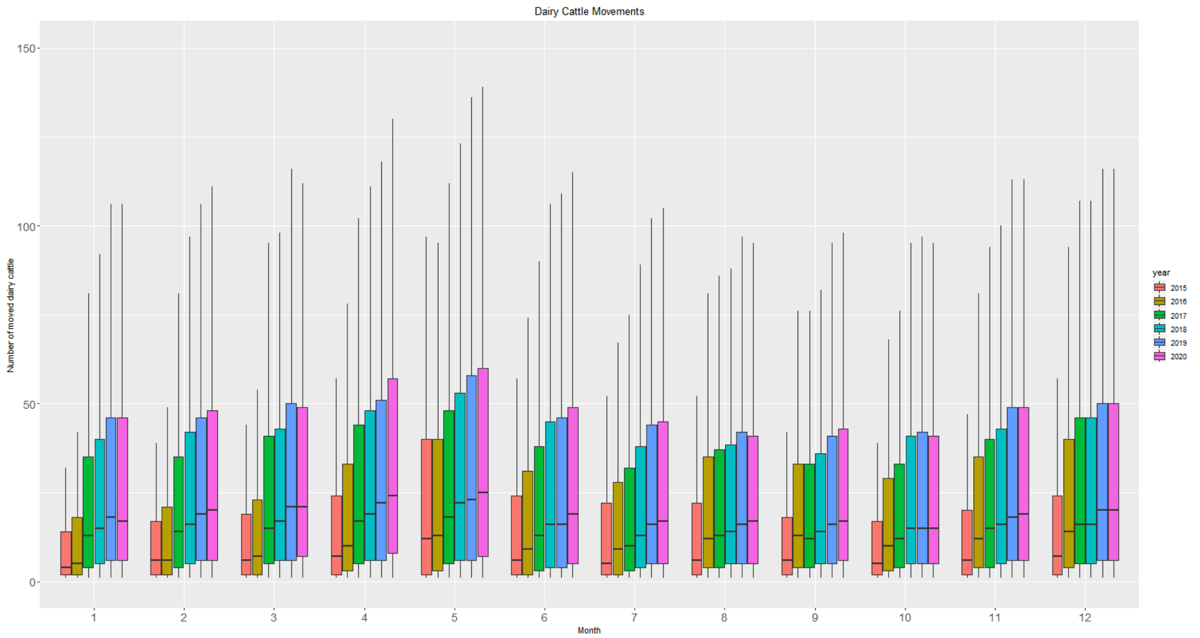
Spatiotemporal changes in cattle movement and explanatory variables were interpreted using exploratory data analysis and exploratory spatial data analysis based on movement data obtained by NAIT and environmental and human data collected from various sources. The results of the spatial interaction model based on the highest, second highest, and lowest cattle flows across the different months from 2015 to 2021 are presented (Table 4.1 and 4.2 in Section 4.4.1 and Section 4.4.2). The GWR results include the description of the stepwise-AIC optimisation procedure with the final set of variables chosen for the modelling, the interpretation of the calculated AICc and R2 values of the models and the parameter estimates explaining the relationship between the exploratory and the dependent variables.

4.2 Temporal Pattern of Cattle Movement

After data processing (Section 3.4), cattle movements were divided into dairy and beef cattle and summarised into the six-year movement data (2015-2021). For convenience, we combined the six yearly data sets of dairy and beef cattle into one dataset (Section 3.4.2). Exploratory data analysis (Section 3.5.1) was performed on both dairy and beef cattle datasets, and a boxplot was used to explore the time patterns (Figure 4.1).

The temporal patterns of the numbers of transported animals are shown in Figure 4.1 (A and B). The total number of cattle movements showed a gradual increase yearly for all the months between 2015 and 2019. The highest number of dairy cattle movements was noted in May, the lowest in January, and the highest peak for beef cattle was noted in April, whereas the lowest in February.

A)



B)

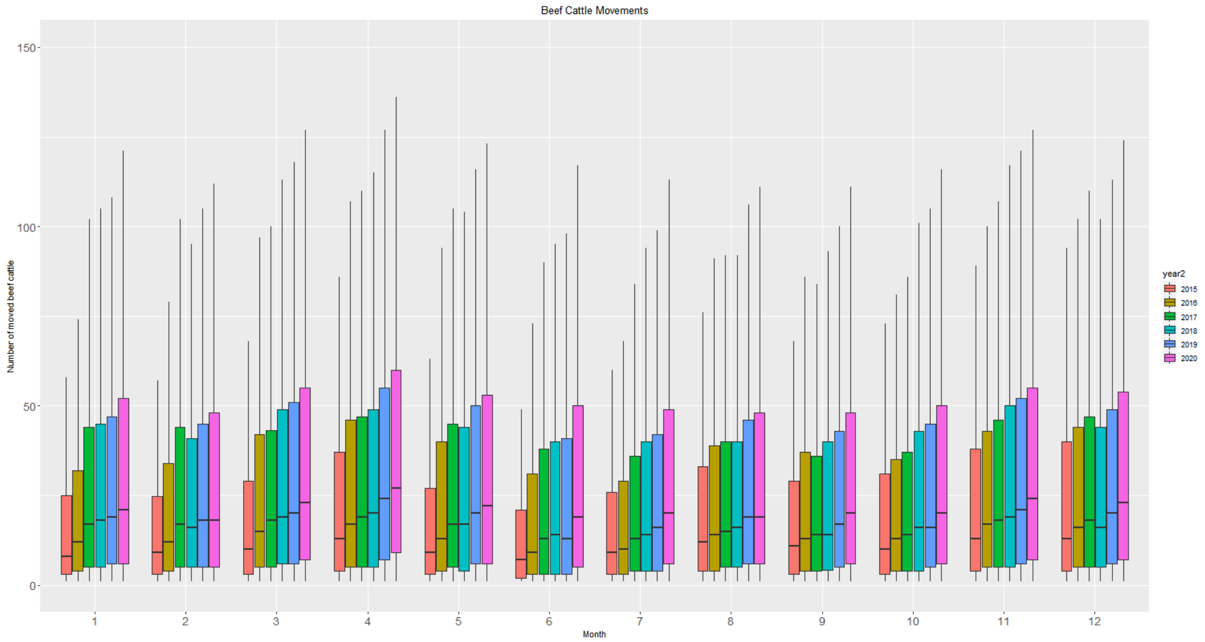


Figure 4.1. A) a boxplot shows the number of dairy cattle over 12 months in 6 years (2015-2021). B) a boxplot shows the number of beef cattle over 12 months in 6 years (2015-2021).

As shown in Figure 4.2, we summarized and compared the movement quantity of the two cattle types from six years of data and showed the range of values for each month. It was found that the highest average number of transported animals was in May and the lowest in February, with the second highest month, June for dairy cattle and November for beef cattle. Based on this, February, May, and June were selected as experimental data sets for the SI modelling of dairy cattle movements, and February, May, and November were selected for beef cattle. Lastly, we selected May data sets from 2016 and 2019 for the two cattle groups for the GWR model comparison.

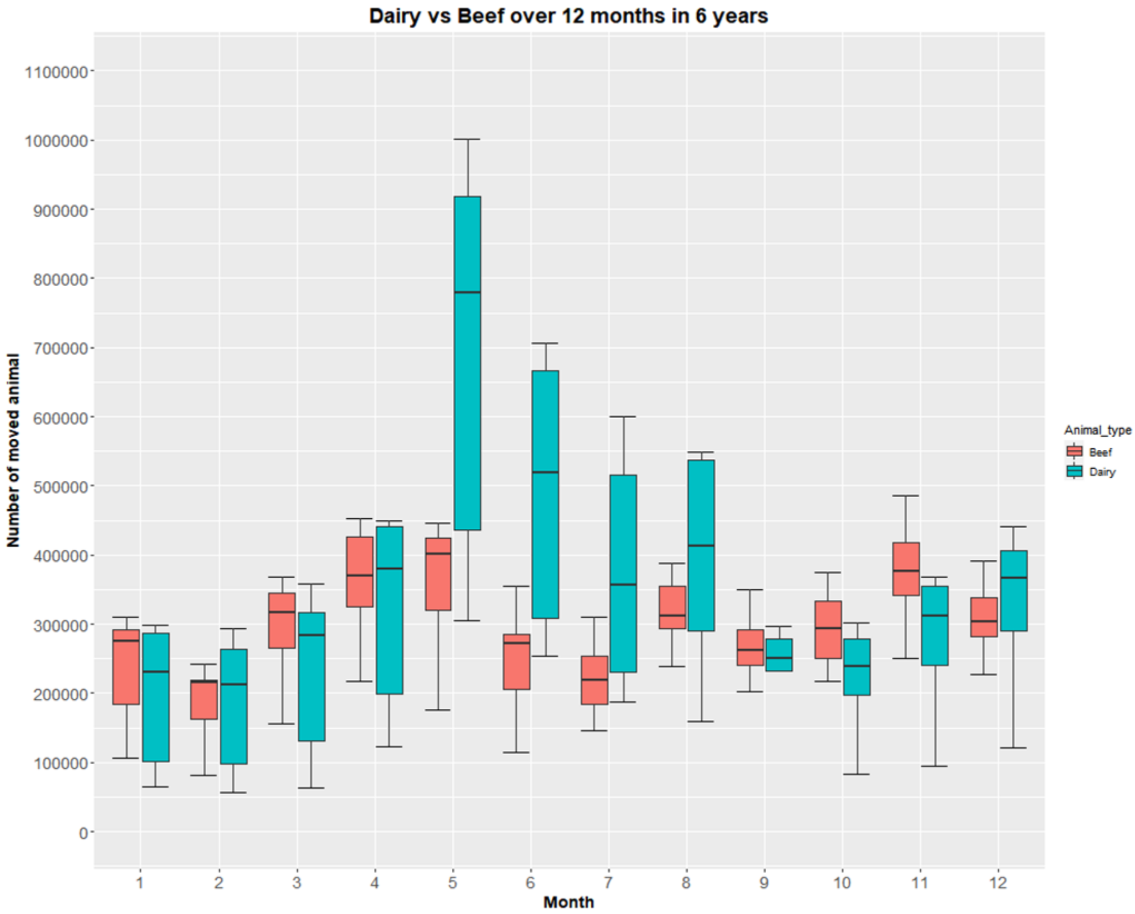


Figure 4.2. A boxplot compares the number of moved dairy and beef cattle over 12 months in 6 years.

4.3 Spatial Pattern of External factors

To explore the factors affecting cattle transportation, we collected variables related to environmental and human factors (Table 3.2 and 3.4 in Section 3.3.2). This study mainly collects variable data from 66 territorial authorities in New Zealand. We visualised spatial patterns of exploratory variables using choropleth maps in Exploratory Spatial Data Analysis (ESDA, Section 3.5.2).

Examining the spatial pattern of explanatory variables, we discussed eight environmental and seven human-based variables for 2016. Firstly, the vapour pressure among the environmental variables was highly correlated with the five temperature variables initially obtained in the correlation matrix (Section 3.6.1), so the vapour pressure would be used as a proxy to represent the spatial distribution related to temperature.

By looking at the distribution of the average vapour pressure for 12 months in 2016, we found that its values were higher on the North Island and lower on the South Island (Figure 4.3). For example, the pressure in February was usually higher than in other months at the same place because February is the hottest month in New Zealand summer (Figure 4.3A). Thus, when the temperature is high, the vapour pressure is high.

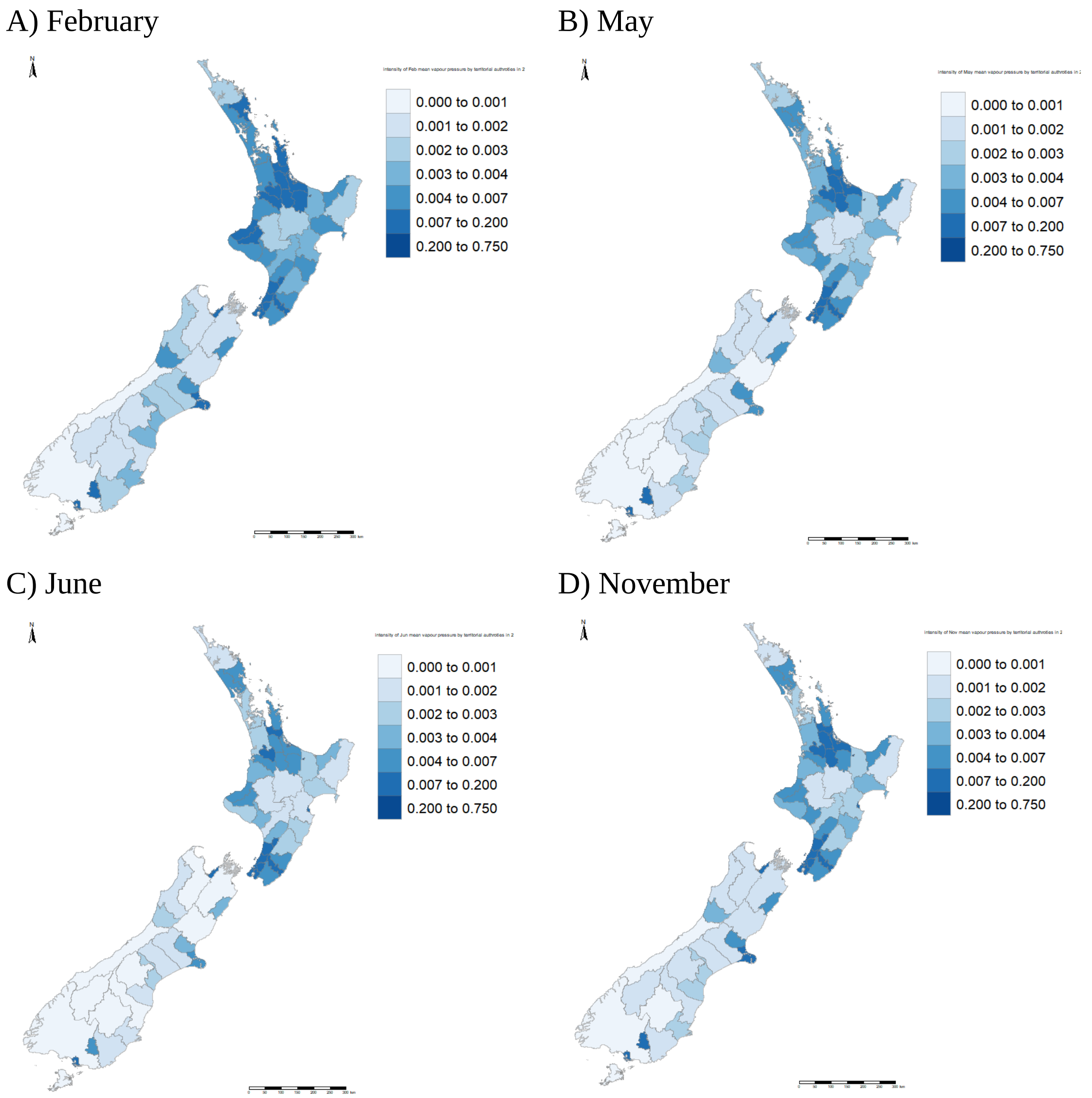


Figure 4.3. Distribution of vapour pressure (Hpa) in 66 territorial authorities for A) February, B) May, C) June, and D) November in 2016.

In Figure 4.4, we found from the distribution of daily sunshine duration that the areas with the most extended sunny episodes are mainly concentrated on the North Island and a small part of the South Island's east coast. With the usual changes in the seasons, the duration of sunshine was changing in which February (Figure 4.4A) and November (Figure 4.4D) were sunnier than the other two months (Figure 4.4B, 4.4C), with February being, on average, the sunniest month of all (Figure 4.4A and 4.4D).

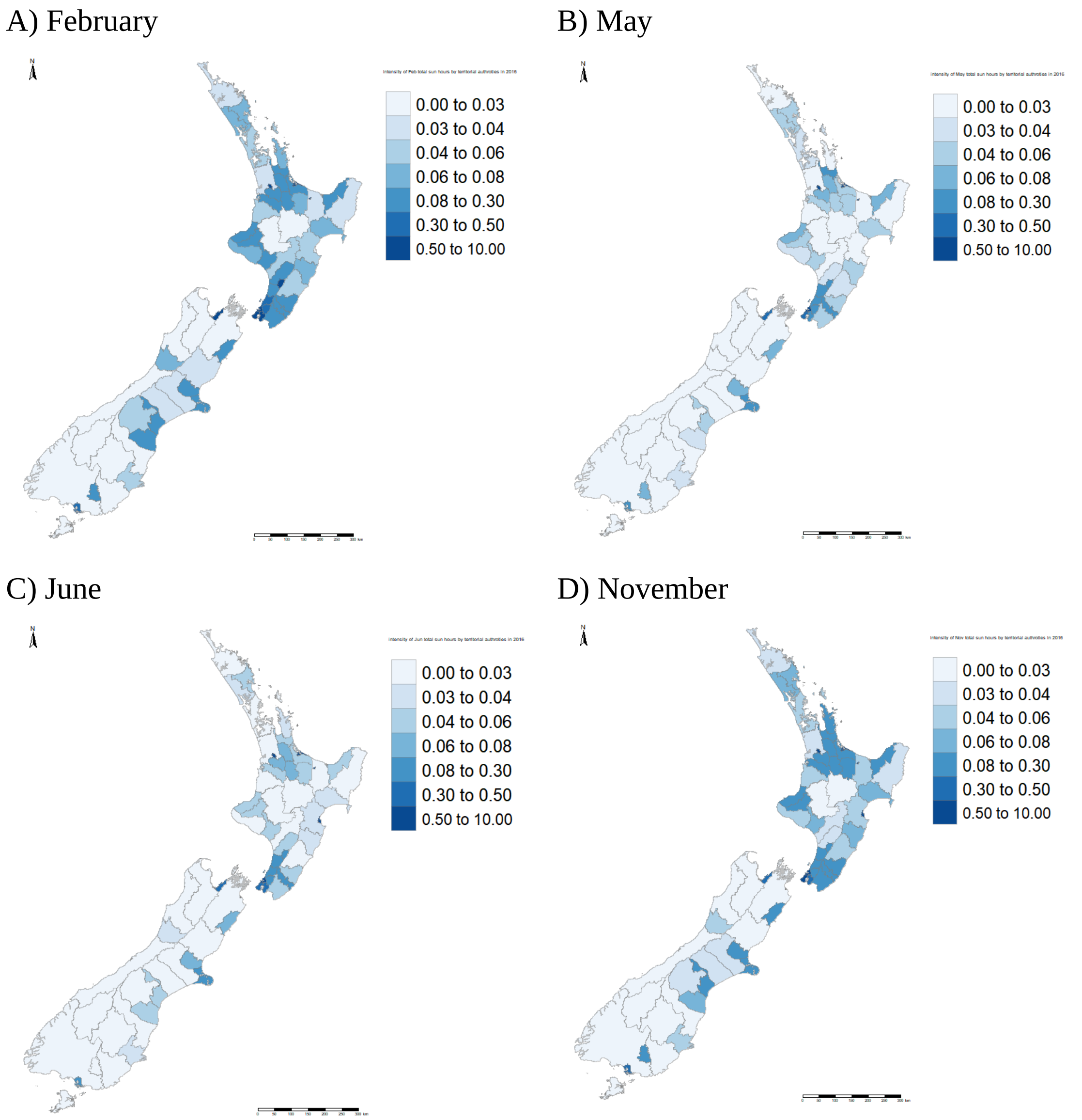


Figure 4.4. Distribution of duration of sunshine (hours) in 66 territorial authorities for A) February, B) May, C) June, and D) November in 2016.

The spatial pattern of rainfall is similar for all the months (Figure 4.5). North Island usually had more areas with rain than the South Island, and there was more rain in winter (Figure 4.5B, 4.5C) than in summer (Figure 4.5A, 4.5D). Also, territorial authorities in North Island were likely to have heavier rainfall, especially around the south tip of North Island.

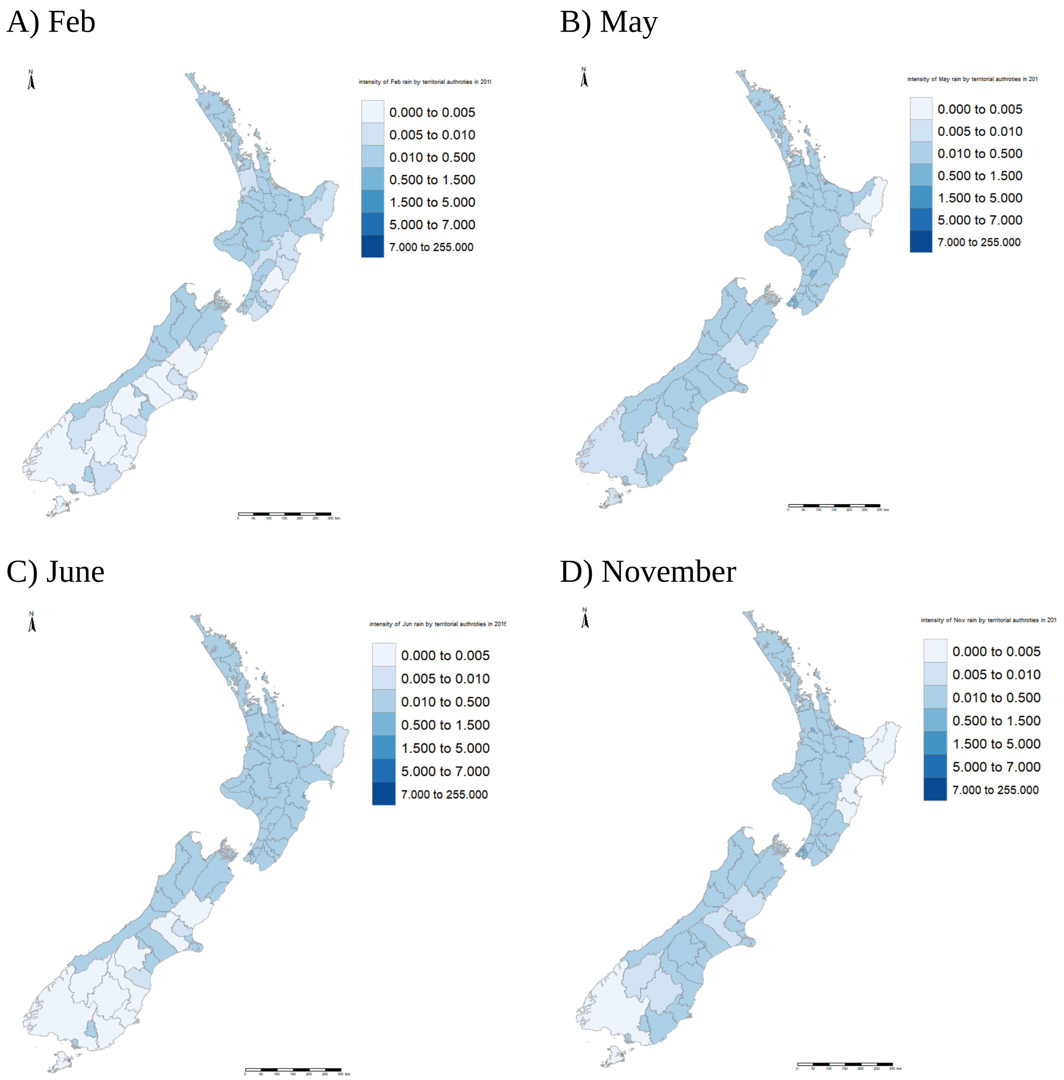


Figure 4.5. Distribution of rainfall (mm) in 66 territorial authorities for A) February, B) May, C) June, and D) November in 2016.

In terms of human variables, they were treated as static variables and did not change much over the years. In Figure 4.6, we can see that the high density of urban roads covers the western half of the North Island and the southeastern part of the South Island. Nevertheless, territorial authorities in the South Island have seven ports to access, and they are more distributed, so the value of distance to the ports is higher.

A) Road B) The nearest port

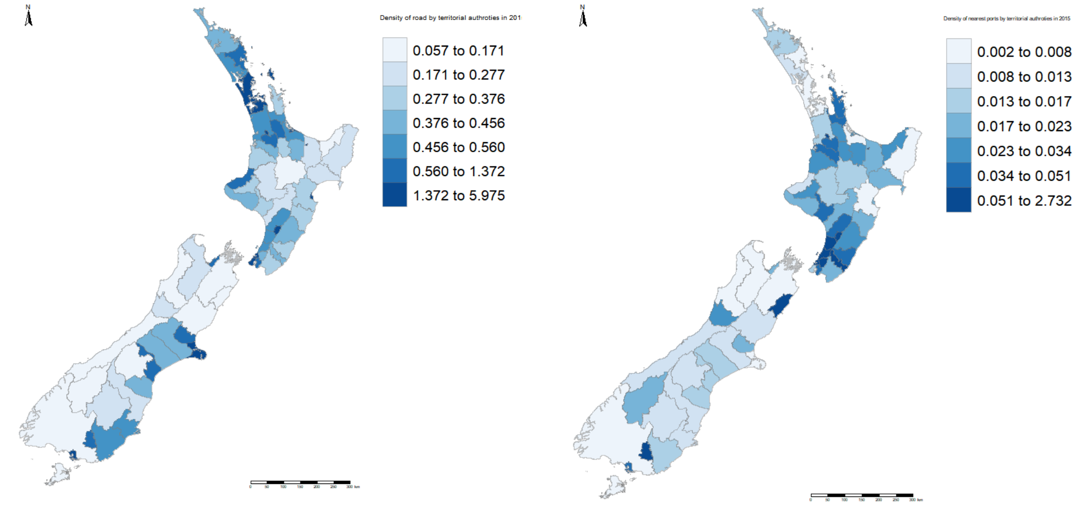


Figure 4.6. The density of A) road and B) the nearest port in 66 territorial authorities in 2018.

According to variables obtained from the census, the spatial pattern of the density of veterinarians, butchers, and dairy and beef cattle farmers had a significant difference under the same interval scale. In Figure 4.7, the density of dairy farmers (Figure 4.7C) had the most various spatial pattern and mainly happened around the Waikato, Taranaki, and Canterbury regions. The number of slaughterers had a similar pattern to the number of dairy and beef farmers (Figure 4.7B) but with a smaller value because the number of slaughterers was not as large as the number of farmers. Also, we are using density to measure. We find that the higher value interval usually appeared in the smaller territorial authorities, such as Hamilton city, Tauranga city, Napier city, Palmerston North city, Wellington city and Invercargill city in Figures 4.7A and 4.7B.

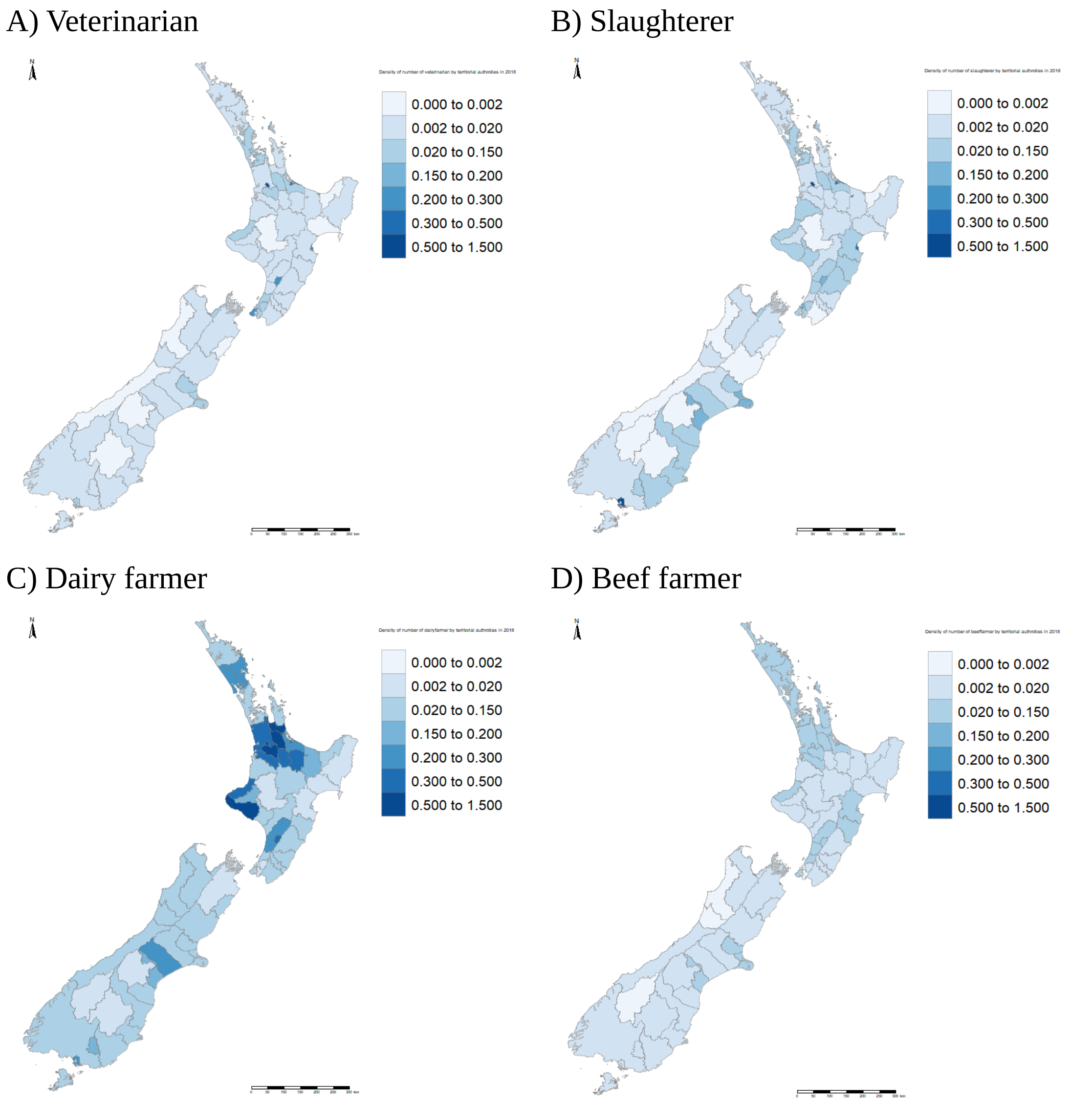


Figure 4.7. The density of A) veterinarian, B) slaughterer, C) dairy farmer, and D) beef farmer in 66 territorial authorities in 2018.

To explore the relationship between environmental explanatory variables and cattle transportation and movement, the SI model and GWR model are needed to evaluate further the factors affecting cattle transportation and movement.

4.4 Spatial Interaction Modelling of Transported Cattle

One of the goals of this research was to determine if the explanatory variables could be used to explain the two cattle types' movements by calibrating the SI model (Section 3.6.3) using trips of two cattle types. In order to address this research objective and understand the decision-making process responsible for cattle movement, we calibrated several temporally disaggregated SI models for times when their mobility was at its highest or lowest but also other months throughout the year. The monthly OD matrices were derived from the NAIT livestock movement data (Section 3.3.1 and Section 3.6.2).

The destination-constrained SI models (Section 3.6.4) presented with dairy and beef cattle flow data from three chosen months (February, May, and June) for six years from 2015 to 2021 were calibrated. The results are presented in Tables 4.1 and 4.2, including parameter estimates, corresponding significance levels, and models' diagnostics (R^2 value).

4.4.1 Dairy Cattle

This section describes the results of the destination-constrained model for the dairy cattle movement. Based on the EDA (Section 3.5.1), February, May, and June (low, peak, and sub-peak) were identified as examples for this research. The results derived from the calibration of the destination-constrained model for the flows of dairy cattle over the six years (2015-2021) are shown in *Table 4.1*. By comparing annual and monthly R^2 values, we found that R^2 from 2017 to 2020 is higher than in 2015 and 2016. In addition, comparing the mean value of R^2 in three months, the mean value of R^2 in February was 0.66, that in May was 0.74, and that in June was 0.70. It shows that May is the most representative month, and the data fit the model better.

The paragraph below describes the parameter estimates listed in *Table 4.1*. This includes α1 - number of slaughterers, α2 - number of dairy farmers, α3 – distance to the nearest port, α4 - number of ports within 200km, α5 - road length, α6 – rainfall, α7 - sun hour, α8 - vapour pressure, and β - distance parameter generated from the destination-constrained model.

The α1 represents the number of slaughterers, and this parameter estimate is generally positive for the studied three months in each year except February 2017 and June 2018, when the parameter shows negative values. A positive value indicates a positive relationship between the number of slaughterers and the level of interaction: as the number of slaughterers in each TA increases, the number of spatial interactions increases. A negative value indicates that as the number of slaughterers increases, the number of moved animals tends to decrease. The larger the positive number, the greater the impact of the number of slaughterers on the flow, and vice versa for a negative value. Comparing the values of α1 for February across the six years, it can be found that the parameter estimate has the highest value in 2016 (0.075) and the lowest in 2017 (-0.013). All the α1 values in May across the years were positive, with the largest in 2015 (0.035) and the lowest in 2020 (0.003). The maximum value of α1 in three months in six years occurred in February 2016, and the minimum value was in June 2018. However, since all the parameter estimates of α1 are close to 0, the influence of this variable can be considered small.

The α2 in *Table 4.1* refers to the number of dairy farmers. This parameter estimate was positive for all the months across all the years, and all exceeded α2=0.60, indicating that this variable significantly impacted the flow size. For the α2 estimates, the highest estimate was observed for May 2017 (0.848) and the lowest for June 2015 (0.622). In general, all three months had relatively high parameter estimates.

The α3 in *Table 4.1* is the distance to the nearest major ports. All the parameter estimates are positive, with Feb 2016 being excluded because the p-value is greater than 0.05. Comparing the values of α3 for February across the six years, it can be found that the parameter estimate has the highest value in 2018 (0.178) and the lowest in 2017 (0.015). All the α3 values in May across the years, with the largest in 2015 (0.251) and the lowest in 2019 (0.094). In June, the highest α3 estimate was in 2020 (0.186), and the lowest was in 2019 (0.115). The results show that this parameter estimate had a relatively strong impact on the flows but not as strong as the number of dairy farmers.

The α4 in *Table 4.1* is the number of major ports within 200 km. The results from the six calibrated models show that the α4 estimates from all February are positive and above 0.1, whereas February 2020 is excluded because the p-value is greater than 0.05. The highest was in 2015 (0.467), and the lowest was in 2018 (0.106). In May, the estimates of α4 were positive except for two interesting negative values in 2016 and 2020. The highest value was in 2015 (0.166), and the lowest was in 2016 (-0.118). The α4 estimates in June were all positive, the highest was in 2016 (0.408), and the lowest was in 2020 (0.084). The results show that as the number of ports increases, the number of transported dairy cattle increases, but in May 2016, the interaction decreased.

The α5 in *Table 4.1* is the length of the road. Comparisons show that the February α5 estimates are all positive, where the highest was in 2018 (0.105), and the lowest was in 2020 (0.026). α5 estimates in May are positive, with the highest in 2016 (0.147) and the lowest in 2015 (0.033). In June, α5 was negative in 2015 (-0.038), and the rest were positive. With a maximum of 0.176 in 2017 and a minimum of -0.038 in 2015. It can be seen that the density of the roads in the TAs has a relatively small impact on the numbers of transported animals within the study period.

The α6 in *Table 4.1* is rainfall. February 2015 and June 2016 were excluded from the results as the parameter estimate values were not statistically significant. In February, the α6 estimate was only positive in 2019 (0.058), with the most influential impact in 2018 (-0.488). In May, α6 was only positive in 2015 (0.048) and had the most influential impact in 2016 (-0.235). The α6 estimate for June had only a positive value in 2019 (0.102), and 2016 (-0.282) had the most influential impact. It can be seen that rainfall impacts the number of transported animals within the study period, but most negatively, which indicates that with rainfall increases, the number of interactions decreases.

The α7 in *Table 4.1* is the total duration of sunshine (per month). The comparison shows that the February α7 estimates were positive in 2018 (0.17) and 2020 (0.291), but the rest showed negative values for all other years 2015 (-0.566), 2016 (-0.174), 2017 (-1.006), and 2019 (-0.169) showing stronger negative relationships. The maximum positive value was 0.291 in 2020, and the significant negative value was -1.006 in 2017. The highest positive value in May's α7 estimate was in 2018 (0.307), while the most negative value was in 2016 (-0.807), and the value in May 2020 is excluded because the p-value is greater than 0.05. In June, the highest positive value was in 2016 (1.031), while the most negative value was in 2018 (-0.454). From this result, we find that the duration of sunshine strongly impacts the flows, positively or negatively. Nevertheless, with changing years, the interaction flows due to the duration of sunshine could be either increased or decreased.

The α8 in *Table 4.1* is water vapour pressure. This variable also has an important influence on the number of flows. We found that 2016 (0.365) and 2017 (0.475) had the only positive parameter estimates in February, where the maximum value was in 2017. For the negative value, the most influential year was 2020 (-1.506), the lowest value across all the years. In May, all values were negative, with the most vital relationship in 2019 (-1.369). α8 estimates were all negative in June, with the strongest in 2019 (-1.250). This indicates that water vapour pressure has been an influential factor in the total number of transported dairy cattle, and the negative estimates indicate that with the increasing water vapour pressure, the number of transported cattle decreases, and vice versa for positive estimates.

The β in *Table 4.1* refers to the distance decay parameter. May 2016 was excluded because the p-value is greater than 0.05. The estimate for February 2015 (-0.048) was the only negative value, and it indicates decreasing interaction. In May, the estimate was the only negative value in 2018 (-0.040). In June, the estimate for 2016 (-0.012) and 2020 (-0.007) had a negative value. However, β had the maximum for February (0.157), May (0.049), and June (0.101) in 2017, which means that for February, May, and June in 2017, with the distance decay increases, the number of transported dairy cattle increases. Generally, the distance decay parameter had a negligible impact on the flows.

Table 4.1. The attraction-constrained model is calibrated for dairy cattle trips from the NAIT programme. α_1 – number of slaughterers; α_2 – number of dairy farmers; α_3 - distance to the nearest ports; α_4 - number of ports within 200 km; α_5 - road length; α_6 - rainfall; α_7 - sun hour; α_8 - vapour pressure; β - distance parameter; # - insignificant, as p-value bigger than 0.05.

All dairy cattle movements (month-year)	Feb-15	Feb-16	Feb-17	Feb-18	Feb-19	Feb-20
parameter	Est. value	Est. value	Est. value	Est. value	Est. value	Est. value
R^2	0.541	0.561	0.726	0.697	0.734	0.730
α_1	0.007	0.075	-0.013	0.044	0.015	0.008
α_2	0.835	0.746	0.752	0.742	0.696	0.741
α_3	0.077	#0.011	0.015	0.178	0.125	0.142
α_4	0.467	0.182	0.170	0.106	0.242	#0.001
α_5	0.031	0.032	0.084	0.105	0.042	0.026
α_6	#0.013	-0.081	-0.025	-0.488	0.058	-0.162
α_7	-0.566	-0.174	-1.006	0.170	-0.169	0.291
α_8	-1.312	0.365	0.475	-0.821	-0.139	-1.506
β	-0.048	0.019	0.157	0.064	0.071	0.043
All dairy cattle movements (month-year)	May-15	May-16	May-17	May-18	May-19	May-20
R^2	0.701	0.689	0.761	0.766	0.760	0.758
α_1	0.035	0.018	0.006	0.006	0.011	0.003
α_2	0.799	0.681	0.848	0.778	0.762	0.773
α_3	0.251	0.147	0.174	0.211	0.094	0.188
α_4	0.166	-0.118	0.074	0.090	0.039	-0.073
α_5	0.033	0.147	0.048	0.043	0.046	0.043
α_6	0.048	-0.235	-0.054	-0.013	-0.051	-0.057
α_7	-0.202	-0.807	-0.029	0.307	-0.094	#0.015
α_8	-0.972	-0.184	-0.661	-0.928	-1.369	-1.048
β	0.008	#-0.004	0.049	-0.004	0.015	0.016
All dairy cattle movements (month-year)	Jun-15	Jun-16	Jun-17	Jun-18	Jun-19	Jun-20
R^2	0.652	0.666	0.730	0.730	0.719	0.730
α_1	0.057	0.038	0.021	-0.002	0.006	0.006
α_2	0.622	0.651	0.773	0.752	0.719	0.741
α_3	0.162	0.157	0.119	0.135	0.115	0.186
α_4	0.221	0.408	0.280	0.140	0.118	0.084
α_5	-0.038	0.052	0.176	0.157	0.114	0.097
α_6	-0.282	#-0.008	-0.084	-0.188	0.102	-0.115
α_7	0.300	1.031	-0.317	-0.454	-0.220	-0.128
α_8	-0.602	-0.729	-0.588	-0.597	-1.250	-1.077
β	0.045	-0.012	0.101	0.062	0.086	-0.007

4.4.2 Beef Cattle

This section describes the results of the destination-constrained model for the beef cattle movement. February, May, and November (low, peak, and sub-peak) were identified as examples of beef cattle in this research based on EDA (Section 3.5.1). The results derived from the calibration of the destination-constrained model for the flows of beef cattle over the six years (2015-2021) are shown in *Table 4.2*. For beef cattle models, comparing annual and monthly R2 values, we found that R2 from 2015 to 2021 have a rising tendency, with the mean values of R2 being for November (0.73), February (0.67) and May (0.69).

The paragraph below describes each parameter estimate in *Table 4.2*. This includes α1 - number of slaughterers, α2 - number of beef farmers, α3 – distance to the nearest port, α4 - number of ports within 200km, α5 - road length, α6 – rainfall, α7 - sun hour, α8 - vapour pressure, and β - distance parameter generated from the destination-constrained model.

The α1 represents the number of slaughterers, and this parameter estimate is positive for all the studied months each year (2015-2021). Comparing the values of α1 for February across the six years, it can be found that the parameter estimate has the highest value in 2017 (0.055) and the lowest in 2016 (0.02). All the α1 values in May across the years, with the largest in 2015 (0.06) and the lowest in 2020 (0.036). The maximum value of α1 in three months in six years occurred in November 2016 and 2019 (both 0.067), and the minimum was in February 2016 (0.02). Similarly, since all the parameter estimates of α1 are no more than 0.1, the influence of this variable can be considered small.

The α2 in *Table 4.2* refers to the number of beef farmers. This parameter estimate was positive for all the months across all the years (2015-2021), and all exceeded α2=0.30, indicating that this variable had a significant impact on the beef cattle flow size. For the α2 estimates, we find that the highest estimate of α2 was in February 2019 (0.65), and the lowest for November 2015 (0.341). It is interesting to see that such an influential parameter has its highest value not in its representative month, and the positive estimate indicates that as the number of beef farmers increases, the number of transported dairy cattle increases.

The α3 in *Table 4.2* is the distance to the nearest major ports. All the parameter estimates are positive, which means that as the parameter increases, the number of spatial interactions increases. Comparing the values of α3 for February across the six years, it can be found that the parameter estimate has the highest value in 2020 (0.418) and the lowest in 2015 (0.155). All the α3 values in May across the years, with the largest in 2019 (0.425) and the lowest in 2016 (0.29). In November, the highest α3 estimate was in 2019 (0.317), and the lowest was in 2019 (0.21). The results show that this parameter estimate had a relatively strong impact on the flows, and it indicates that with the distance to the nearest port increases, the number of transported dairy cattle increases.

The α4 in *Table 4.2* is the number of major ports within 200 km. The results from the six calibrated models show that the α4 estimates have a positive value in 2015 (0.187) and 2019 (0.343), and the rest of the months are negative where the most influential impact in 2017 (-0.328). In May, the estimates of α4 were negative except for two positive values in 2015 (0.274) and 2017 (0.11). The most negative value was in 2019 (-0.272). The α4 estimates in November were positive except in 2019 (-0.035), the highest was in 2015 (0.379), and the lowest was in 2017 (0.035). The results show that the parameter has a positive or negative impact on the volume of flows.

The α5 in *Table 4.2* is the length of the road. Comparisons show that α5 estimates for February were positive in 2016 (0.054) and 2018 (0.027), and the rest of the months had negative values where the most negative value was in 2018 (-0.122). α5 estimates in May are positive except in 2020 (-0.05), where the highest was in 2018 (0.019). In November, α5 was only positive in 2015 (0.073), and the rest were negative where the most negative value in 2018 (-0.095). The density of the roads in the TAs has a relatively small impact on the numbers of transported animals within the study period.

The α6 in *Table 4.2* is rainfall. November of 2018 was excluded from the results as the parameter estimate values were not statistically significant. In February, the α6 estimate was positive in 2017 (0.066) and 2019 (0.177), and the most negative value in 2018 (-0.621). In May, α6 was positive in 2017 (0.123), 2018 (0.06), and 2020 (0.063), negative in 2015 (-0.025), 2016 (-0.2), and 2019 (-0.055). The α6 estimate for November had positive value in 2015 (0.184), and 2020 (0.041), and negative value in 2016 (-0.344), 2017 (-0.149), and 2019 (-0.394). It can be seen that rainfall impacts the number of transported animals within the study period, where a negative value indicates that with rainfall increases, the number of interactions decreases.

The α7 in *Table 4.2* is the total duration of sunshine (per month). November of 2019 was excluded from the results as the parameter estimate values were not statistically significant. The comparison shows that the February α7 estimates were positive in 2017 (0.145) and 2020 (0.561), and the rest showed negative values in 2015 (-1.292), 2016 (-0.906), 2018 (-0.764), and 2019 (-0.062). The highest α7 estimate value in May was positive in 2019 (0.383), while the small negative value was in 2020 (-0.13), and the rest were no less than α7 = -0.50. In November, the positive values were in 2015 (0.37) and 2020 (0.327), and the negative values were in 2016 (-0.257), 2017 (-0.656), and 2018 (-0.099). We find that the sunshine duration strongly impacts the flows for most of the months, positively or negatively.

The α8 in *Table 4.2* is water vapour pressure. The result from November 2017 was excluded as the parameter estimate values were not statistically significant. We found that 2016 (1.196) and 2017 (0.558) had a strong impact on the flows in February, and also the negative value in 2015 (-1.226) and 2020 (-1.806). In May, all values were negative, with the most significant year being 2020 (-0.915). However, α8 estimates in November were only negative in 2020 (-0.168), and the most positive one was in 2019 (0.829). This indicates that water vapour pressure has been an influential factor in the number of transported cattle, and the negative estimates indicate that with the increasing water vapour pressure, the number of transported cattle decreases.

The β in *Table 4.2* refers to the distance decay parameter. The estimate for February 2019 (-0.115) was the most negative value. In May, the estimate had its highest negative value in 2016 (-0.148). In November, the highest estimated value was in 2015 (0.026), and 2020 (-0.084) had the most negative value. From this result, we can see that the distance decay parameter negatively impacts the number of transported cattle, which means that with the distance decay increases, the number of transported cattle decreases.

4.4.3 Comparison between dairy and beef cattle

The results of the destination-constrained model for the two cattle showed similarities and differences in the response of the two cattle to the explanatory variables. Among them, their similarity lies in their high dependence on farmers, which will change with the change in the number of farmers. In addition, the transfer of both cattle breeds has specific infrastructure requirements and positively reflects ports-related variables. Although the two kinds of cattle are not wholly similar in terms of environmental variables, the three kinds of environmental variables negatively impact cattle transportation and movement. According to the results, the difference is that the number of farmers has less impact on beef cattle, while the port-related variables substantially impact beef cattle more than dairy cattle. In addition, the results also indicate that the transportation movement of dairy and beef cattle can be affected by different external factors.

Table 4.2. The attraction-constrained model is calibrated for beef cattle trips from the NAIT programme. α_1 – number of slaughterers; α_2 – number of dairy farmers; α_3 - distance to the nearest port; α_4 - number of ports within 200km; α_5 - road length; α_6 - rainfall; α_7 - sun hour; α_8 - vapour pressure; β - distance parameter; # - insignificant, as p-value bigger than 0.05.

All beef cattle movements	Feb-15	Feb-16	Feb-17	Feb-18	Feb-19	Feb-20
parameter	Est. value	Est. value	Est. value	Est. value	Est. value	Est. value
R^2	0.582	0.628	0.696	0.698	0.713	0.714
α_1	0.028	0.020	0.055	0.035	0.041	0.054
α_2	0.611	0.426	0.527	0.538	0.650	0.565
α_3	0.155	0.324	0.182	0.274	0.283	0.418
α_4	0.187	-0.328	-0.101	-0.289	0.343	-0.087
α_5	-0.091	0.054	-0.066	0.027	-0.111	-0.122
α_6	-0.123	-0.244	0.066	-0.621	0.177	-0.184
α_7	-1.292	-0.906	0.145	-0.764	-0.062	0.561
α_8	-1.226	1.196	0.558	0.088	-0.250	-1.806
β	-0.068	0.010	-0.010	-0.014	-0.115	-0.089
All beef cattle movements	May-15	May-16	May-17	May-18	May-19	May-20
R^2	0.633	0.676	0.720	0.714	0.719	0.733
α_1	0.060	0.045	0.050	0.047	0.056	0.036
α_2	0.497	0.454	0.543	0.498	0.457	0.490
α_3	0.346	0.290	0.308	0.324	0.425	0.248
α_4	0.274	-0.094	0.110	-0.025	-0.272	-0.076
α_5	0.015	0.012	0.007	0.019	0.017	-0.050
α_6	-0.025	-0.200	0.123	0.060	-0.055	0.063
α_7	-0.573	-0.794	-0.938	-0.640	0.383	-0.130
α_8	-0.840	-0.537	-0.617	-0.208	-0.573	-0.915
β	-0.134	-0.148	-0.097	-0.124	-0.119	-0.121
All beef cattle movements	Nov-15	Nov-16	Nov-17	Nov-18	Nov-19	Nov-20
R^2	0.682	0.725	0.730	0.726	0.738	0.751
α_1	0.066	0.067	0.066	0.049	0.067	0.048
α_2	0.341	0.550	0.489	0.545	0.482	0.575
α_3	0.294	0.299	0.225	0.210	0.317	0.300
α_4	0.379	0.165	0.035	0.165	-0.035	0.230
α_5	0.073	-0.036	-0.033	-0.095	-0.028	-0.073
α_6	0.184	-0.344	-0.149	#-0.004	-0.394	0.041
α_7	0.370	-0.257	-0.656	-0.099	#-0.014	0.327
α_8	0.173	0.367	#0.014	0.241	0.829	-0.168
β	0.026	-0.023	-0.031	-0.039	-0.027	-0.084

4.5 Cattle GWR Modelling

In this section, we aim to explain the local relationships between a dependent variable (Table 4.3) and a set of independent variables (Table 3.2 and 3.4, Section 3.3.2) using GWR. Based on exploratory data analysis, the number of dairy cattle transported each year was the lowest in February, the highest in May and the second-highest in June. The lowest number of beef cattle movements were observed in February, the highest in May and the second highest in November. To address and explain these peaks, we focused our modelling on the identified months across the years: dairy cattle in May and beef cattle in May for 2016 and 2019. As shown in Table 4.3, the dependent variables are the numbers of inflowing and outflowing dairy and beef cattle. Independent variables include the number of dairy or beef farmers, the number of slaughterers, the distance to the nearest port, the total number of ports, road length, rainfall, vapour pressure, and sunshine hours (Table 3.2 and 3.4, Section 3.3.2).

Table 4.3. Description of the dependent variables in GWR modelling

Dependent Variable	**Description**
Inflowing dairy cattle	The number of dairy cattle flows into a territorial authority
Inflowing beef cattle	The number of beef cattle flows into a territorial authority
Outflowing dairy cattle	The number of dairy cattle flows out from a territorial authority
Outflowing beef cattle	The number of beef cattle flows out from a territorial authority

4.5.1 Stepwise-AIC Optimisation

Through a standard procedure, “Akaike Information Criterion (AIC)” (Section 3.6.5), to optimise a set of variables before calibration, a set of independent variables corresponding to the dependent variables was identified. We unified the combinations of independent variables for May 2016 and 2019 and calibrated the GWR model with the corresponding dependent variables to make the models comparable. Table 4.4

presents a final set of variables chosen for each dependent variable. The final GWR results include coefficient estimates, AICc, and R2, where the lower AICc stands for better model fit.

Table 4.4. Independent variable's selection based on AICc optimisation for GWR modelling

Dependent / **Independent**	Inflowing dairy cattle	inflowing beef cattle	outflowing dairy cattle	outflowing beef cattle
Dairy/Beef farmer	Included	Included	Included	Included
Slaughterer	Included	Included		Included
The nearest port	Included			
Number of ports			Included	
Road length				
Rainfall	Included		Included	Included
Vapour pressure		Included	Included	Included
Hours of sunshine			Included	

4.5.2 Poisson GWR Calibration

From the calibrated models, we have both the global linear model (Table 4.5) and Poisson GWR models' diagnostics (Table 4.6). Looking at the global linear models' diagnostics (Table 4.5), we found that the Pseudo R2 values for the models were generally lower in May 2016, except for beef inflow models in which the Pseudo R2 value in May 2016 (0.29) was bigger than in May 2019. For the AICc value, all models for May in 2016 had a lower AICc value than those for May in 2019, indicating that models for May in 2016 have a better model fit in global linear modelling.

Table 4.5 Global linear model's diagnostics of dairy inflows and outflows and beef inflows and outflows for May 2016 and 2019 model calibration.

Global Linear Model Diagnostics

Dairy inflow			Dairy outflow		
	May-16	May-19		May-16	May-19
Pseudo R^2	0.70	0.70	Pseudo R^2	0.70	0.75
AICc	136542.6	374958.2	AICc	136203.5	310540.5
Beef inflow			Beef outflow		
	May-16	May-19		May-16	May-19
Pseudo R^2	0.29	0.28	Pseudo R^2	0.27	0.29
AICc	191523.9	332036	AICc	177258.9	291183.5

From the calibrated Poisson GWR models (Table 4.6), we found that the inflowing dairy (0.88) and beef cattle (0.8) for May in 2016 had higher Pseudo R2 than May in 2019 (Dairy: R2=0.86, Beef: R2=0.72). Nevertheless, for the outflowing cattle models, the outflowing dairy cattle had identical Pseudo R2 for both 2016 (0.92) and 2019 (0.92), and the outflowing beef for May 2019 (0.78) had a higher Pseudo R2 than in May 2016 (0.77). Similar to global linear models, the AICc values were generally lower in May 2016 than in May 2019 for all dairy and beef cattle models, where the smallest AICc value was in May 2016 (34911.5). However, for the outflowing beef cattle models, we find that the Pseudo R2 and AICc values had a different explanation of the model and variable fit (Table 4.6), where lower AICc indicates better model fit, and lower Pseudo R2 indicates less explanation of variables. Therefore, the dependent variables can have different sets of independent variables explained.

Table 4.6 Poisson GWR model's diagnostics of dairy inflows and outflows and beef inflows and outflows for May 2016 and 2019 model calibration.

Poisson GWR Model Diagnostics

Dairy Inflow			Dairy Outflow		
	May-16	May-19		May-16	May-19
Pseudo R^2	0.88	0.86	Pseudo R^2	0.92	0.92
AICc	52250.8	181205.2	AICc	34911.5	104355.5
Beef inflow			Beef outflow		
	May-16	May-19		May-16	May-19
Pseudo R^2	0.8	0.72	Pseudo R^2	0.77	0.78
AICc	54338.19	127905.2	AICc	56848.05	89097.17

To visualise the results and investigate the local effects different factors have on the size of incoming and ongoing flows to different regions, we mapped significant parameter estimates (at a 95% confidence level with 1.96 < t-values < -1.96). The parameter estimate is essentially the slope of the regression line for the data at each location. Therefore, when looking at a map, a positive parameter estimate corresponds to increased values of dependent variables in places with an increase in the value of the independent variable. A negative parameter implies a decrease in the dependent variable with an increase in the independent variable.

4.5.3 Interpretation of outflow of Dairy Cattle Estimates Map

The parameter estimate maps derived from the calibration of the GWR model for the relationship between the outflowing number of dairy cattle and the independent variables ‘number of dairy farmers‘ in two years (2016 and 2019) are shown in the figures below (Figure 4.8). By comparing the spatial relationship in May 2016 and 2019, we found that the whole New Zealand had positive estimates, where their highest estimates concentrated around the southernmost tip of the North Island and the northernmost tip of the South Island. The positive estimates of dairy farmers mean that there are more outflowing dairy cattle with a greater number of dairy farmers. Generally, the variable ‘number of dairy farmers’ had more impact on the outgoing dairy cattle in the South Island in May 2016 than in 2019 (Figure 4.8). However, the largest estimates were bigger in 2016 (0.007), and 2019 (0.005) had a smaller parameter estimate (Figure 4.8).

a) Outflow of dairy cattle in May 2016 b) Outflow of dairy cattle in May 2019

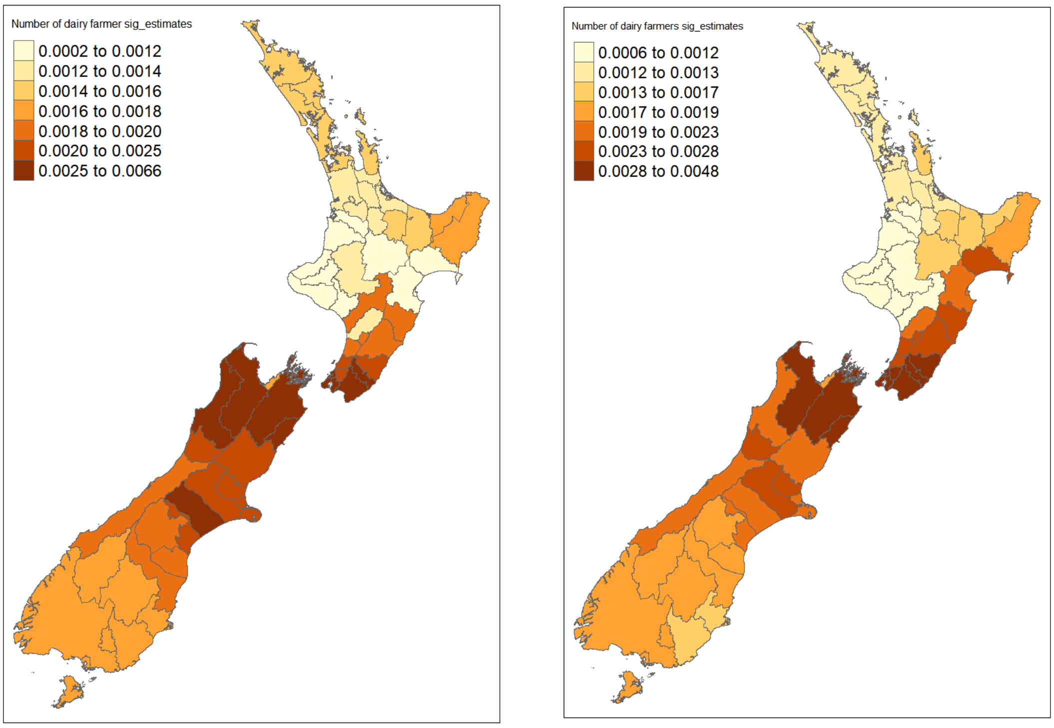


*Figure 4.8. Variable 'number of dairy farmers' influence on outgoing dairy cattle in May 2016 and 2019 showed in **a)** and **b** in New Zealand territorial authorities.*

The 'number of ports' variable is used as an alternate variable related to port to show the relationship between outflowing dairy cattle and primary ports. The maps (Figure 4.9) below show the relationship pattern in New Zealand. We found that the highest positive estimates were concentrated around the southernmost tip of the North Island, and the highest negative estimates were concentrated around the northmost tip of the South Island. Still, the largest positive value was higher in the 2016 model than in 2019, but the largest negative value was higher in 2019. However, the pattern in the northernmost and middle of the North Island had changed from positive to negative, meaning there are fewer outgoing dairy cattle with a greater number of primary ports within 200 km. Also, the pattern around the westernmost tip of the North Island had a negative value changed to a positive value, which means that there are more outflowing dairy cattle with a greater number of primary ports within 200km.

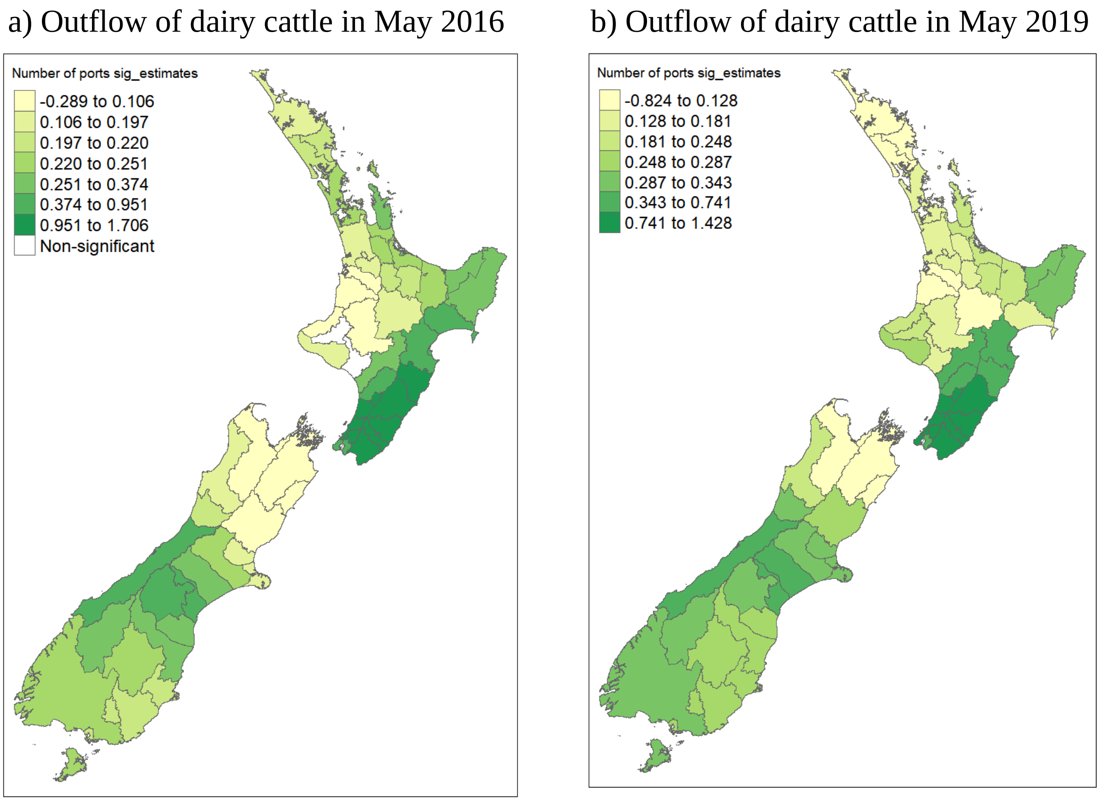


Figure 4.9. Variable 'number of ports' influence on outgoing dairy cattle in a)2016 and b)2019 in New Zealand territorial authorities.

For the rainfall variable, the pattern was changeable in the middle of the North Island and the northern part of the South Island in 2016 and 2019. For the estimates in both 2016 and 2019, the positive estimates were focused on the north part of the North and South Island, where the highest positive estimates were larger in 2016, but the positive estimates in 2019 had more levels. The positive parameter estimates imply that with the higher amount of rain, more cattle are being moved out of the TAs. For the negative estimates, they were mainly located in the lower half of the North and South Islands. The patterns of rainfall estimates were changing, where the higher negative rainfall estimate around the middle of the North Island in May 2016 was turned to a lower estimate in May 2019, and there also were negative values changed to a positive value in the east of the North Island and the northernmost of the South Island. The negative parameter estimates imply that fewer cattle are transported to other regions with higher rain levels. The results show the effect of rain changes over the two years; for the positive parameter estimate, the largest interval was between 0.004 to 0.013 in 2016, but in 2019, it was between 0.007 to 0.011. For the negative parameter estimate, the values ranged from -0.027 in 2016 to -0.01 in 2019 (Figure 4.10).

a) Outflow of dairy cattle in May 2016 b) Outflow of dairy cattle in May 2019

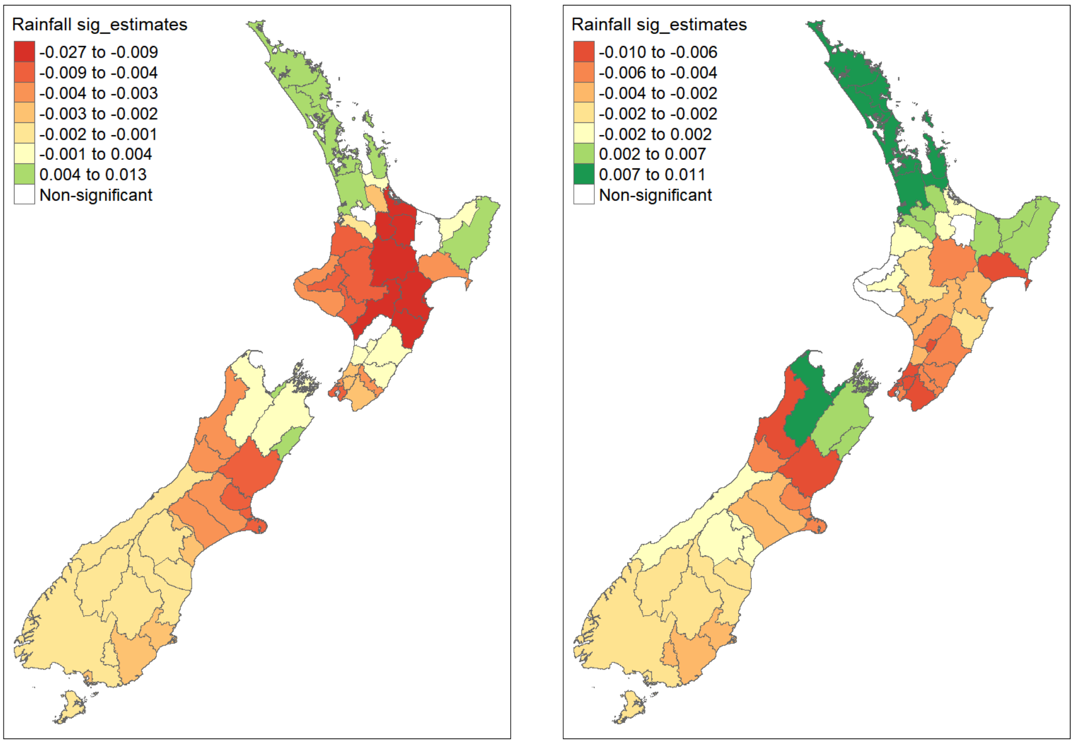


Figure 4.10. Variable 'Rainfall' influence on outgoing dairy cattle in a)2016 and b)2019 in New Zealand territorial authorities.

The parameter estimates for the daily amount of sunshine in 2016 and 2019 had an interesting changing pattern for both the North and South Islands. For values in 2016, the most negative values were mainly found in the middle of the North Island, including the region of Waikato, Manawatu-Wanganui, Hawke's Bay, and Bay of Plenty (Figure 4.11). The most positive values were found in the Northland, Tasman, Nelson, Marlborough and Southland regions (Figure 4.11). For values in 2019, the most negative values were mainly found across the region of the West Coast and Canterbury on South Island with Taupo and Wairoa district on the North Island, and the most positive value was found across the Manawatu-Wanganui, Wellington, Tasman, Nelson, and Marlborough region (Figure 4.11).

However, their pattern was spotted changing, where the positive estimates around the upper north of the North Island and the lower south of the South Island were changed to negative (Figure 4.11). The negative estimates around the lower south of the North Island were changed to positive (Figure 4.11). Also, the strongest negative and positive parameter estimates for 2016 had more effect than in 2019. In general, the negative values here imply that there are fewer outgoing dairy cattle where there are long hours of sunshine, and the positive estimates imply more outgoing dairy cattle where there are long hours of sunshine.

a) Outflow of dairy cattle in May 2016 b) Outflow of dairy cattle in May 2019

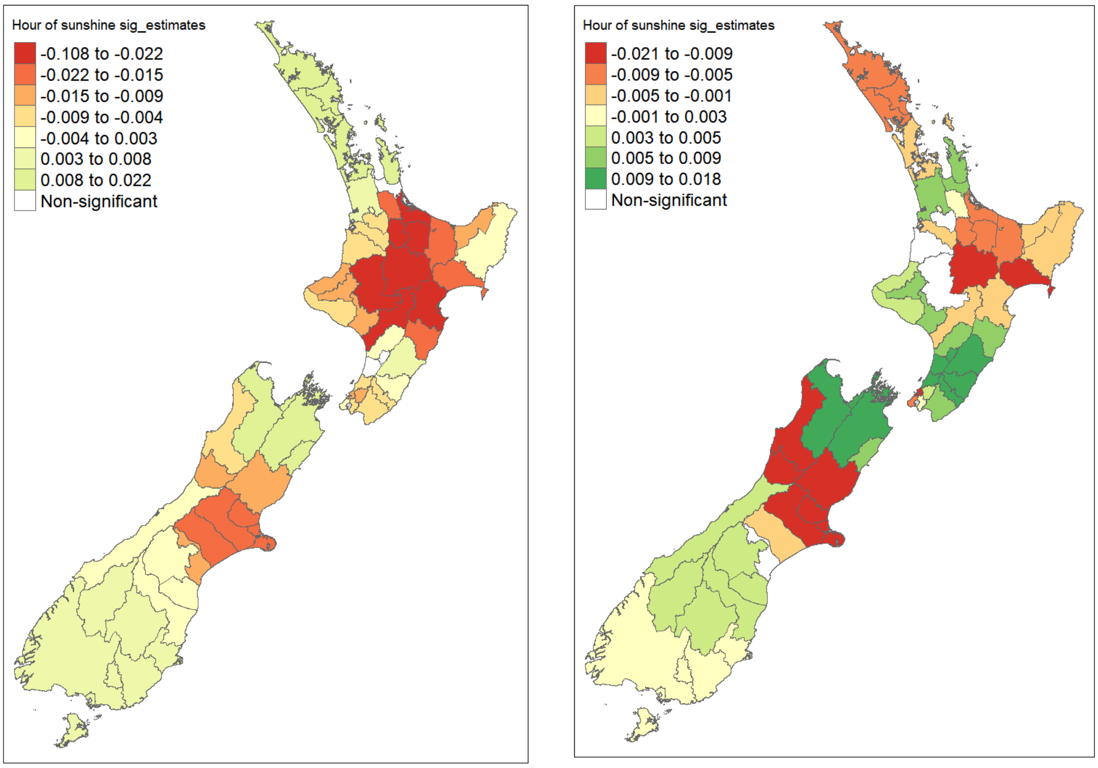


Figure 4.11. Variable 'Hour of sunshine' influence on outgoing dairy cattle in a)2016 and b)2019 in New Zealand territorial authorities.

Vapour pressure is used as a proxy of temperature, and higher vapour pressure represents higher temperature and vice versa. In the two study years: 2016 and 2019, the maps showed changing pattern, where the values being the most negative in 2016 were located around the Gisborne region and a small part of the Wellington region in North Island, and positive values in 2016 were spotted in the Northland, Otago, and Southland region (Figure 4.12). For the values in 2019, most of the pattern in 2016 remained the same, but there with stronger negative estimates spotted, such as the TAs in Waikato, Bay of Plenty, Hawke's Bay, and Wellington in North Island and West Coast, Canterbury, Marlborough, Tasman, and Nelson region in South Island (Figure 4.12). In general, the largest negative and positive estimate interval for 2016 was weaker than in 2019 (Figure 4.12). The negative values here imply that there are fewer outgoing dairy cattle where there is higher vapour pressure, and the positive estimates imply more outgoing dairy cattle where there is a higher vapour pressure.

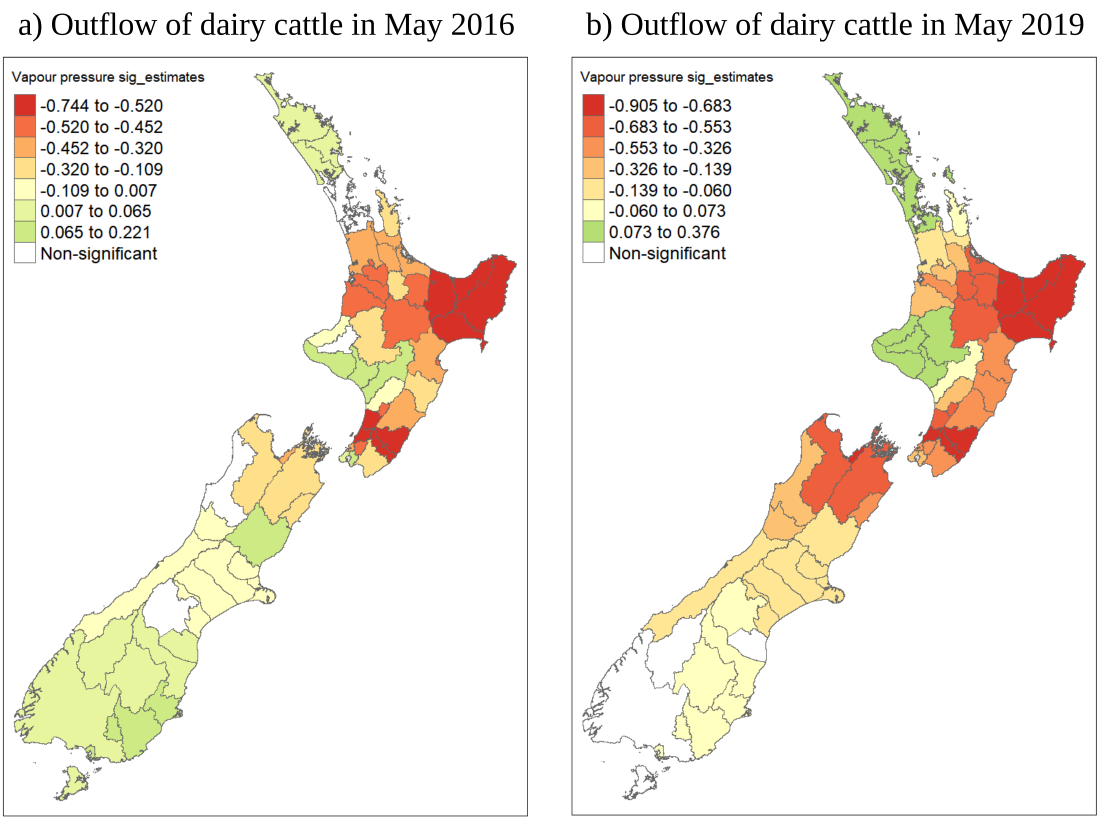


Figure 4.12. Variable 'Vapour pressure' influences outgoing dairy cattle in a)2016 and b)2019 in New Zealand territorial authorities.

4.5.4 Interpretation of Inflow of Dairy Cattle Estimates Map

In Figure 4.13, the maps show the relationship between the inflow of dairy cattle and the number of dairy farmers in May for 2016 (a) and 2019 (b), respectively. In Figure 4.13, we found that the whole New Zealand had positive parameter estimates, where the highest estimates values were concentrated around the Wellington region in the North Island and the upper part of the West Coast, Canterbury, Tasman, Nelson, and Marlborough region in the South Island for the spatial relationship in May 2016. In 2019, the pattern had mainly shifted from the south to the east in the Bay of Plenty, Gisborne, and Hawke's Bay region, North Island. The positive estimates of dairy farmers mean that there are more outflowing dairy cattle with a greater number of dairy farmers. Generally, the variable 'number of dairy farmers' has more impact on the inflowing dairy cattle in the South Island in May 2019 than in 2016 (Figure 4.13). However, the largest estimates were bigger in 2016 (0.009), and 2019 (0.002) had a smaller estimate (Figure 4.13).

a) Inflow of dairy cattle in May 2016 b) Inflow of dairy cattle in May 2019

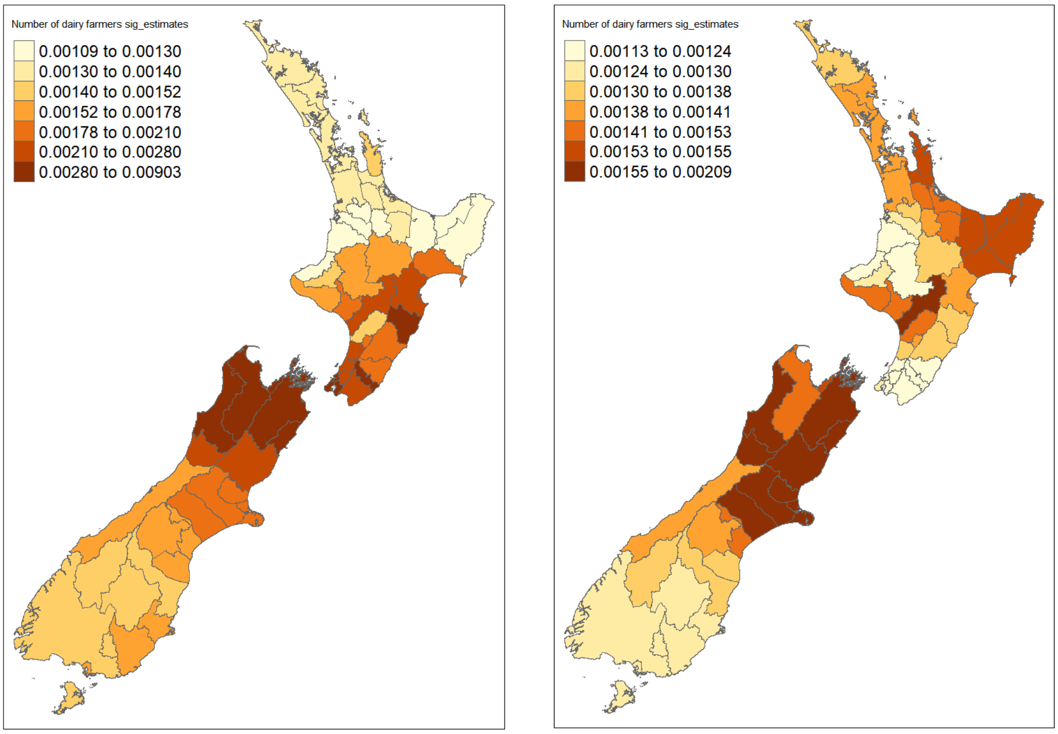


*Figure 4.13. Variable 'number of dairy farmers' influence on inflowing dairy cattle in May 2016 and 2019 showed in **a)** and **b** in New Zealand territorial authorities.*

Figure 4.14 shows the two maps of the relationship between the inflow of dairy cattle and the number of slaughterers in May for 2016 (a) and 2019 (b). In 2016, the values of parameter estimates indicated a strong relationship contained both positive and negative values, where negative values covered almost the whole New Zealand, with the negative values mainly in the Waikato, Taranaki, Manawatu-Wanganui, Hawke's Bay, Wellington, and Nelson regions *(Figure 4.14).*

In 2019, the parameter estimates had mainly become positive, with some negative values located in the Taranaki and Manawatu-Wanganui region *(Figure 4.14)*. The strongest positive estimates can be seen in Waikato, Bay of Plenty, and Gisborne, mainly on North Island. The change in patterns could be caused by the change in the social structure (Nungesser and Winter, 2021), marketing demands (Nguyen et al., 2007), or data inaccuracy.

a) Inflow of dairy cattle in May 2016 b) Inflow of dairy cattle in May 2019

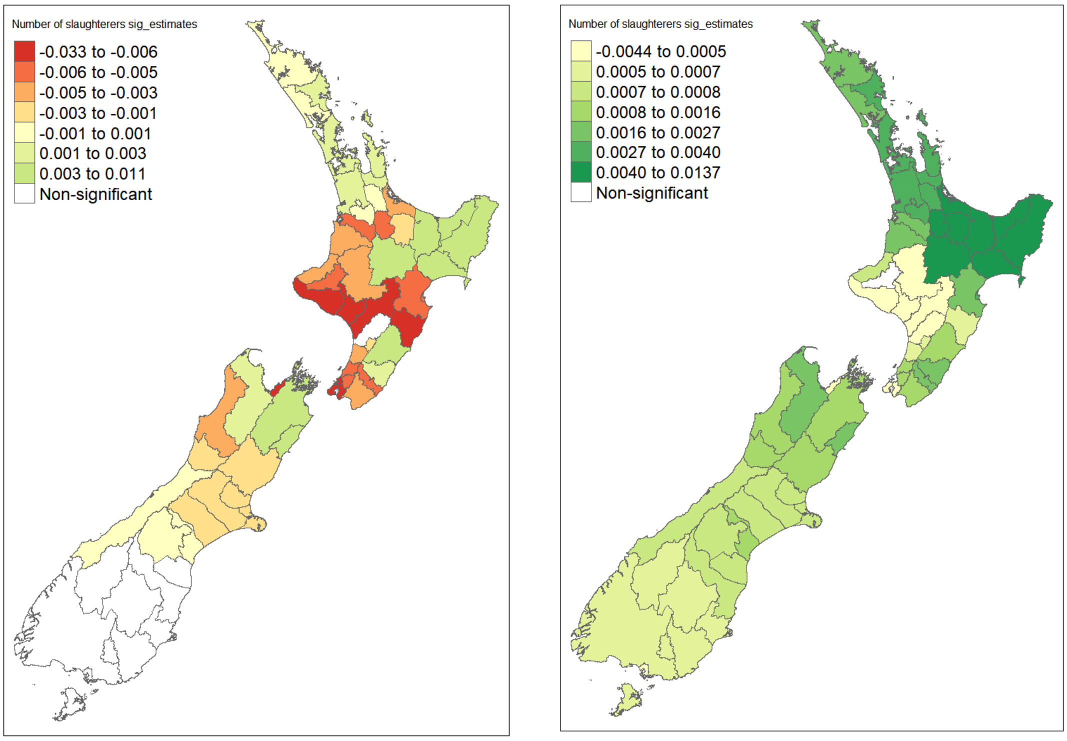


*Figure 4.14. Variable 'number of slaughterers' influence on inflowing dairy cattle in May 2016 and 2019 showed in **a)** and **b** in New Zealand territorial authorities.*

The parameter estimates for the nearest port in 2016 and 2019 had an interesting changing pattern for both the North and South Islands (*Figure 4.15*). In 2016, the strongest positive estimates were found in the Taupo and Wairoa district and the Wellington region on the North Island, and the strongest negative values were found in the Central Hawke's Bay district and West Coast and Canterbury region on the South Island *(Figure 4.15*). For values in 2019, the strongest positive estimates were shifted mainly in Waikato, Bay of Plenty, and the Tasman region (*Figure 4.15*). However, the negative estimates were spotted in the lower south of South Island (*Figure 4.15*). The maps have shown us that the higher TAs closer to the primary port, the higher the positive estimates, but the pattern can change with other factors' influence.

a) Inflow of dairy cattle in May 2016 b) Inflow of dairy cattle in May 2019

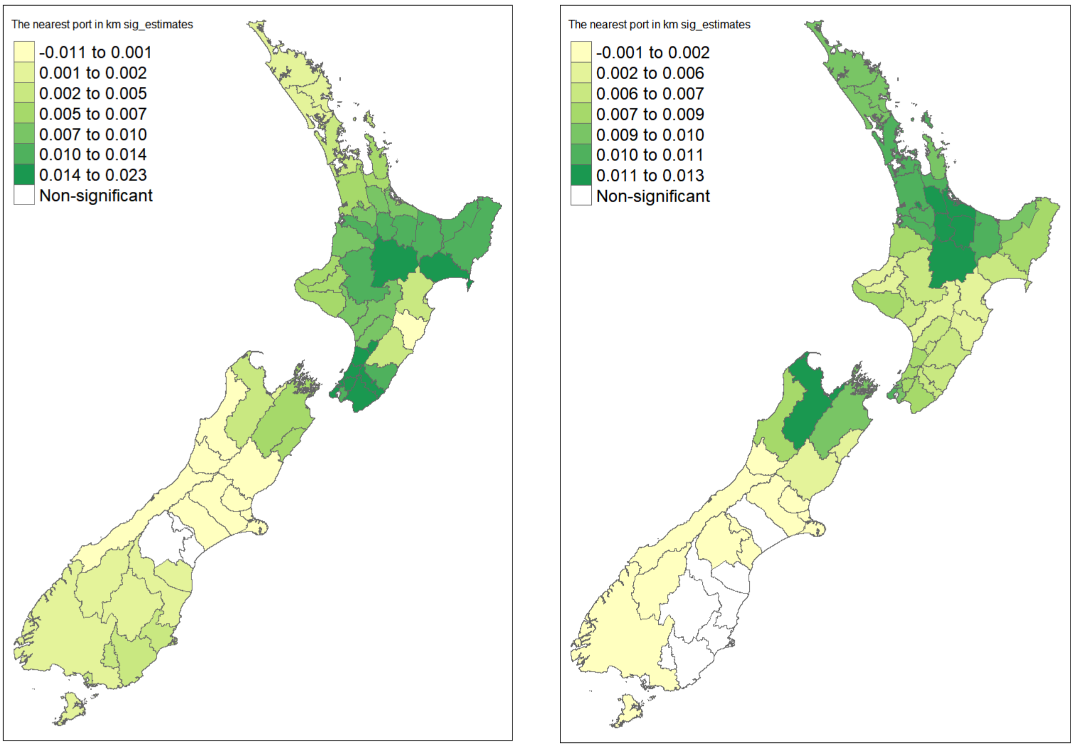


Figure 4.15. Variable 'number of slaughterers' influence on inflowing dairy cattle in May 2016 and 2019 showed in ***a)*** *and* ***b*** *in New Zealand territorial authorities.*

The rainfall parameter estimates maps were shown for May 2016 and 2019, and the patterns were similar (*Figure 4.16*). As shown in *Figure 4.16*, the strongest positive estimates were mainly focused on the Bay of Plenty and Gisborne region for 2016 and 2019. The strongest negative parameter estimates were mainly located in the whole South Islands for 2016, except Nelson and Marlborough region in 2019. However, the patterns of estimates changed, where the highest negative rainfall estimates in South Island from May 2016 were shifted from the Southland region to the upper regions in May 2019, and the positive parameter estimated values around the Northland and Auckland region in 2016 became negative (*Figure 4.16*).

a) Inflow of dairy cattle in May 2016 b) Inflow of dairy cattle in May 2019

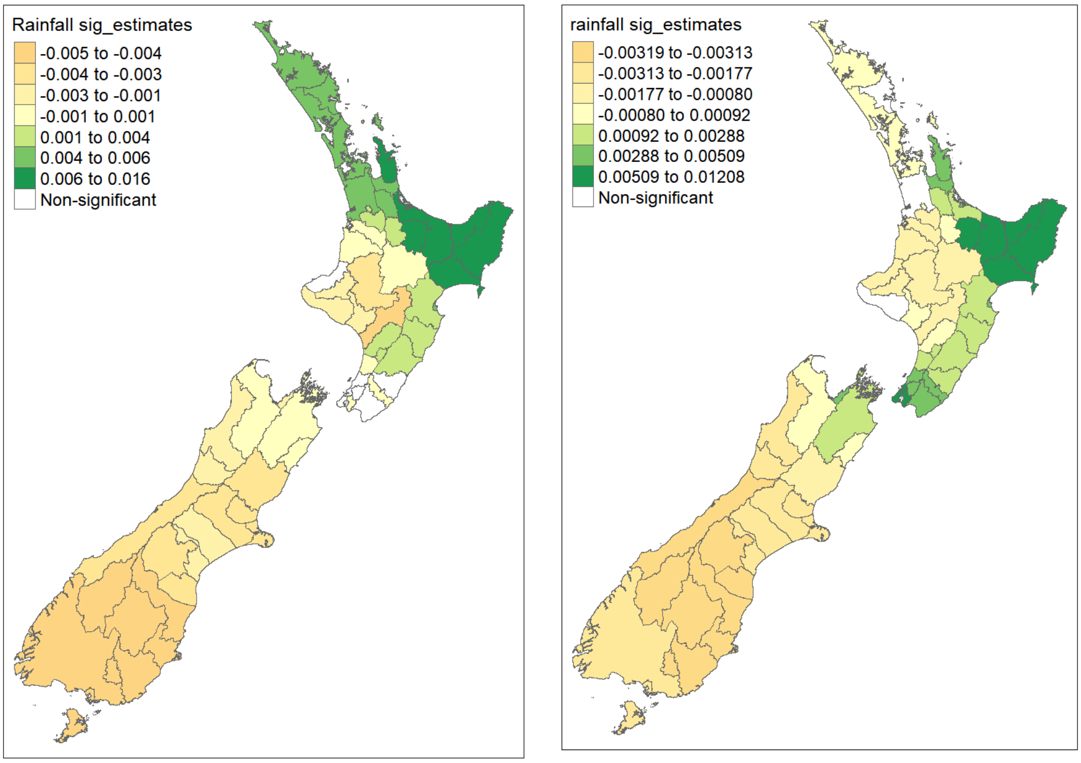


*Figure 4.16. Variable 'number of slaughterers' influence on inflowing dairy cattle in May 2016 and 2019 showed in **a)** and **b** in New Zealand territorial authorities.*

4.5.5 Interpretation of Outflow of Beef Cattle Estimates Map

Compared to the result of dairy cattle GWR modelling, the outflow of beef cattle estimates had fewer parameters fit in the set of variables. In *Figure 4.17*, the maps show that the relationship pattern between beef cattle's outflow and the number of beef farmers in May for 2016 (a) and 2019 (b) were similar. As *Figure 4.17* shows, we found that the parameter estimates were all positive for 2016 and 2019, where the highest estimates interval was mainly concentrated around the Wellington region on the North Island. However, there were changes from lower to higher estimates between 2016 and 2019, such in Hauraki, South Taranaki, Ruapehu, Kaikoura and Timaru districts. Also, changes from a higher value to a lower, such as Waikato and Hamilton. Generally, the impact of the number of beef farmers on the outflowing beef cattle had minor changes between 2016 and 2019 (*Figure 4.17*).

a) Outflow of beef cattle in May 2016 b) Outflow of beef cattle in May 2019

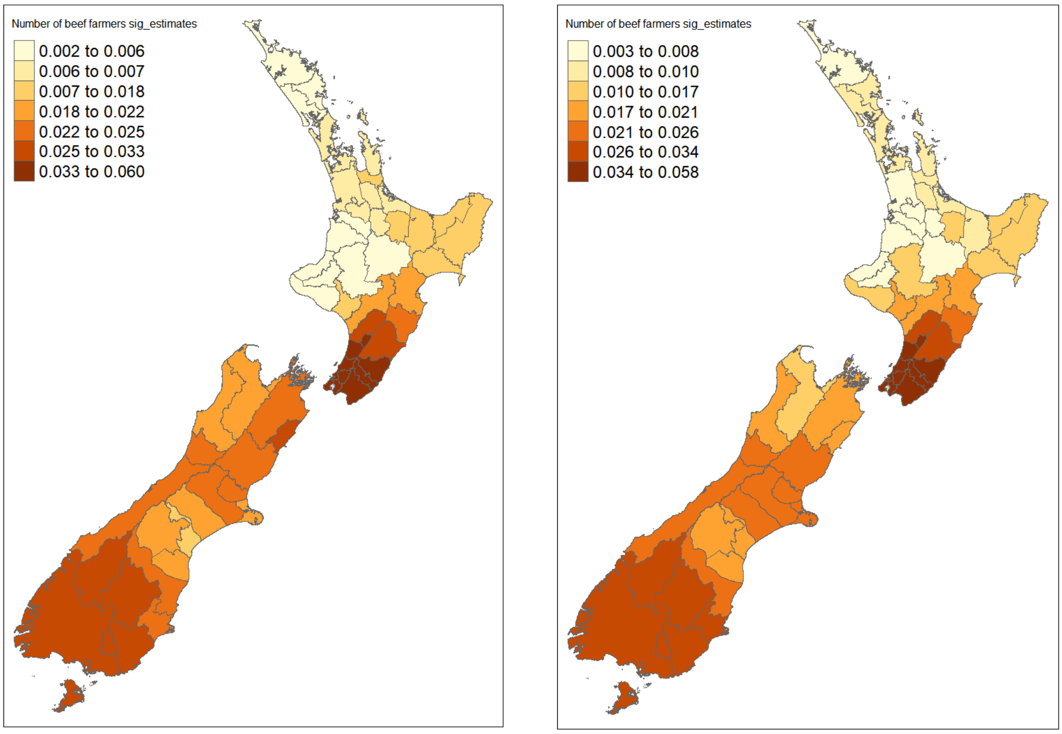


*Figure 4.17. Variable 'number of beef farmers' influence on outflowing beef cattle in May 2016 and 2019 showed in **a)** and **b** in New Zealand territorial authorities.*

For the 'number of slaughterers', as *Figure 4.18* shows, we found that the positive parameter estimates were more in 2019 than in 2016. The positive estimates were mainly located in the middle of North Island and the upper part of South Island, including Waikato, Bay of Plenty, Gisborne, West Coast, Tasman, Nelson, Marlborough, and Canterbury region 2019. The negative parameter estimates in 2016 remained in the same area in 2019 but slightly changed from strong to mild estimates.

a) Outflow of beef cattle in May 2016 b) Outflow of beef cattle in May 2019

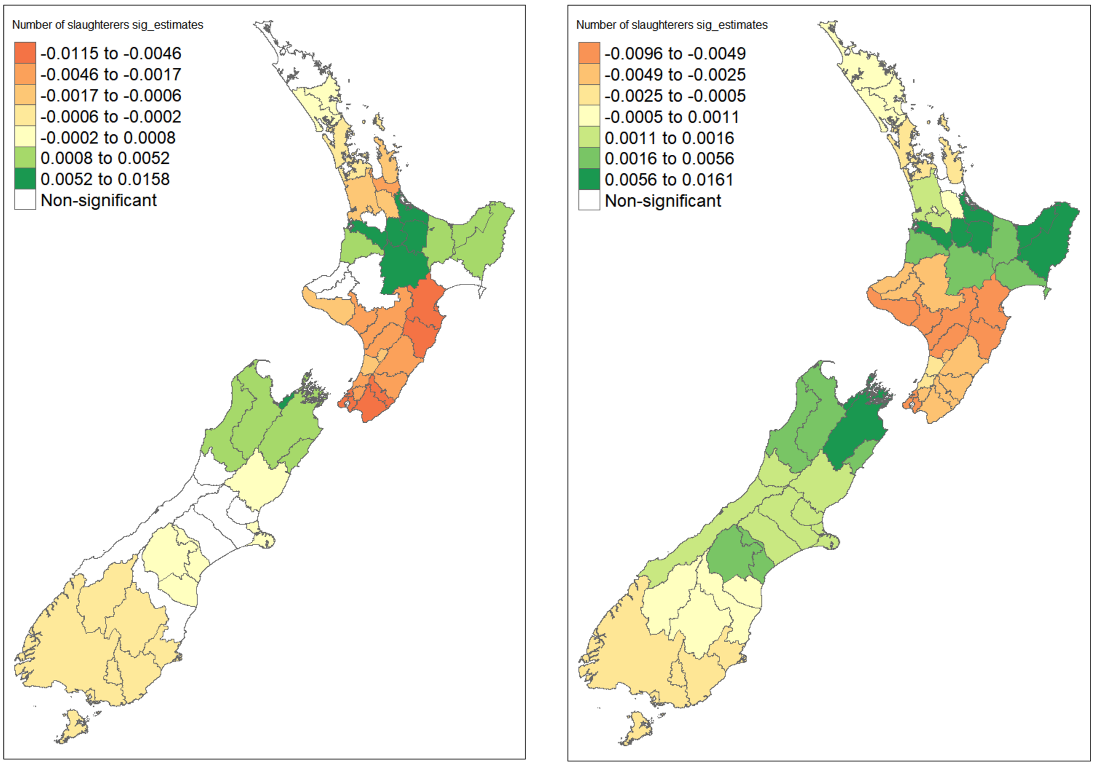


*Figure 4.18. Variable 'number of slaughterers' influence on outflowing beef cattle in May 2016 and 2019 showed in **a)** and **b** in New Zealand territorial authorities.*

The relationship between vapour pressure and the outflow of beef cattle shows a similar pattern between 2016 and 2019. *Figure 4.19* shows that the most vital negative estimates were located in the upper part of North Island, including the Northland and Auckland regions, in both 2016 and 2019. However, the Tasman, Nelson, and Marlborough region areas slightly changed between 2016 and 2019. Also, some territorial authorities, such as Gisborne, Selwyn, and Waimakariri districts, had negative estimates in 2016, turning to positive values in 2019 (*Figure 4.19*). The places where positive values changed to negative covered Rangitikei and Central Hawke's Bay districts.

a) Outflow of beef cattle in May 2016 b) Outflow of beef cattle in May 2019

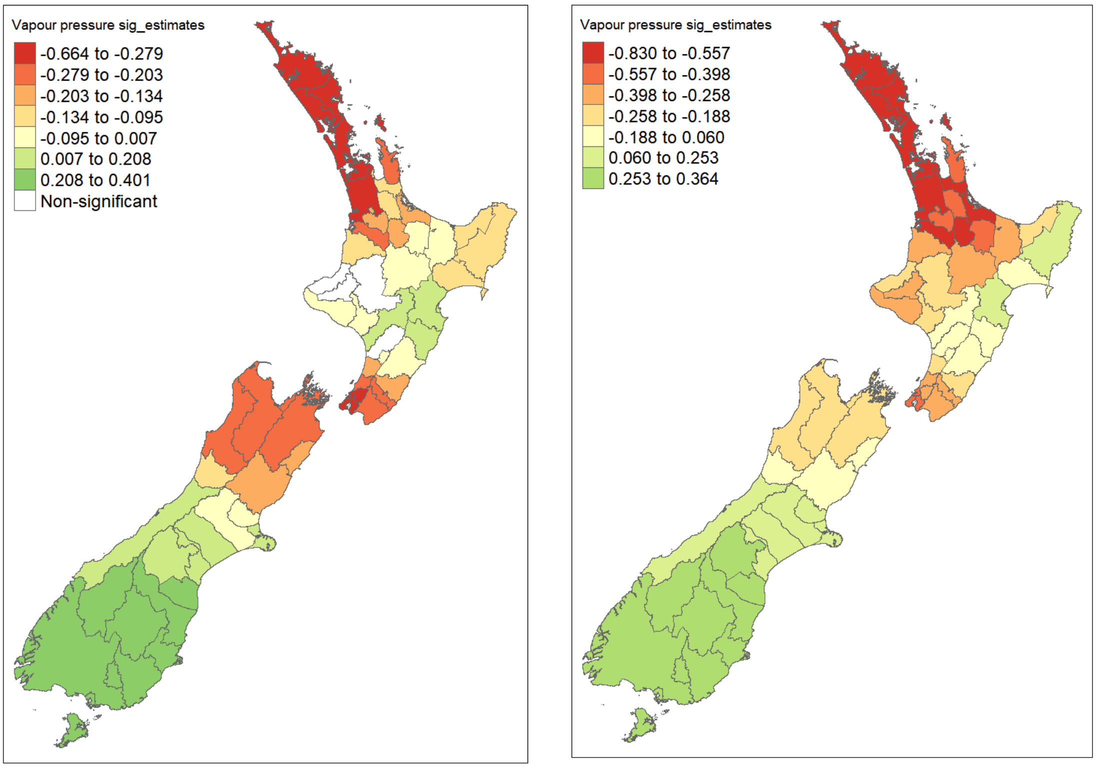


*Figure 4.19. Variable 'Vapour pressure' influence on outflowing beef cattle in May 2016 and 2019 showed in **a)** and **b** in New Zealand territorial authorities.*

4.5.6 Interpretation of Inflow of Beef Cattle Estimates Map

There were changes when comparing the pattern of the number of beef farmers for the inflow of beef cattle between 2016 and 2019 in *Figure 4.20*. The two maps all showed positive parameter estimates for the sixty-six TAs, and most patterns were similar but with different values. For example, regions like Wellington and Southland had higher estimates, but the estimates interval in 2016 (0.034-0.051) was higher than in 2019 (0.032-0.044). Also, some authorities changed to lower estimate intervals but also changed to higher estimate intervals, such as Ruapehu district (lower to higher) and Gisborne district (higher to lower).

a) Inflow of beef cattle in May 2016 b) Inflow of beef cattle in May 2019

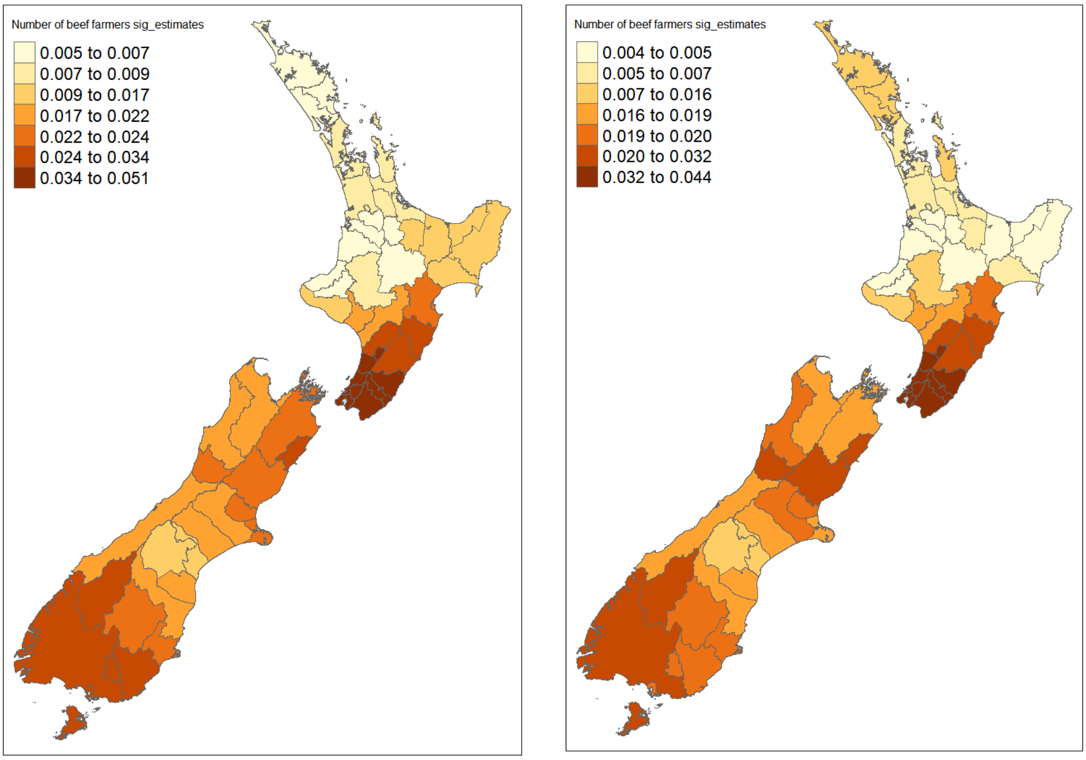


*Figure 4.20. Variable 'number of beef farmers' influence on inflowing beef cattle in May 2016 and 2019 showed in **a)** and **b** in New Zealand territorial authorities.*

The number of slaughterers' estimates is shown in *Figure 4.21*. There also were interesting changes between 2016 and 2019. For example, the negative values in 2016 were more substantial than in 2019. The negative values were located in the Auckland, Waikato, Hawke's Bay, and Southland region in 2016. Still, they had narrowed to only two Tas (Tararua and Central Hawke's Bay) in North Island and expanded to include the Otago region on South Island in 2019 (*Figure 4.21*). Also, the most vital positive estimates were mainly shifted from the Marlborough and some parts of the Waikato region in 2016 to the whole Waikato, Bay of Plenty, and the Gisborne region in 2019.

a) Inflow of beef cattle in May 2016 b) Inflow of beef cattle in May 2019

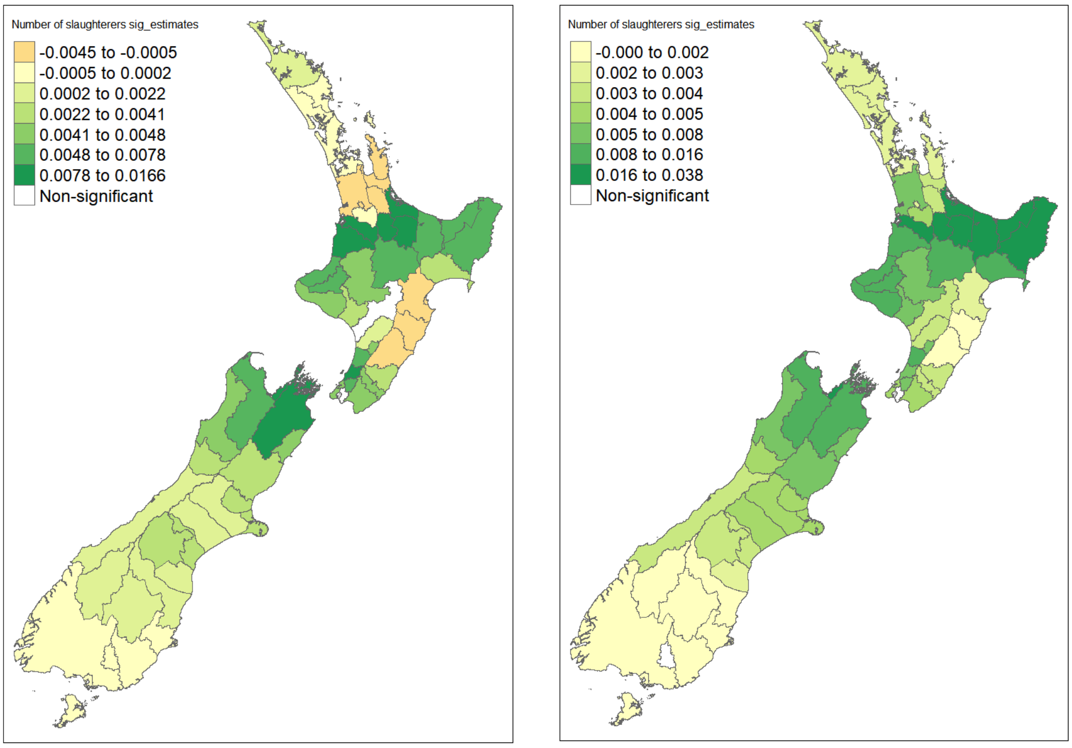


*Figure 4.21. Variable 'number of slaughterers' influence on inflowing beef cattle in May 2016 and 2019 showed in **a)** and **b** in New Zealand territorial authorities.*

The vapour pressure estimates maps show a similar pattern for most TAs between 2016 and 2019, but slight changes happened in some of the TAs (*Figure 4.22*). For example, the changes happened in the middle of North Island, where the Waikato region had the stronger relationship between the dependent and independent variables, and the Gisborne region had changed from negative values to positive. Also, the changes were spotted in the regions across Tasman, Nelson, and Marlborough on South Island. Additionally, the higher positive estimates across South Island, Southland and Otago regions had shifted to the mainly Canterbury region.

a) Inflow of beef cattle in May 2016 b) Inflow of beef cattle in May 2019

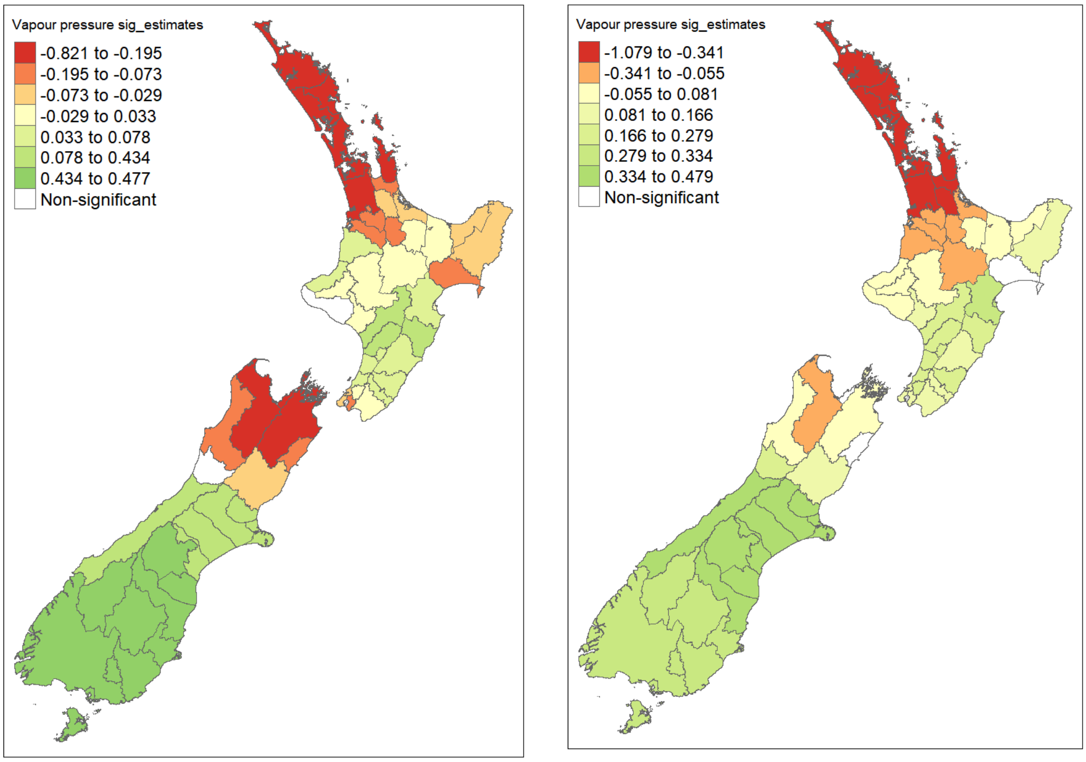


*Figure 4.22. Variable 'Vapour pressure' influence on inflowing beef cattle in May 2016 and 2019 showed in **a)** and **b** in New Zealand territorial authorities.*

4.6 Summary

This chapter summarises the different methods used to evaluate cattle transport movements and their relationship to explanatory variables. The results of exploratory data analysis indicate that dairy and beef cattle transportation movement peaks around May and low peaks around February. The exploratory spatial data analysis results showed that the environmental variables in 2016 and the density maps of static human-based variables showed that the duration of sunshine, rainfall, and vapour pressure was higher on the North Island than on the South Island. In addition, human-based variables are primarily distributed in most areas of North Island. The destination-constrained model in SI modelling showed that the number of dairy farmers, the nearest distance to the port, the number of the nearest port, and three environmental variables positively or negatively affected the flows of dairy and beef cattle depending on the season and year. The relationship between the explanatory variables and the inflow and outflow of cattle in 2016 and 2019 was modelled using GWR, showing that the spatial relationship between the individual explanatory variables and the inflow and outflow of cattle changed over time, positive or negative. Also, some regions remained positive or negative in 2019 compared to 2016.

5 Discussion

This chapter explains and discusses the results obtained in this research. We use the derived results to discuss the implication of temporal patterns of transporting cattle and potential factors influencing dairy, and beef cattle transport flows in the North and South Islands of New Zealand. Further, we attempt to discuss how these results can contribute to understanding disease transmission. Finally, the limitations of this study and the areas needing improvement are discussed.

5.1 Peak and off-peak of Transporting Cattle Movement and Its Implication

Many factors affect the timing of transporting livestock animals. It can be driven by environmental factors, such as season and climate, and human factors, such as market demand and artificial mating. Those factors can cause livestock to move from farm to farm, and the moving time varies from animal to animal. Exploratory Data Analysis (EDA) was used to visualise and understand potential trends in the data (Tukey, 1977; Komorowski et al., 2016). EDA (Section 3.5.1) was used to explore the data sets of dairy and beef cattle, respectively, to find similarities and differences in the temporal patterns between the two types of animals. Between 2015 and 2020 in New Zealand, dairy and beef cattle seemed to be mainly transported in May, and the lowest numbers were recorded in February (Figure 4.2). The second highest movement-related month was June for dairy cattle and November for beef cattle (Figure 4.2).

Based on the cattle farm operation calendar and seasonal cattle transport movements recorded by Morris (2017), Back (2017), and Mycoplasma Bovis Programme in New Zealand (2022), we summarised the possible causes of cattle movement each month (Table 2.1 in Section 2.6). As shown in Table 2.1, the off-peak movement is around February; we can see that cattle are transported in January due to drought, and then in February and March, cattle that need to be slaughtered are sent to the slaughterhouse (Prosser, 2017). Therefore, there is a downward movement of cattle in February compared to the May movement. Our data shows that May is the month with a high peak movement. This is because cattle are sent to slaughterhouses, sent to be sold and because many farmers receive the new cattle they purchased. The

May peak can also be explained through the annual 'Gypsy Day' when cattle farms across the country move sites, employees, and farmers in advance of the winter (Adams-Hutcheson, 2017; Tipples et al., 2010). The sub-peak of dairy cattle transportation activity was June showing continuous movements due to Gypsy Day. In November, the sub-peak of beef cattle transportation activity was due to the need to move weaned calves to a dedicated calf feeder site and the arrival of spring cattle sales (Table 2.1, Section 2.6).

We have a particular understanding of the cattle transport movement in New Zealand through the peak, sub-peak, and low peak periods reflected by the data. The benefit of this result is that it allows us to look at the time patterns of cattle movements that reflect human activity and potential impacts. For example, from February until May, culled cattle always move to slaughterhouses. It is because people are preparing for the start of winter. Studies have shown that dietary intake of meat, dairy products and eggs increases significantly in winter (Shahar et al., 2001; Raju and Suryanarayana, 2005; Rossato et al., 2015). In addition, detecting peaks can help us better manage cattle to prevent infectious diseases. According to Jordan et al. (2020), a study of the Mycoplasma Bovis outbreak in New Zealand from 2015 to 2019 showed that cattle transportation movements during the outbreak were very high. Their study showed that the peak of infection in May, July, and November in 2017 corresponds to the time pattern found in this study. Therefore, our study has certain reliability. According to the time mode of cattle transportation and movement in this study, we can carry out health detection of cattle before moving in the peak period and transport sick cattle in isolation to slow down the spread of disease. Following guidance from New Zealand Mycoplasma Bovis Programmes (2022), farms will be placed on directive notices when cattle have a high risk of bovine Mycoplasma infection. In other words, cattle on the farm need to be tested for infection and licensed before being sold or transported (Mycoplasma Bovis programmes, 2022).

5.2 Explanation of External Factors

This study's spatial distribution of the monthly rainfall averages seems to differ from the often reported daily or annual picture. According to a National Institute of Water and Atmospheric Research (NIWA) review of New Zealand's climate, in the north and central parts of New Zealand, more rain falls in winter than in summer, while winter is the driest season on the South Island. However, the west coast of the South Island is the wettest part of New Zealand. The data we used when averaged per TA do not show the same strong pattern on the west coast of the South Island.

When obtaining the data on gases leading to climate change in this study, we could not obtain the directly related data, but we collected the vapour pressure. Vapour pressure is a gaseous water vapour molecule, and we know that gaseous water has a set of mechanisms leading to climate change (Schneider et al., 2010). However, this study found that vapour pressure might represent climate change more intuitively. As we found in the correlation matrix in Section 3.6.1 (Figure 3.3), vapour pressure was highly correlated with temperature. Wei et al. (2021) also show that the wetting or drying trend is an essential indicator of regional and global climate change. Looking into the effect of cattle movements on climate change is beyond the scope of this dissertation. Nevertheless, the greenhouse gases are related to where the cattle are and will depend on why, when, and how the animals will be transported. Understanding the effect of transportation patterns can have significant environmental implications for the region and can be used to strengthen the management and promotion of sustainable farm development.

According to the population distribution related to infrastructure construction and cattle occupation, the North Island may have more cattle market demand and convenience than the South Island. According to Stats NZ (2019), in 2017, there were 2.6 million dairy cattle and more than 1 million beef cattle in the South Island, while there were nearly 4 million dairy cattle and 2.6 million beef cattle in the North Island.

Even though we did not successfully include economy-related external factors in this study, as an important external factor, it will cause the possibility of livestock moving to meet market demand, domestic or international (Bowling et al., 2008). Therefore, relevant variables must be acquired to enhance research reliability in future studies.

5.3 Cattle Transportation Movement Assessment

Environmental factors and human activities are essential factors affecting livestock transporting movement flows. Many variables could represent environmental factors and human activities, and most of them even influence each other, such as the relationship between vapour pressure and temperature. Based on the literature review and available data support, we selected the variables shown in the previous section (Section 5.3.1). In this study, these variables were used to select the destination-constrained model in the SI model to give estimated values to investigate whether and to what extent the explanatory variables were the cause of cattle transport departure (Fotheringham and O 'Kelly, 1989). In addition, this study also used the GWR model to estimate the relationship between explanatory variables and dependent variables (inflow and outflow of cattle) and showed the spatial distribution of the relationship through maps (Brunsdon and Fotheringham, 1998).

5.3.1 The effect of external factors on the flows

According to our results, the environmental variables obtained in this study and the variables representing human activities can affect the transportation activities of cattle over time and have different effects on dairy and beef cattle. For example, the sunshine duration variable in May has a positive effect on the level of transported dairy cattle in some years and a negative effect in other years, but the size of the estimated value also represents the strength of the influence of the variable on the flow. Among the explanatory variables for dairy cattle, according to the results of the peak, off-peak and low peak months in each year, the number of cattle farmers, the nearest distance to ports, the number of ports within 200 km, and the length of urban roads have a positive effect on the total flows of cattle. That is to say, the greater the estimated value of variables, the more cattle will be transported and leave the area of interest. Among environmental variables, the estimated value of most variables is mainly negative, meaning that the stronger the value of the environmental factor, the lower the total number of flows, and the estimated intensity is quite strong. While in some cases, the parameter estimates show strong positive effects, such as hours of sunshine in June 2016 for dairy cattle (Table 4.1¸Section 4.4.1).

Different from dairy cattle, the number of ports within 200 km of beef cattle has continuous and different effects on the outflow of beef cattle. The length of urban roads in the February and November models has mainly negative effects but has relatively little effect on the outflow of beef cattle (Table 4.2, Section 4.4.2). Environmental variables' effect on beef cattle's outflow was mainly negative, except for November vapour pressure. In addition, the positive parameter estimate of the road length variable for beef cattle in May usually showed a negative pattern in 2020, indicating the impact of COVID-19 lockdown in New Zealand on commodity transportation (Snow et al., 2021; Wen et al., 2021).

5.3.2 The Effect of External Factors on Inflowing or Outflowing Cattle

The maps showing the spatial distribution of parameter estimates for 2016 and May 2019 data generated by the GWR local model provide an intuitive regression of dairy and beef cattle inflows and outflows. After optimizing the variables selection, the local model parameter estimates generated by the remaining variables mostly correspond to the results from the destination-constrained SI model. However, there are some differences worth mentioning. For example, the May 2016 estimate of the number of ports shows a positive effect for most TAs in the dairy cattle's GWR model, but the May 2016 estimate of the same variables for the SI model is negative. According to the spatial distribution, positive values for this variable are more reliable because most of the areas where positive values are located are close to the main ports, so the outflow of dairy cattle is proportional to this variable.

In addition, through the mapping, we found that the relationship between the numbers of outflowing dairy cattle and each explanatory variable was distributed in similar locations, for example, from the middle to the lower part of the North Island and from the upper part of the middle to the top of the South Island (*Figure 4.8, 4.9, 4.10, 4.11*, and *4.12*, Section 4.5.3). Stats NZ (2021) shows the distribution of dairy cattle in New Zealand as mainly in Waikato (central) on the North Island and Canterbury (central and eastern) on the South Island. Therefore, we conclude that observing the relationship between mobility and explanatory variables in major dairy farming areas can help us better explain the effect of variables on dairy cattle transportation flows. At the same time, observing the relationship between the flow of dairy cattle and explanatory variables can also help identify the high-risk areas that the flow may bring (Czarnota, Wheeler, and Gennings, 2015; Rahman et al., 2021).

5.3.3 Disease Control Practices

In this study, SI and GWR were used to analyse the transport flow of dairy and beef cattle allowing us to investigate the Spatio-temporal distribution of the flows, which can successfully use disease control and management. This also proves that Bowling et al. (2008) 's management method of animal identification and traceability meets the purpose of production management and disease outbreak control to a certain extent. At the same time, our GWR research results found that the stronger the relationship between the explanatory variable and the dependent variable is closely related to the flow quantity. Therefore, future disease control and management plans can also be planned. However, to fundamentally solve the problem of infectious diseases, science and technology mean to intervene (Peled et al., 2012; Poddar and Kishore et al., 2022; Selokar et al., 2020; Soenen et al., 2010).

6 Conclusion

This section summarises the main results of transport movement patterns for dairy and beef cattle between sixty-six TAs in New Zealand. In addition, the study's limitations are summarised, and some directions and suggestions for future research are provided.

6.1 Summary

Overall, the primary objective of this dissertation is to make a preliminary assessment and visualise the patterns of dairy and beef cattle transport flows in the sixty-six TAs in New Zealand using GIS and computational models. First, we reviewed relevant literature to explain the interaction between livestock and human society and the environment and reviewed the risk of livestock movement for disease control. Then, we reviewed the use cases of spatial interaction and GWR models to evaluate the value of the two methods in this study. The external factors and the data characteristics of cattle movement flow were summarised.

To evaluate the transportation movement patterns of dairy and beef cattle, the dataset of cattle movement flows was processed, and the original data set was divided into separate data sets (different species and time of the year). The temporal patterns of dairy and beef cattle transportation flows were analysed using exploratory data analysis. The results showed that the peak movement time of dairy and beef cattle was in May, dairy cattle's sub-peak movement time was in June, and beef cattle in November. In New Zealand, there has been a significant incidence of bovine mycoplasma infection (Jordan et al., 2021). The peak of infection is highly consistent with the peaks of cattle movement detected in this dissertation. As a result, these are the months with the greatest risk of disease transmission. In addition, we used exploratory spatial data analysis to analyse the spatial patterns of external factors potentially affecting the level of flows. The results indicate that the climate and infrastructure in most of the North Island and individual areas of the South Island are favourable for cattle transportation.

With limited research in the area and the availability of livestock data, we decided to test whether the magnitude of these flows can be explained using SI models and GWR. Datasets used for SI covered OD matrices for movement peak, sub-peak, and low peak periods of dairy and beef cattle, and a set of external environmental factors was used to explain the level interaction. Highly correlated explanatory variables were eliminated to improve the model's accuracy. The data for moving peak, sub-peak, and low peak months for dairy and beef cattle were modelled using the destination-constrained model with explanatory variable sets. The results showed that the transportation flows of dairy cattle and beef cattle were affected by the number of farmers, port variables, urban highway length, precipitation, insolation length, and water vapour pressure and would change with seasons and events. In addition, GWR was used to investigate the spatial distribution of the relationship between explanatory variables and the inflow and outflow of dairy and beef cattle. The results show strong relationships between exploratory and dependent variables, mainly in the middle and the lower part of the North Island and in the upper part of the South Island.

The study found that New Zealand cattle movements strongly correlated with human and environmental factors. Moreover, the factors affecting movement change over time and space and can be affected by events like the COVID-19 pandemic. However, due to the study's limitations, this study failed to explore more external factors further. The limitations of the study are described in the next section.

6.2 Research Limitations and Future

By comparing the existing literature and government agency reports, the results of this study seem to be reliable to some extent but also have a set of limitations. This section describes the study's limitations and recommendations for future follow-up studies. The limitations of this study can be divided into three aspects: data, modelling, and general limitations study.

The limitation of data quality is reflected in the data on cattle movement, which lacks the precise location of the farm, so we use the central point of the TA to assume the distance between the starting point of cattle movement and the port. The limitations of variable acquisition are reflected in the limited data representing external factors. For example, this study could not obtain the beef price of TAs and milk price. Additionally, one problem is with some values taking averages per region and assigning them to TAs, which may cause inaccuracy.

The modelling limitations are reflected in all the modelling of SI and GWR in this study. The SI modelling shows good results on the relationship between total flow and explanatory variables, but it cannot be counted on a smaller scale. However, the limitation of GWR is that we cannot control the combination of variables to compare the relationship between the outflow and inflow cattle and the explanatory variables when modelling the outflow and inflow cattle, respectively, by using the obtained explanatory variables. In the end, we only chose 2016 and 2019 when comparing year-to-year models. Also, a multiscale GWR (MGWR) can provide a more flexible and extensible framework to examine multiscale processes (Fotheringham, Yang, and Kang, 2017), which might perform a better result for this study. However, due to the research time limit, an MGWR does not get a chance to be applied. Thus, more work is required to address these issues, look at the phenomena for GWR, and apply MGWR to compare their future results.

Finally, if supported by a questionnaire survey of farmers, the overall direction of this study will provide us with better insights to help us improve the acquisition of external factors affecting cattle transportation and movement. For example, in future research interviews, the ways of transportation can be asked to obtain variables about roads, railways, or waterways.

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