Food security and impacts of disasters such as climate change on global food supply

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Originality

All co-authors, sources and assistance obtained in the development of this dissertation have been acknowledged. This dissertation is an original and to the best of my knowledge, is of my own work. This manuscript has not been submitted for another degree at the University of Sydney or any other university.

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Attributions

Chapter 2: **Meta-analysis of climate impacts in Australia**

I was the lead author on this paper, carrying out raw data collection and manipulation, analysis and writing of the manuscript. Professor Manfred Lenzen and I co-designed the research. Professor Manfred Lenzen and I drafted the Matlab code for undertaking the regression analyses. Dr Maximillian Kotz undertook the robustness analysis. All authors assisted in paper editing and approval of the final manuscript. Associate Professor Arunima Malik also taught me how to generate my own maps using SA2 regions.

Chapter 3: **Spillover economic losses due to an outbreak of Fusarium wilt TR4 in the Philippines**

I was the lead author of this manuscript. I conducted data collection and manipulation, analysis and writing of the manuscript. I co-designed the research with Professor Manfred Lenzen and Associate Professor Arunima Malik. Jacqueline Kernahan completed some of the introduction, discussion, and a section of data collection for the completion of her Masters of Complex Systems. All co-authors including Professor Tania Sorrell, Professor Mikhail Prokopenko and Dr Vitali Sintchenko provided paper revisions.

Chapter 4: **Nutritional and economic losses resulting from climate-induced disasters on traditional food sources in Tonga and Fiji**

I was the lead author of this manuscript. I conducted data collection and manipulation, analysis and writing of the manuscript. Professor Manfred Lenzen, Dr Ujjwal KC, Dr Steven Crimp, Dr Lilly Lim-Camacho and Professor David Raubenheimer helped co-designed the methodology of the paper. Professor Iain Suthers shared some sources that assisted with data collection. Dr Ujjwal KC and Professor Manfred Lenzen provided revisions of the paper.

I confirm the above statements are accurate.

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My supervisors Dr Mengyu Li and Professor Manfred Lenzen can confirm that the above attribution statements are correct.

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Abstract

Disasters can result in damages such as impacts to production output, income, employment, trade, supply chain disruptions and macronutrient availability. To alleviate the impacts of disasters, the impacts need to be quantified so that production loss trends and sectoral and regional losses can be identified. This dissertation quantifies disaster impacts and determines trends between disaster variables across different studies to identify vulnerable sectors and regions. Chapter 2 demonstrates how data can be restructured, as all disaster studies explore different regions and sectors, with a range of impact years and study years, using different severity measurements and describe production losses with different units. A total of 5030 data points on historic and predicted disaster events in Australia were categorised and restructured so that these data could be analysed together. We focused on climate disasters caused by rain, drought, flood, bushfire, cyclone and heatwave events. Multiple regression analysis was conducted on these data to compare production loss with other disaster variables. Chapter 3 extends the disaster analysis by exploring the impact of an international disaster. Input-Output (IO) analysis was adopted to determine regional and economic sectoral spillovers from an outbreak of Fusarium wilt TR4 in the Philippines in 2015 on banana crops. Chapter 4 focuses on the traditional food sources of root crops (cassava, taro, yam and sweet potato) and fish in Tonga and Fiji. IO analysis was used to provide spillover scenarios into different regions and sectors resulting from climate-induced production losses in the root crops sector and fishing sector. Data restructuring was then conducted on 445 data points, and multiple regression analysis was performed to determine trends between climate impact variables and production losses. A nutritional database for different regions in the Pacific Islands was formed, allowing the regression analysis to be further extended so that macronutrient losses caused by carbon dioxide increases and cyclones on root crops and fishing could be analysed. The results indicate that all regions and sectors post-disaster, experience economic spillovers. Interestingly, the greatest regional spillovers do not necessarily relate to the impacted regions' main trade partners. The regression analysis highlights that climate disasters impact Australian livestock production more than cropping. In Fiji and Tonga, climate disasters are predicted to reduce root crop production more than fish availability. The year of impact and study year has a positive relationship with climate-induced production losses, suggesting that, the more recent the study and later the impact year, the greater the production loss. All macronutrient availability declines post-climate disaster, affecting food security. The results of this manuscript will assist in identifying the regions and sectors that will be impacted by disasters, providing insights for developing disaster decisions and accelerating disaster recovery.

Glossary

Climate: represents the atmospheric conditions for a long period of time (in other words, normal or mean course of weather).

Climate disaster/climate-induced disaster: extreme weather events that have resulted from the enhanced greenhouse effect, causing a sudden calamitous weather event that impacts the functioning of communities.

Climate variables: in this dissertation, climate variables refer to the year of study, year of disaster impact, disaster severity, type of impact (e.g., drought, cyclone, flood), the region of the disaster and the sector impacted.

Direct requirements matrix: also referred to as the **A** matrix, holds information on the inputs required to create $1 of output.

Final demand matrix: holds consumption information on the goods and services in their final form for final usage, also referred to as **y**.

Identity matrix: often referred to as **I**, is the same size as **T**, and is populated with 1s in the diagonal and 0s elsewhere. **I** represents an economy where there are no inter-sectoral interdependencies present.

Industrial Ecology Virtual Laboratory (IELab): a cloud-based research platform with analytical capabilities for environmental foot-printing, life cycle assessment, Input-Output analysis and other sustainability analysis.

Input-Output analysis: a macro-economic method that can be used as an economic scenario modelling tool, which utilises inter-industry datasets to provide a holistic examination of direct and indirect disaster impacts on different production layers along supply chains.

Intermediate demand matrix: contains economic information on goods and services that flow between different sectors, also referred to as **T**.

Value-added matrix: holds information on the inputs required to create the goods and services, also referred to as **v**.

Weather: the atmospheric conditions for a brief period of time.

Year of impact: the year the historic/predicted climate occurred/is expected to occur.

Year of study: the year the climate disaster study was conducted.

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Introduction

Disasters can be natural hazards (e.g., tsunamis, volcanic eruptions and earthquakes), naturally formed (e.g., climate disasters), or man-made (e.g., terrorism, technological disasters, and transportation incidents) (Okuyama et al., 2004). The impacts of disasters are experienced directly and indirectly due to the flow-on effects caused by the disaster (Galbusera and Giannopoulos, 2018). These disaster impacts can include business interruptions, supply chain disruptions, employment loss, macronutrient availability declines, infrastructure damage and reduced income. It is essential to conduct disaster analysis to quantify disaster impacts so vulnerable regions and sectors along the supply chain can be isolated. Disaster impact assessment can also assist with optimising where resources should be allocated and to decrease recovery time. The analysis also aids in determining the potential location and post-disaster output calculations (Okuyama and Santos, 2014). For clarity, this dissertation assumes that *hazards* are the occurrence of the event and *disaster* is the event's impact (Okuyama, 2007).

1. Research gaps

Since the 1970s, the global incidence of recorded disasters has increased fivefold and continues to rise (UNDRR, 2023). In the last two decades, 62 million people residing in regions that do not have operational early-warning systems, were directly affected by disasters (UNDRR, 2023). These regions are typically developing countries. Developing countries contribute approximately 1% of global emissions; however, over the past 50 years, they have experienced 70% of climate-disaster-related deaths (UNDRR, 2024). Numerous studies highlight the social and economic inequalities between developed and developing nations, including Hallegatte et al. (2020) who found that climate disasters disproportionately affect lower-income populations. Dell et al. (2012) quantified how climate variability, particularly in tropical areas, increase poverty and decrease GDP growth. This disruption mainly occurs in the agricultural sector, which many lower-income communities rely upon for their livelihoods. De Sario et al. (2023) linked increased temperatures to lower labour productivity, exacerbating poverty levels. Burke and Hsiang (2014) found climate-induced economic disruptions cause conflict to rise, destabilises social systems and isolates vulnerable populations. Additionally, developing nations experience more significant impacts from disasters due to poor infrastructure, a lack of finances for disaster research and disaster recovery, and because of their geographical location (e.g., in low-lying areas or along tectonic plates) (The Commonwealth, 2024). Due to the expense and time involved in conducting post-disaster impact assessments, these regions lack disaster impact data, resulting in developing and lower-income countries being unrepresented in studies. Disaster research in these developing regions is also skewed towards significant disaster events, as the smaller ones often are unreported (UNDRR, 2023). These disasters are perceived as “silent” as whilst they are unreported, they still have drastic impacts (UNDRR, 2013).

Most studies that explore the impacts of disasters typically focus on direct impacts (Galbusera and Giannopoulos, 2018). The agricultural sector has, therefore, become one of the most widely examined sectors in disaster analysis due to its reliance on natural resources, making it a directly impacted sector (Poore and Nemecek, 2018). Consequently, other sectors are less researched. Whilst the direct impacts of disasters are generally assessed, there is a research gap as studies do not explore the ripple effect along supply chains (Galbusera and Giannopoulos, 2018). Frequently, disaster impact research does not consider the impacts felt globally or beyond administrative boundaries, which is crucial to determine because of the economic ties between regions and countries (Koks and Thissen, 2016). Additionally, most current studies are oversimplified as they do not provide a holistic disaster assessment, exploring only one impact variable rather than multiple impact variables such as gender household consumption, value-added products, emissions, trade, income, inter-industry transactions, nutrient intake and resource use. Finally, economic impacts of man-made and natural disasters were not typically assessed until the mid-1990s, in response to globally impactful disasters such as the Kobe Earthquake and Northridge Earthquake (Okuyama, 2007). Prior to these disaster events, disaster assessments mainly focused on the direct impacts such as lives lost and damage to infrastructure, rather than indirect supply-chain losses, social, economic or environmental impacts (McDonald et al., 2015, Okuyama, 2007).

Various methods can be employed to conduct disaster analysis. Firstly, Computer General Equilibrium (CGE) modelling can be adopted, which combines economic data with economic theory to determine the impact of shocks within an economy computationally (Okuyama and Santos, 2014). CGE modelling is praised by its ability to explore price changes of products post-disaster, handle supply constraints and consider import and input substitutions. CGE modelling can also model both short and long-term economic impacts, thus accounting for post-disaster recovery, growth trajectories and investments over time (Okuyama and Santos, 2014). This disaster analysis method is beneficial for larger changes to an economy when compared to other analysis methods. However, CGE modelling can be labour-intensive, and the results often portray optimistic market flexibility, leading to the underestimation of economic impacts (Okuyama and Santos, 2014). Social accounting matrices (SAM) are another disaster analysis method. SAMs model a specific year in an economy, showing the institution-to-institution, industry-to-institution and industry-industry economic transfers (Betho et al., 2022). A disaster 'shock' can be applied to the matrix to model the disaster impacts. The impacts of the disaster, however, can only be assessed on heavily aggregated sectors, so complex sectoral interactions cannot be explored (Okuyama and Santos, 2014). Therefore, this generates less reliable results than other disaster assessment methods as a holistic analysis of disaster impacts on disaggregated sectors along supply chains cannot be assessed. SAMs are also unable to model behavioural adjustments such as production patterns and consumption changes (Zlati et al., 2021).

Each disaster and its impacts are unique, making disaster assessment challenging (Okuyama, 2007). This forms another complication when deriving the effects of disasters. All disaster research is disjointed as each study examines different impact types in different regions and sectors, in various impact and study years, with unique methods to determine severity, using different production loss units. Due to the misaligned information across studies, comparing climate change variables between studies is challenging. All these disaster variables need to be categorised and restructured into sectors and regions with consistent nomenclature, have consistent production loss units, and be allocated a score according to their disaster severity before the data can be assessed and compared, so that trends are able to be observed. In this paper, we define climate variables as the year of study, year of disaster impact, disaster severity, type of impact (e.g., drought, cyclone, flood), the region of the disaster and the sector impacted.

2. Overview of methods

This dissertation adopts three methods to address the above research issues: Multi-Regional Input-Output (MRIO) analysis, data restructuring and multiple regression analysis.

2.1 Input-Output analysis

Input-Output (IO) analysis is a top-down economic approach that uses IO tables to show the financial flow of goods between different sectors. Nobel prize-winner Wassily Leontief developed IO analysis in the 1930s (Leontief, 1936), and it is currently the most widely used method to explore the spillover impacts of a disaster (Okuyama, 2007). Unlike many disaster analysis methods, IO analysis can be extended using MRIO analysis to model the economic flow of goods between different regions (e.g., states and territories in Australia) or globally. MRIO analysis is beneficial as it allows both the direct and indirect economic spillovers of disasters into different regions and economic sectors along the supply chain to be observed. Numerous studies have implemented IO analysis to quantify the impact of disasters, including environmental footprint modelling of the global healthcare system (Lenzen et al., 2020), exploring the effects of floods in Germany (Schulte in den Bäumen et al., 2014) and modelling economic losses caused by earthquakes in Japan (Okuyama, 2007, Okuyama and Santos, 2014).

An MRIO table contains a $\mathbf{T}$, $\mathbf{y}$, and $\mathbf{x}$ matrix. The $\mathbf{T}$ matrix is the intermediate demand matrix, containing economic information on goods and services that flow between different sectors (Fry et al., 2018). The $\mathbf{T}$ matrix has the dimensions of $N \times N$. Within the $\mathbf{T}$ matrix, the sectors are ordered in groups, starting with primary sectors, then secondary sectors, and finally tertiary sectors. Primary sectors are those that convert natural resources into raw materials, such as agriculture, forestry and fishing. The secondary sectors then process these raw materials, such as food and beverages, textiles and construction. Tertiary sectors provide transport, education, financial, administration and tourism services. The $\mathbf{y}$ matrix is the final demand matrix, which holds consumption information on the goods and services in their final form for final usage. The $\mathbf{y}$ matrix contains consumption information from the following: government, households, inventory, exports and capital formation and is the size $L \times N$ (Lenzen et al., 2019). Finally, the $\mathbf{x}$ matrix represents the total output matrix, with the dimensions $M \times N$.

The above matrices can be used to calculate the direct requirements matrix, $\mathbf{A}$, which holds information on the inputs required to create \$1 of output (Faturay et al., 2020). The $\mathbf{A}$ matrix is computed through $\mathbf{A}_{ij} = {}^{\mathbf{T}_{ij}}/_{\mathbf{x}_{ij}}$. An identity matrix, $\mathbf{I}$, is frequently used in IO analysis, the same size as $\mathbf{T}$, which is populated with 1s in the diagonal and 0s elsewhere. $\mathbf{I}$ represents an economy where there are no inter-sectoral interdependencies present (Miller and Blair, 2022). Leontief's fundamental equation can summarise IO analysis $\mathbf{y} = (\mathbf{I} - \mathbf{A})\mathbf{x} = \mathbf{x} - \mathbf{T} \Leftrightarrow \mathbf{T} + \mathbf{y} = \mathbf{x}$ (Leontief, 1936). The steps for calculating post-disaster production possibilities using IO analysis are further expanded on in Chapters 3 and 4.

The Industrial Ecology Virtual Laboratory (IELab) is a cloud-based research platform with analytical capabilities for environmental foot-printing, life cycle assessment, and other sustainability analysis (Lenzen et al., 2017). The IELab was employed to generate the IO table, where constraints (data feeds) were selected so that the table contained the required information on the economic flow between different sectors and regions within the economy. The IELab uses data from IO tables, inter-regional trade, economic accounts, state accounts and information on agricultural commodities to populate the $\mathbf{T}$, $\mathbf{y}$, and $\mathbf{x}$ matrices (Lenzen et al., 2017).

2.2 Database establishment

Data on past disasters and future predicted disaster scenarios were collected from literature, studies, and data from specialist and statistical organisations, as well as government and non-government reports. These disaster studies normally provide information on the region where the impact occurred, the economic sector that was affected, the impact type, and often the severity of the disaster. This dissertation reclassifies the regions and sectors by considering statistical classification methods for consistency as the current literature defines sectors and regions differently. A ranking scale of 0-5 for disaster severity was also used, as some studies explore many disaster scenarios. When a study did not state the severity and the impacts did not imply a suggestion, a score of 2.5 was provided as an average. Examples of how studies are allocated a severity score can be seen in Table 1. Production loss units were also converted into a fraction between 0 and 1. Examples of how different production loss units are dealt with are explored in Chapters 2 and 4. By restructuring data, analysis can be conducted to determine trends and compare disaster variables.

Table 1: Description of how disasters are allocated a severity score.

Severity score	Description
0	*Used if there were negligible climate disaster impacts.*
1	*Allocated if the study had a best-case scenario. If the study had multiple scenarios, the scenario with the lowest production impact was allocated a 1.*
2	*Used if the study provided other scenarios where production impacts were between best-case scenario and average expected impacts.*
2.5	*Allocated for average climate disaster impacts or when the study did not specify the level of impact.*
3	*Used if the study provided other climate scenarios with production impacts between average scenario impacts and considerable disaster impacts. This is a moderate production impact.*
4	*Used if the study provided other climate scenarios with production impacts between worst-case scenario and a moderate disaster scenario. This is a considerable production impact.*
5	*Allocated for a worst-case scenario or if the climate event was extreme with large production losses. If the study had multiple scenarios, the one with the greatest production loss was allocated a 5.*

2.3 Regression analysis

Regression models are practical statistical methods that examine relationships between a dependent and independent variable (Soussana et al., 2010). Simply put, linear regression links two correlated variables x and y using the equation $y = a + bx$, so that the value of one variable can be estimated (Hazra and Gogtay, 2016). Here, a is the vertical intercept and b is the slope of the line. The results also produce an R-squared (R^2) value, a statistical measure indicating the proportion of variance in the dependent variable that can be explained by the independent variable (Hamilton et al., 2015). Multiple regression modelling expands on linear regression by allowing correlations between a dependent variable and many independent variables to be explored (Soussana et al., 2010). Analysis with multiple variables is beneficial as most quantitative climate disaster research that has been conducted only compares one variable to another, so a holistic picture of disaster impacts cannot be captured. Regression modelling has successfully been adopted to determine the disaster trends and impacts. Examples include exploring the effects of bushfires and floods on sectoral gross output in Australia at a state level between 1978 and 2014 (Ulubaşoğlu et al., 2019), examining the impact of climate change in the Mississippi and Morocco on crop yield (Mourad et al., 2017, Shammi and Meng, 2021), and to assess weather observations to determine the economic effects of climate change (Kolstad and Moore, 2020). These studies, however, only use historical data in their regression models and do not consider studies that provide future predictions.

In this manuscript, we employ the regression methods of ordinary least squares (OLS), logarithmically transformed OLS, weighted least squared (WLS) and logarithmically transformed WLS to the restructured data to explore relationships between climate-related production losses and production variables (e.g., year of study, disaster severity, year of impact, type of impact, region and sector). As some data points may not be as reliable as other data points depending on the way the production impact was calculated in the study, we employed three WLS weighting methods for the data: WLS with manually assigned weights, WLS with optimally assigned weights and a combination of both manually and optimally assigned weights. Each data point had a weighted score between 0 (low reliability) and 1 (high reliability). The process of calculating these eight regression methods and establishing the manually assigned and optimally assigned weights can be found in Chapters 2 and 4. In this dissertation, non-independence is assumed as there is no indication that data points from each study could be correlated.

3. Method limitations

IO analysis has limitations in its methodology, which are essential to address when ascertaining the reliability of any results. Firstly, IO analysis cannot consider price changes post-disaster, which may occur as supply disruptions typically result in price increases (Okuyama and Santos, 2014). IO analysis also only depicts a snapshot of a specific economic year and therefore cannot consider dynamic adjustments within an economy over time e.g., altering trade patterns and productivity shifts. The results, therefore, may overestimate or underestimate long-term economic impacts (Randall, 2020). Each sector is also expected to have a fixed input structure for the chosen economic period, thus assuming constant returns and no changes to the scale of production (Wang et al., 2019). It is also assumed that sectors within an IO model produce a homogenous product, using identical production processes. In practice, however, production, methods and productivity vary between business operations, resulting in oversimplified results. Products are therefore also assumed to not be produced jointly between multiple sectors (Wang et al., 2019). Many other limitations stem from the data used to generate the IO tables. IO tables rely on allocating expenditure data to specific regions and sectors; any incorrect allocations or missing data that form the tables will influence the analysis and result reliability. Occasionally, sub-national data is necessary to develop an IO table at a finer level than what is available from the IELab data, as each country has different levels of data availability on regions, sectors, household expenditure, inter-industry transactions, and employment. When the granularity of data is not at the correct level for the analysis, it can produce unreliable results. Chapter 4 explores how to deal with data gaps by augmenting an IO table. IO analysis also does not account for the substitution of commodities; for example, if country A supplies country B with wheat and country A cannot meet the demand from country B due to a drought that reduced wheat supply, country B could import wheat from another country (Okuyama and Santos, 2014). Finally, collecting and collating data to produce IO tables is also time and resource-intensive; therefore, these tables are rarely updated (Tukker et al., 2018).

Limitations are also present when using multiple regression analysis to compare climate disaster variables. Some studies believe that when climate variables are used to estimate future climate trends, it may result in a biased estimate of climate change impacts (Kolstad and Moore, 2020). If climate variables are used as explanatory variables in the model, it can yield unreliable results as the climate is not stationary (it changes throughout time, even in a day). Multiple regression analysis can also suffer from multicollinearity, resulting from two or more independent variables having a high correlation in the model (Bansal and Singh, 2023). Correlation coefficients are between -1 and +1. When values are close to -1 or +1, it suggests a stronger correlation. Multicollinearity, therefore, makes it challenging to interpret regression coefficients and causes technical difficulties when computing a multiple regression model (Bansal and Singh, 2023). A correlation matrix can help recognise multicollinearity in a multiple regression analysis, which we discuss in Chapters 2 and 4. Finally, large amounts of data are required for a more accurate correlation analysis. As each independent variable aids in explaining the variance in the dependent variable, large quantities of data are required to ensure statistical reliability, by forming more precise regression coefficient estimates (Kaplan et al., 2014). Coefficients, therefore, become sensitive to small data changes. Small datasets additionally, can lead to high standard errors (standard deviation of the sample population), making it challenging to interpret relationships between statistically significant variables (Pennsylvania State University, 2024). Results are then prone to bias as they do not represent the population well.

4. Dissertation aims

The main objective of this dissertation is to determine trends between disaster variables and model the impacts of disasters using MRIO analysis and multiple regression analysis. The aims of this dissertation are as follows:

1. Harmonise misaligned data to analyse trends and correlations between production losses and different disaster variables (e.g., disaster severity, region, sector, year of impact, year of study and disaster impact type).
2. Quantify the spillover impacts of disasters such as climate change on different regions and sectors using MRIO analysis.
3. Identify regions and sectors that will be more prone to economic losses due to climate disaster impacts.
4. Calculate nutritional losses where staple foods suffer from climate-related production losses.

5. Structure and research contribution

The dissertation is structured into the following chapters:

Chapter 2 contains a meta-analysis that assesses the effects of climate disasters in Australia. Misaligned Australian production loss data is restructured and aligned (objective 1) so multiple-regression analysis can be used to draw conclusions and trends between the explained variable of production loss and the explanatory variables of disaster impact type. Australia was selected as a study region as it is one of the first developed nations that will experience climate disasters at a large scale, acting as an example for other developed nations across the world.

Chapter 3 builds on the previous chapter by exploring the impacts of a disaster internationally. IO analysis is adopted to explore the economic spillover implications of a Fusarium wilt TR4 outbreak in 2015 in the Philippines so that the regions and sectors most impacted by the outbreak are identified (objectives 2 and 3). The Philippines was selected as a case study region due to its strong trade, defence and investment relationship with Australia. Exploring the flow-on effects of a Fusarium wilt TR4 outbreak into other regions, including Australia, is therefore interesting. The banana sector was selected as an impact type due to the global trade reliance on the Philippine banana industry. Finally, there was sufficient trade, banana production data and national economy data available to conduct this research.

Chapter 4 examines the impact of climate disasters on the traditional food sources of root crops (cassava, taro, yam and sweet potato) and fish in Tonga and Fiji. IO analysis is employed to quantify the economic spillovers of production losses on these staple foods resulting from climate disaster scenarios (objectives 2 and 3). Climate disaster data is aligned and restructured so multiple regression analysis can be performed to examine relationships between disaster variables and production loss (objective 1). A nutritional database containing daily macronutrient consumption for different regions in the Pacific Islands is established. The regression analysis results are then combined with the nutritional database to calculate macronutrient losses caused by cyclones and carbon dioxide increases (objective 4). Fiji and Tonga were selected as a case study region due to their long-standing economic, political and cultural ties with Australia. Both Fiji and Tonga are important regions to examine as there is little literature on the spillover impacts of climate disasters in these regions, and they have a moderate amount of data available to conduct analysis. Fiji and Tonga are also regions expected to be highly vulnerable to climate change. We chose to focus on the traditional food sources of root crops and fish as these products are integral to the diets of communities within these regions, thus impacting food security.

Chapter 5 examines the conclusions of this dissertation and provides suggestions for future research.

6. Theoretical frameworks

The findings from this dissertation can be linked to interdependence theory. Interdependence theory is a social exchange theory that analyses relationships and social interactions, focusing on how each outcome depends on the actions of other people (American Psychological Association, 2025). IO analysis, explored in Chapters 3 and 4 is a practical extension of this theory as it views the entire global economy as a single system, assessing how an impact to one sector or region can have flow-on effects to other regions and sectors across the world (Leontief, 2018).

Resilience theory can also be linked to the results of this dissertation. This theory explores the ability of people to adapt, absorb and anticipate climate disasters and extremes (Carlson et al., 2012). The theory of resilience can be applied, as by modelling the relationships between climate disaster variables (e.g., disaster severity, region, sector, year of impact, year of study and disaster impact type), one can examine which sectors and regions absorb most of the climate impacts. Through this, governments and communities can determine how to increase the resilience of these regions and sectors by applying disaster management strategies.

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Meta-analysis of climate-related effects on production in Australia

Abstract

Climate-related disasters result in production losses that have sectoral and regional impacts. Australia is prone to such disasters, causing supply chain disruption, price hikes, loss of employment and decreased output. In this work we align and compare more than 5,000 observations of primary data from climate disaster research across all states and territories in Australia, and then adopt multiple regression analysis to determine common explanatory factors of climate impacts in Australia. More specifically, we aim to determine relationships between production losses caused by climate disasters and: the type of economic sector, the regional location within Australia, the year of projected climate impact, the year that the study was written, and the severity and the type of the projected disaster. Our analysis focuses on climate disasters caused by rain, drought, flood, bushfire, cyclone and heatwave events. Our results confirm obvious relationships such that increased severity and increased future occurrence mean higher losses. However, we also find an interesting positive relationship between climate-induced production losses and the year the study was written, indicating that the new information gathered by more recent studies paint an unequivocally grimmer picture of climate-induced losses. Our results also indicate that livestock production will experience more severe impacts than cropping, that tourism is the economic sector that is affected the most outside of agriculture, and that rain, cyclones and heatwaves result in larger production losses than drought, flood and bushfire. Our findings can be utilised to determine future projections of production losses for specific sectors, regions, disaster years, study years, disaster severity and type. The results can also assist with resource allocation and management strategies to mitigate disaster impacts.

1. Introduction

Between 1990 and 2024, more than 26,000 climate-related disasters were recorded, resulting in significant economic losses worth trillions of dollars (Centre for Research on the Epidemiology of Disasters, 2023). These losses cause substantial knock-on effects, such as supply chain disruptions, price hikes, output reduction and unemployment. To date, quantifying the economic impacts of climate disasters has proven to be challenging due to the complicated interactions between climate change, economic and political processes, land use patterns and human behaviour (DeFries et al., 2019). Knowledge about potential disaster impacts, however, is important for forming disaster plans, resource allocation, policy adaptation, and to assist with disaster impact prediction (Okuyama and Santos, 2014).

Currently, there exists published research on the broad global impacts of climate change. Recent temperature increases of around 1°C have increased poverty levels and inequality, which are expected to further increase with rising temperatures (IPCC, 2018). At 2°C temperature increase, 5-40% of seagrasses and animal species will be exposed to harmful temperature conditions (IPCC, 2023). A rise of 4°C could result in a 9% increase in heat-related deaths (Vicedo-Cabrera et al., 2018), the extinction of around 50% of tropical marine species, and 4 billion people could suffer water scarcity (IPCC, 2023). Climate change is thought to be contributing to the sixth mass extinction (Wallace-Wells, 2019). Whilst many studies explore these broad global climate impacts, there is little coherent and aligned information that allows exploration of how the impacts of climate disasters are distributed across regions and economic sectors (in this paper referred to as *regional* and *economic-sectoral impacts*) (Ulubaşoğlu et al., 2019). The interaction of physical climatic processes, demographic and geographic factors, as well as sectoral economic responses all play a role in the final impact of a given climate-related event. These interactions are rarely researched, resulting in a large range of underestimated and poorly understood climate risks (Rising et al., 2022). Australia is predicted to suffer an increase in severe climate disasters such as flooding, fires, droughts, heat waves and cyclones (Ide, 2023). Australia is therefore interesting to examine as it will be a 'guinea pig' country, being one of the first developed countries to experience climate disasters at a large scale, providing an example for future management (Wallace-Wells, 2019). Australia's considerable spatial variability in climates and resource endowments also provides an intriguing setting (Ulubaşoğlu et al., 2019).

Most research available on climate disasters explores the direct economic impacts. This includes how climate change will impact food manufacturing (Clark and Tilman, 2017, Clune et al., 2017), the tourism industry (Semenza and Ebi, 2019), mining (Singh et al., 2010), and agriculture (Clark and Tilman, 2017, de Vries and de Boer, 2010, Nijdam et al., 2012, Tilman and Clark, 2014). These studies, however, often only analyse a small range of sectors, regions, outcomes or products (Nijdam et al., 2012). Most studies that examine the impact of climate disasters focus on agriculture (Poore and Nemecek, 2018), as this is the sector that typically experiences the largest direct impact compared to other sectors. Studies also often only investigate one climate disaster type, but should explore the simultaneity of climate impacts as this is what occurs in reality (Poore and Nemecek, 2018). Studies that examine the impact of climate change typically only explore the impact of a climatic disaster in one area, rather than translating the flow-on effects of this climate disaster on other factors such as on other regions and sectors (Poore and Nemecek, 2018). Additionally, there are currently more studies conducted on the regional impacts of climate change, than sectoral impacts (Sakaue et al., 2015). It is essential, however, that both are assessed so that a holistic picture of climate disaster repercussions can be drawn. Whilst a specific sector or region can experience a direct hit from a climate disaster, additional impacts are likely felt as ripple effects along supply chains into different sectors and regions. These impacts may result from factors such as supply and demand reductions, impacts to transport availability and routes, and loss of essential services including water and electricity. Furthermore, available research is published in different years, expresses their results in different units, refers to different impact years, and examines different economic sectors in different regions, under different assumptions of warming trajectories, which we will refer to as *severity*. Such misaligned information prevents the analysis of broader trends or correlations. We chose to focus on Australia as the case study country for conducting a meta-analysis of climate impacts. Before we delve into the study, it is worth presenting definitions of key terms we use (italicised here): as per the Australian Bureau of Meteorology, *weather* refers to the atmospheric variables for a brief period of time, whereas *climate* represents the atmospheric conditions for a long period of time (in other words, normal or mean course of weather) (Bureau of Meteorology, 2024). We also use the terms *climate disaster* and *climate-induced disaster*, which refer to extreme weather events that have resulted from the enhanced greenhouse effect, resulting in a sudden calamitous weather event that impacts the functioning of communities.

Our work has two key aims: the first aim of this paper is to combine and harmonise the misaligned information from the literature on climate impacts in Australia, categorising by the type of production, sector and region impacted, the severity of assumed climate change scenarios, year of study and year of impact, so the information can be ordered, compared, correlated, and analysed. The second aim is to use the collected data to conduct a meta-analysis to assess the relationship between climate change attributes and attributes of production losses. In the following sections, we first explore how data were collected for Australian climate disasters for numerous economic sectors, regions, severities, disaster years, study years, different impact types, and align them to identify general trends and relationships. The alignment of this information has not been conducted before. We will justify how we categorised regions and economic sectors. Case studies, literature, and data from statistical and specialist organisations, as well as government and non-government reports (on both historical and future predictions) will be used to conduct regression modelling to explore this research gap and display how climate change impacts economic sectoral production in Australia. We will also discuss how to deal with proxy data for production shortfalls. This will be conducted across 114 economic sectors and 16 regions in Australia to form a holistic disaster analysis that explores the whole economy. A justification of multiple regression is outlined, followed by an examination of the correlations between different climate disaster attributes. Finally, we will discuss how these relationships in different climate disasters may have occurred. We present interesting insights from our assessment: climate-related disasters would result in greater losses in livestock production than cropping; secondary and tertiary sectors are not immune to losses due to interconnected supply chain networks, and rain, cyclones and heatwaves result in larger production losses than droughts, floods and bushfires.

2. Materials and Methods

First, we will explain how the climate disaster data are structured, containing one *explained* variable – fractional production loss – and a set of *explanatory* variables: region, economic sector, year of impact, climate severity, type of impact and study year. In this study, the explanatory variables 'region' and 'sector' require the most explanation, as we had to settle on a particular aggregation of available regional and sectoral entities. We then provide an example of how we process the data and explain our multiple regression model.

2.1 Data

Climate change disaster data were collected for Australia from 46 peer-reviewed literature, government reports and statistics. These studies typically contain information about the region within Australia where the climate impact occurred or may occur, the type of impact (e.g., bushfire, flood, drought), the impacted economic sector and often the severity of the assumed climate change scenario. Our meta-analysis collates the misaligned information and sorts it into categories so that the data can be analysed. We reclassify economic sectors and regions, as all studies define regions and sectors differently. We explicitly reference official statistical classifications, and justify our delineation based on regional and sectoral characteristics such as unique production regimes, climate types, and vulnerability to climate change impacts. We justify our climate severity measure, and then explain how we handle production impacts recorded with different units of measurement. Each study adopted different methods to determine future production loss scenarios, further justifying the misalignment of climate-disaster studies.

We applied the following eligibility criteria to determine if a study could be included: i) study relevance: we ensured the study was conducted in the required geographical location of Australia and directly explored climate impacts on sectors and regions within Australia, ii) peer-review and reputability: we then removed studies that were not peer-reviewed, from statistical organisations or government bodies to ensure academic rigor. Grey literature was considered if the literature provided valuable insights, iii) comparability: we then only retained studies that explored production impacts with comparable units, or a production impact proxy that could be converted to the same units if they differed, iv) temporal coverage: we also ensured that the selected studies covered a range of timeframes so relationships between production losses and disaster variables could be drawn.

2.1.1 Explained variable – production impacts

Sectoral production loss data were collected for losses caused by rain, drought, flood, bushfire, cyclone and heat. Data were collected for both future predictions of climate impacts and historic climate disaster events. Most production losses used in this study were from agricultural sectors as they are exposed to the climate and typically are directly hit.

Production impacts in literature are not reported with the same units of measurement, thus resulting in various proxies, such as tonne loss, produce weight loss, income loss, monetary value decrease, and percentage impact decrease. Here, we formatted all collected Australian climate disaster-induced production impact data into percentage production impacts. Some studies required calculations to convert their native measure into a percentage. For example, a loss value expressed in units of tonnes was converted by comparing that loss to the total output in tonnes for the respective region. When values were given by a percentage change in the Consumer Price Index (CPI), we assumed that an increase in consumer prices indicated an inversely proportional production loss leading to shortages and price increases. In such cases, we determine production loss as:

$$loss = 1/(1 + CPI\ percentage\ change) \tag{1}$$

The values from a study by Ulubaşoğlu et al. (2019) contained historical data on the sectoral impact of Australian bushfires and floods, expressed as the number of people affected by floods and bushfires as a percentage of the total population, and reported for a regression form,

$$\log_{10}(y + 1) = \beta \log_{10}(x + 1), \tag{2}$$

where x are flood and bushfire intensities[1], y are production losses, and β is the respective regression coefficient. Accordingly, we unravelled this regression as:

$$\gamma = 10^{\beta \log_{10}(x+1)} - 1\ . \tag{3}$$

[1] See footnote 17 in Ulubaşoğlu *et al*. to explain the $(x + 1)$-transformation.

Finally, some economic sectors chosen for this study (e.g., fruit) were more aggregated than the sectors in the production loss data (e.g., bananas). To overcome this, economic sub-sector weights were applied to scale down the percentage loss as

$$subsector\ loss = aggregate\ sector\ loss\ \frac{total\ production\ of\ subsector\ (e.g.,\ \ bananas)}{total\ production\ of\ aggregate\ sector\ (e.g.,\ \ fruit)}, \tag{4}$$

as the climate impact affects only part of our aggregate sector.

2.1.2 Explanatory variable – regions

We break down Australia into seven territories and states (New South Wales, Victoria, South Australia, Western Australia, Northern Territory, Queensland, Tasmania) and then into further two or three sub-regions[2] by combining Statistical Area Level 2 (SA2) regions (Australian Bureau of Statistics, 2016). Regions used in this study were selected based on two criteria: a) being a main food-producing area and/or b) being a region that is predicted to be at a high risk of climate disasters (see Table 1, or section 7.2 *Justification of region selection* of the Appendix for more detail). Many of these SA2 groupings are supported by and built on the *'about my region'* map (ABARES, 2019).

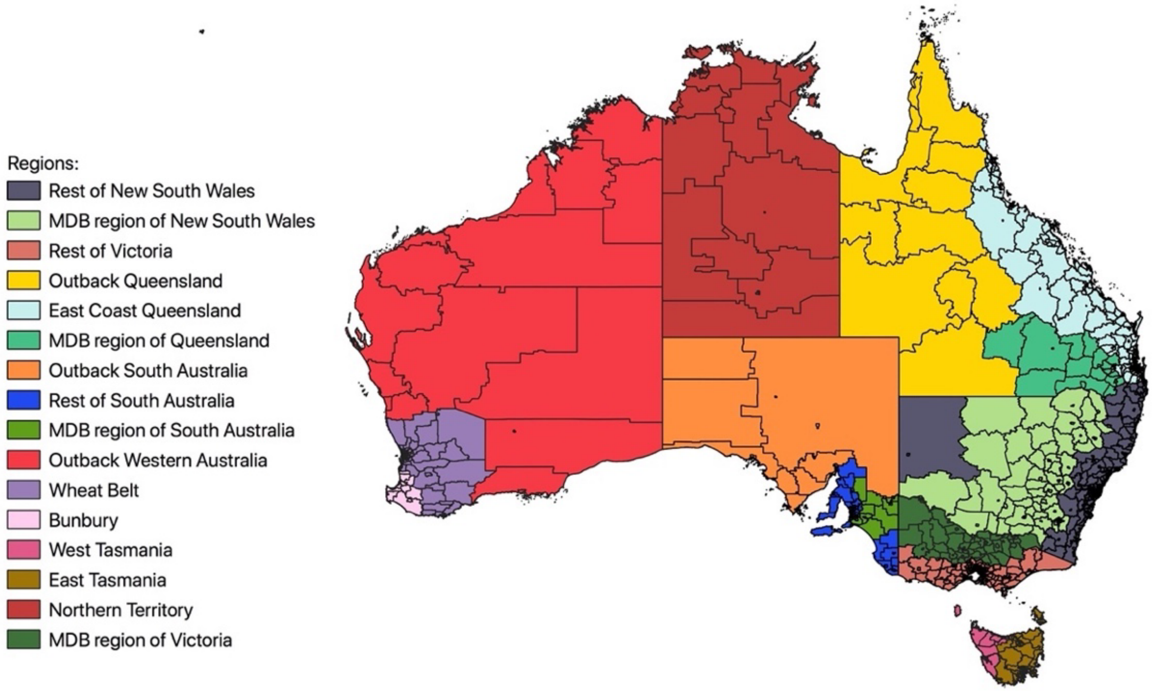

Figure 1: Delineation of Australian regions, categorised through aggregation of the ABS SA2 regional classification.

Abbreviations: Murray Darling Basin (MDB), Rest of New South Wales (NSW), MDB region of NSW, Rest of Victoria (VIC), MDB region of VIC, Outback Queensland (QLD), East Coast QLD, MDB region of QLD, Outback South Australia (SA), Rest of SA, MDB region of SA, Outback Western Australia (WA), Wheat Belt, Bunbury, West Tasmania (TAS), East TAS and the Northern Territory (NT).

[2] The Northern Territory is classified as its own region as it produces only 1% of Australia's agricultural production ABARES. 2019. *About my region* [Online]. Available: https://www.agriculture.gov.au/abares/research-topics/aboutmyregion [Accessed 6 June 2021].

Table 1: Australian regions selected for this study, their climate vulnerability and agricultural importance (population and area figures derived from (ABS, 2011)).

Region	Area	Population	Main Agricultural Outputs	Climate Vulnerability
Rest of NSW	15% of NSW (Murray-Darling Basin Authority, 2020).	6,505,027	Dairy, cattle, horticulture, poultry, sheep and lambs, wool.	Wind, bushfires, storms, flooding and heatwaves.
MDB region of NSW	75% of NSW (Murray-Darling Basin Authority, 2020).	1,074,580	Horticulture, wool and dairy.	Heatwaves, droughts and change of river flow.
Rest of VIC	50% of Victoria	5,016,737	Dairy, beef, poultry, horticulture, sheep and lambs (Agriculture Victoria, 2021).	Temperature increase, heatwaves, variable rain and bushfires.
MDB region of VIC	50% of Victoria	517,789	Horticulture, sheep and lambs, and cattle.	Decreased rain, temperature increase, and heat waves.
Outback QLD	Covers the western part of Queensland from the boarder of NSW, along the border of the Northern Territory, stretching up to the tip of Cape York (ABARES, 2019).	83,095	Cattle and calves, wool, and mangoes.	Droughts, bushfires, increased temperature and increased downpours, rising sea levels and less frequent, but more intense cyclones around Cape York.
East Coast QLD	Includes the coastal area from Cairns down to the Gold Coast.	4,261,152	Bananas, sugarcane, avocados, cattle and calves, cotton, mandarins, poultry, strawberries, mushrooms, macadamias, livestock, cereal and peanuts	Bushfires, flooding and severe storms tropical cyclones and heat waves (Queensland Government et al., 2017).
MDB region of QLD	15% of Queensland (Murray-Darling Basin Authority, 2020).	129,851	Cotton, cattle and calves, sorghum and eggs.	Temperature increase, heatwaves, bushfires, rain decrease and intense down pours.
Outback SA	Eyre Peninsula and the northern part of the state, based on the Australian Bureau of Agricultural and Resource Economics (ABARES) 'about my region' (ABARES, 2019).	87,326	Native vegetative grazing, wheat, barley, wool, canola, sheep and lambs, pulses, cattle and calves, oats, hay and milk (ABARES, 2019).	Rainfall declines, temperature increase and bushfires.
Rest of SA	Barossa, Yorke- Mid North, Adelaide and some of southeastern South Australia.	1,441,811	Wine grapes, wool, potatoes, wheat, barley and pulses.	Droughts, heatwaves and decreased rainfall.
MDB region of SA	8% of South Australia	109,095	Wine grapes, oranges, almonds, wheat, potatoes and barley (ABS, 2017).	Increased temperature, droughts, bushfires, heatwaves and increased evaporation (Department for Environment and Water, 2023, Murray-Darling Basin Authority, 2023)
Outback WA	Combines the ABARES 'about my region' Outback North	227,860	Wheat, canola, barley in the southern area and cattle and calves, melons and maize in	Temperature increase, rain decrease, drought, increased bushfires and a

	and Outback South together (ABARES, 2019).		the northern part of the region (ABARES, 2019).	decrease in tropical cyclones (increased intensity).
Wheat Belt	8% of Western Australia, covering 197,300km^2. 63% of the region is covered by agricultural land (ABARES, 2019).	1,964,832	Dryland cropping (wheat, barley and wool), sheep and lambs, canola, oats, hay, cattle and calves, eggs and pluses. This region produces 6.5 AU$B, accounting for 60% of total gross value of Western Australia's agricultural production (ABARES, 2019).	Droughts, heat stress, increased temperature, less frost, less winter and spring rain, higher intensity rainfalls, increased evaporation, reduced humidity in spring and winter and harsher bushfires.
Bunbury	29% of the WA (ABARES, 2019).	162,252	Milk, cattle and calves, avocados, potatoes, wine grapes, carrots, apples, wool, hay and onions (ABARES, 2019).	Drier and hotter weather and a decrease in annual average rainfall.
West TAS	33% of Tasmania (22,400km^2) (ABARES, 2019).	113,970	Milk, cattle and calves, potatoes, onions, applies, hay, strawberries, mushrooms, beans and cherries (ABARES, 2019).	Decreased frost days, decreased chill hours, drought increase, heat waves, increased wind speed, evaporation increased, bushfires, rainfall decreased by approximately 18% in the summer and 15% in the winter (ACE CRC, 2010, Tasmanian Government, 2023).
East TAS	66.28% of Tasmania (ABARES, 2019).	397,225	Wool, cherries, sheep and lambs, eggs, wine grapes, lettuce, milk, cattle and calves, and potatoes (ABARES, 2019).	Increase in rainfall by 20-30% (Tasmanian Institute of Agriculture and Tasmanian Government, 2012). This will result in a slightly warmer south than west and more rain in east Tasmania than northwest Tasmania. Other impacts include heat waves, increased wind speed and bushfires (Tasmanian Government, 2023).
NT	1,420,000 km^2 (ABARES, 2022, Department of Treasury and Finance, 2023).	231,331	Cattle, mango, peanuts, melons, hay, orchard fruit, melons and bananas (ABARES, 2022).	Heatwaves, ocean acidification, ocean temperature increase, heavier rainfall, drought (Jackson, 2023, National Environmental Science Program Earth Systems and Climate Change Hub, 2020). Decrease in tropical cyclones, however, they will be more intense and bushfires (National Environmental Science Program Earth Systems and Climate Change Hub, 2020).

As there are no standardised agricultural regions in Australia, various government bodies, organisations and researchers have defined regional entities differently, such as the Murray Darling Basin (MDB) (ABARES, 2022, Agriculture Victoria, 2021, Government of South Australia, 2021, Williams, 2002). We therefore, selected one of these differing delineations for the MDB. Some regions selected for this study do not fit neatly into the ABS SA2 regions, such as: i) the 'Far South West' SA2 region in Queensland, as the MDB only covers approximately one-third of that region, and ii) South Australia's MDB, where half of the MDB region is in a large SA2 region labelled 'Outback', and where the MDB covers only a small part. To overcome such issues, we allocated each SA2 region based on: a) membership to a certain catchment area, b) climate disaster types likely to occur, c) economic activity, d) the level of disaggregation, and e) the percentage of the respective SA2 region inside each selected region (see Table 2).

Table 2: Example of how SA2 regions were allocated to regions used in this study when overlaps occurred.

Region	**Issue**	**Membership catchment area**	**Climate disaster likely to occur**	**Economic activity likely to occur**	**Level of disaggregation**	**SA2 decision**
Far South West (QLD)	The MDB covers about a third of this region. There is an issue of where to allocate this region to (Outback or MDB).	- Lake Eyre - Bulloo-Bancanna	- Drought - Heat waves	- Gas extraction - Grazing of livestock	Low - only one large SA2 region	Outback QLD
Outback (SA)	The MDB region covers only 8% of SA. About a third of the SA MDB region is in the SA2 region 'Outback', however, it only covers a small portion of the 'Outback' region.	- MDB - Australian Gulf - Lake Eyre	- Drought - Heat waves	- Cooper Basin - Olympic Dam - Mining - Gas extraction	Low - only one large SA2 region	Outback SA

2.1.3 Explanatory variable – sectors

Sector delineations (Appendix Table 2) were based on the Australian Input-Output Product (IOPC) (1284 labels) and Input-Output Industry Group (IOIG) (116 labels) classifications (Australian Bureau of Statistics, 2022). As most climate-induced production losses occur in agriculture, we allowed for a higher disaggregation by choosing IOPC labels. Similarly, textiles and clothing were left disaggregated as they are closely related to agricultural production of fibres such as cotton and wool. The same holds for chemicals used for weed, pest, and disease management, and to promote plant growth (e.g., superphosphate, mixed fertilisers and pesticides). Agriculture and food are separated, following the official statistical delineation of primary and secondary industries. We also disaggregated i) transportation modes (e.g. road and rail) as they are critical conduits for disaster ripple effects (Australian Government, 2023), and ii) mined ores as they supply essential raw materials for electricity and agriculture. Finally, disaggregated IOPC classes were also kept where the literature provided detailed sectoral information, e.g. Cyclone Debbie wiping out 90% of banana crops (Lenzen et al., 2019), however IOIG only distinguishes 'fruit'. The remaining sectors were delineated as IOIG labels, or were even further aggregated if not linked to food and fibre systems.

2.1.4 Other explanatory variables – year of impact, year of study and climate scenario severity

We recorded the year that the climate disaster occurred, or was predicted to occur. Some studies mentioned no specified study year but included a projected temperature rise. In these cases, that temperature rise was translated into a disaster year by cross-checking with climate change trajectories (Collins, 2013). The year that the study was conducted was also recorded.

A severity ranking was recorded for each study, based on assumptions of future climate change. Some studies provide their own severity ranking, for example, a binary score such as 'worst-case' to 'best-case', or provide a ranking in a 0-to-5 range. In this study, a score from 0-5 was used to indicate climate severity, where scenarios of 'best-case' and 'worst-case' were allocated a score of 1 and 5 respectively. If there were negligible climate impacts, a score of 0 was provided. A score of 2.5 was allocated as a halfway point if no severity information was provided. We did not use Representative Concentration Pathways (RCP) values because the vast majority of studies did not offer sufficient information that would have allowed us to allocate an RCP value to them.

2.2 Example data processing

A study by Lenzen et al. (2019) indicates that Cyclone Debbie in 2015 resulted in a 90% production loss of banana crops on the east coast of Queensland (see Figure 1). Bananas form part of the IOIG 'fruit' sector (see Appendix Table 4), and therefore, Eq. 4 was used to determine the fractional loss of bananas within the entire 'fruit' sector. The year 2019 was taken for the year of the study, and 2015 was taken as the disaster year. The type of impact is 'cyclone'.

2.3 Multiple regression

We adopt multiple regression analysis to obtain a relationship between explanatory and explained variables. This relationship allows us to predict production losses for different sectors and regions under different climate scenarios. Ordinary least squares (OLS), logarithmically transformed OLS, weighted least squares (WLS), and logarithmically transformed WLS regression models were applied. The use of logarithmically transformed variables within a regression model is often implemented to overcome potential non-linear relationships between the dependent and independent variables (Benoit, 2011). Using the logarithm of one or more variables makes the effective relationship non-linear, whilst maintaining the linear model. It also assists with skewed data sets by improving the fit of the model by transforming the distribution of variables closer to that of a normal distribution. In our case, the year of study and year of impact are comparatively large and distant numbers in our explanatory set, hence they were logarithmically transformed in some regression experiments. We used WLS regression to test for non-constant variance in errors (heteroscedasticity). As some observations are less reliable than others, a weight was assigned to each observation. The preferred way to select a weight is through using the reciprocal error variance, where data with smaller variances have a larger weight than those with larger variances, which have smaller weights (Montgomery et al., 2012, Minitab, 2023). Most studies, however, do not provide information on weights. We, therefore, devised our own weighting method.

In the WLS and logarithmically transformed WLS regression, weights were assigned to each study with a maximum score of 1 and minimum score of 0 (which removes the study from the analysis and, therefore, reduces the degrees of freedom). These weights were assigned using one of three methods: 1) optimised weighting, 2) manually assigned weighting or 3) both. Optimised weights were generated through software that allocates each data point a weight by removing outliers that are more than two standard deviations away from the mean. Manually assigned weights were accumulated based on the following criteria below. Some of the criteria are subjective and therefore, this should be considered when interpreting the results are they could be prone to bias.

i) Reliability: A score of +0.2 was allocated for reliable sources that had a consistent and stable methodology, +0.1 for a consistent methodology, but lower-quality data, and +0 for inconsistent results.
ii) Sample size: +0.2 was assigned for a sample size greater than 50, +0.1 for a sample size of 10-49, and +0 for less.
iii) Assumptions to justify conclusions and to produce the methodology: +0.2 was provided if the study clearly described assumptions supporting its methodology and conclusions. +0.1 was given if the study described some assumptions. +0 was assigned if no assumptions supporting the methodology and conclusions of the study were outlined.
iv) Clarity: +0.2 was allocated if there was a clear explanation on how the results were obtained. +0.1 was provided if there was some uncertainty in how the results were derived and if greater depth was required in the methods so the calculations could be repeated. +0 was assigned if the information was unclear and there was uncertainty on how these results were obtained, e.g., no to limited description of methods and uncertainty on how different production impacts from various climate scenarios were obtained.
v) Production impact proxy: +0.2 was allocated if the study provided production impact percentages, instead of a different production impact proxy (such as CPI, see 2.1.1). +0.1 was provided if the study required calculations to convert the production impacts into a percentage. +0 was given if the production proxy required a conversion into a production loss percentage and if further sub-sector weighting was required (e.g., bananas in the fruit sector see 2.1.1).
vi) -0.1 was assigned if the study focused on productivity gains due to increased photosynthesis from rising carbon dioxide levels, whilst neglecting other climate impacts.

This resulted in eight regression specifications, with the β_i being the regression coefficients:

OLS: $y = \beta_1 S + \beta_2 R + \beta_3 Y + \beta_4 Q + \beta_5 D + \beta_6 + \varepsilon$ (5)

Semi-logged OLS: $y = \beta_1 S + \beta_2 R + \beta_3 \, log_{10}(Y) + \beta_4 \, log_{10}(Q) + \beta_5 D + \beta_6 + \varepsilon$ (6)

WLS, optimised weights: $wo \; y = wo(\beta_1 S + \beta_2 R + \beta_3 Y + \beta_4 Q + \beta_5 D + \beta_6 + \varepsilon)$ (7)

WLS, manually set weights: $wm \; y = wm(\beta_1 S + \beta_2 R + \beta_3 Y + \beta_4 Q + \beta_5 D + \beta_6 + \varepsilon)$ (8)

WLS, optimised manual weights: $wom \; y = wom(\beta_1 S + \beta_2 R + \beta_3 Y + \beta_4 Q + \beta_5 D + \beta_6 + \varepsilon)$ (9)

Semi-logged WLS, optimised weights: $wo \; y = wo(\beta_1 S + \beta_2 R + \beta_3 \, log_{10}(Y) + \beta_4 \, log_{10}(Q) + \beta_5 D + \beta_6 + \varepsilon)$ (10)

Semi-logged WLS, manual weights: $wm \; y = wm(\beta_1 S + \beta_2 R + \beta_3 \, log_{10}(Y) + \beta_4 \, log_{10}(Q) + \beta_5 D + \beta_6 + \varepsilon)$ (11)

Semi-logged WLS, optimised manual weights: $wom \; y = wom(\beta_1 S + \beta_2 R + \beta_3 \, log_{10}(Y) + \beta_4 \, log_{10}(Q) + \beta_5 D + \beta_6 + \varepsilon)$ (12)

where y is production loss, S is the economic sector, R is the region, Y the year of impact, Q the year of study, and D climate severity. R and S are dummy variables, i.e., binary values and are allocated a 1 if a disaster occurred in that specific region or sector respectively, and a 0 if not. The use of dummy variables is required as regions and sectors are categorical, non-numeric variables. Dummy variables are a standard method to transform categorical data into binary variables, enabling their inclusion in the regression analysis (University of Southampton, 2024). Since the addition of all dummy variables would yield 1, and hence introduce perfect collinearity, one of the *R* and *S* variables were excluded from the set, and a constant added, so that regression coefficients have to be interpreted as relative to the population average. β_6 is the constant and ε represents the error term. *wo* represents using optimised weights, *wm* denotes using manually assigned weights and *wom* indicates adopting first manually set and then optimised weights.

Prior to the regression analysis, a correlation matrix was established for all explanatory variables to deal with multicollinearity. We aggregated any variable pair that were correlated higher than 0.84. The distribution of the correlation coefficients can be seen in Appendix Figure 2. The regression analysis then included 42 low - or uncorrelated explanatory variables. Considering a sample size of 5,030, we obtained 4,989 degrees of freedom. We also conducted a Student *t*-test; levels of significance were determined by comparing the examined data sets means in relation to their standard deviation to ascertain the likelihood that the data sets are different (Ibinson and Vogt, 2017). This is explained in the probability values p of the test. If $p \leq 0.01$, $p \leq 0.05$, $p \leq 0.1$, $p \leq 0.33$, then the results are recorded as '***', '**', '*', '.', respectively, where the level of statistical significance decreases the greater the *p*. When there is no significance present between variables, no '*' or '.' was recorded. An R^2 value was calculated to examine the proportion of variance for the explained variable described by the explanatory within a regression model, thus depicting how well the data fit within the model. Outliers were also removed, such as data from a study by Holz et al. (2021), which suggests that ryegrass production will increase by up to 100% in some areas of Tasmania due to a rise in carbon dioxide by 2085 (Holz et al., 2021). This study was removed because no other studies featured similar results. Results were then plotted as climate-induced production losses against economic sectors, regions, disaster severity, year of study and year of impact. Finally, the Northern Territory (NT) was removed from the explanatory variable set because the dummy variable set of all regions produces a sum that is perfectly correlated with the constant. This also means that the constant is the mean production loss for the NT. Some climate variables are aggregated in the results and not analysed separately as they are correlated with each other, therefore, reducing multicollinearity in the regression. This correlation may result from these climate variables often occurring simultaneously to each other in practice e.g., cyclones are associated with increased rain and heat.

Non-independence can occur between data in a regression analysis when the data are not statistically independent to each other, resulting in biases (McDonald, 2014). Non-independence may result from various reasons e.g., when the same regions, sectors and farms are measured multiple times in different studies, causing correlated results. Non-independence can also occur from clustered data such as when the data is continually taken from different farms that reside in the same climatic region. The studies collected could also use the same primary data, resulting in an overlap of information, again resulting in non-independence. Whilst this study assumes independence as all data are from different studies, a sensitivity analysis was conducted in the form of a robustness test which also confirms independence in this study (Wiedmann and von Eye, 2016).

3. Results

Of the 5030 Australian production loss data points collected, droughts are the most widely researched impact type, closely followed by floods and bushfires (Figure 2). Droughts and floods may have been most frequently studied as heat and bushfire are often seen as drought-related, and rain as flood-related. Most studies providing climate scenario information assumed a worst case. The majority of available data referred to disaster impacts occurring around 2080, suggesting a research interest for climate disasters in the long-term. The majority of the studies we were able to locate were published after 2016, indicating increased knowledge about regional and sectoral impacts. Data availability was also greatest for regions in Australia known to be main food-producing areas, as more climate research is conducted on these areas due to the risk climate change poses on food supply. This is apparent with the MDB in NSW having the greatest data availability, as when combined with the MDB regions of SA, VIC and QLD, the MDB region accounts for 40% of Australian food supply, often labelled the 'Food Bowl of Australia' (Koehn et al., 2020), and covers 14% of Australia's mainland (Murray-Darling Basin Authority, 2020). The NT has the least available production loss statistics, which can be attributed to less research being conducted on the climate impacts due to only producing 746 AU$m of Australia's total 70,857 AU$m agricultural output in 2022 (ABARES, 2022). The Tasmanian regions could also have fewer data due to being smaller in size and large areas of Tasmania are covered in national parks, making it less productive, or because some studies suggest climate impacts are predicted to be less extreme in Tasmania than the rest of Australia, rendering other areas a higher research priority (ACE CRC, 2010).

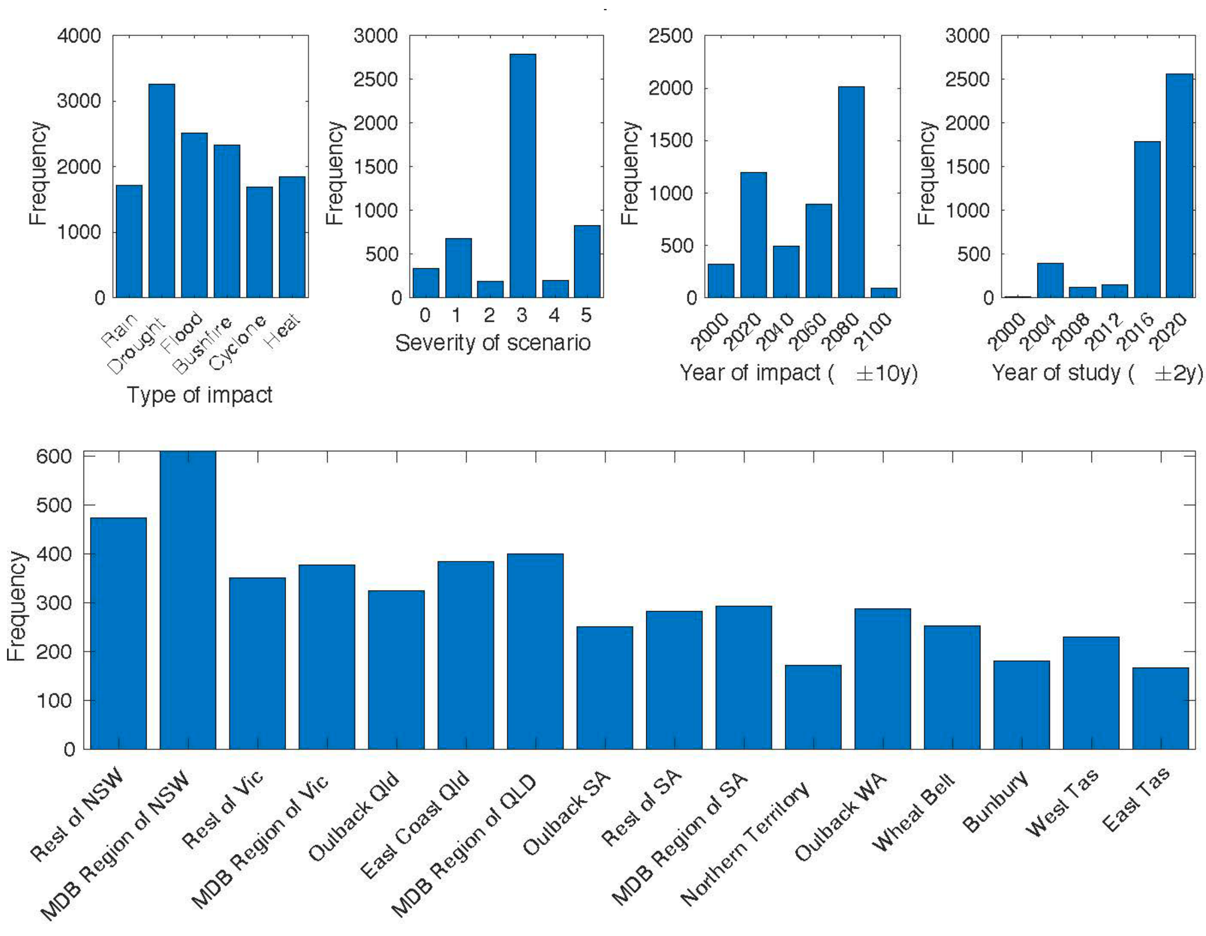

Figure 2: The distribution of metadata from a total of 5030 observations. The large peak at intermediate severities represents the half-way score of 2.5 chosen for studies that did not contain scenario information.

The suitability of the eight regression methods was assessed by comparing the different regression R^2 values (Table 3). OLS regression models had the lowest R^2 compared to the WLS regression methods, because of less reliable and outlier observations unduly influencing trends. In all instances, conducting logarithmic regressions resulted in a lower R^2, indicating that the temporal trends of climate impacts and increased knowledge are best approximated by linear trends. Optimised WLS weighting methods generally produced higher R^2 than could be obtained from manual weighting, because the latter can easily miss outliers from studies deemed reliable based on the described criteria. However, the optimised-weight method may miss studies that can manually be deemed less reliable, and that may weaken trends. Therefore, the non-logarithmic WLS regression with combined manually set and then optimised weights generated the best regressions with the highest R^2. In the following, we choose this method to report on relationships between climate disaster-induced production losses and all explanatory variables. Note that excluding certain dummy variables and including a constant means that regression coefficients describe the deviation from a production loss average over years, regions, sectors, severities and impact types.

Table 3: R^2 values of each regression method.

Regression method	**Equation**	$\boldsymbol{R^2}$
OLS	5	0.491
Logged OLS	6	0.487
WLS manual	7	0.531
WLS optimised	8	0.534
WLS manual optimised	**9**	**0.563**
Logged WLS manual	10	0.526
Logged WLS optimised	11	0.528
Logged WLS manual optimised	12	0.559

Production losses show a highly significant relationship between the year of study, year of impact, disaster severity and all disaster impact types: rain, cyclone, heat, drought, flood and bushfire (Table 4). Logically, the regression coefficients for climate change severity and year of impact are positive, meaning that generally losses are higher under more severe climate change scenarios, and further into the future. Rain, cyclones, heat and drought cause above-average production losses, and floods and bushfires cause below-average production losses. The region where the disaster occurred appears to not significantly affect production losses. Livestock production (beef cattle, sheep and lambs) is significantly and to an above-average extent affected, whereas cropping (oats, sorghum, wheat, barley, rice, oilseeds and legumes) (Table 4) is significantly but to a below-average extent, affected by climate change. Similar relationships hold for hospitality and trade respectively. In terms of exposure to production losses, food and other manufacturing, but also mining and transport, are not significantly different from the economy-wide average.

We further assess the robustness of these results to potential structured correlations of variables within groups. This may be an important statistical problem to address if, for example, certain disasters occur more frequently within certain regions, or if sectors in certain regions are more vulnerable to particular disasters. These structured correlations may provide bias assessments of regression parameter uncertainty and significance if left unaddressed. Table 6 of the Appendix, therefore, presents additional analysis in which results of the regression are reported as having used robust standard errors clustered within different groups. The primary group within which such correlations are likely to occur is within regions since both the occurrence of disasters and sectoral vulnerability are most likely correlated spatially. Clustering standard errors by region provides very similar parameter estimates as our main specification with similar levels of significance (Appendix Table 6). Results are furthermore consistent when clustering by both disaster type sector, or both, with the exception that the year of impact loses significance when clustering by disaster type. This likely results from the changing occurrence of certain disasters over time. This robustness test also confirms independence between data.

Finally, we note that the relationships identified in Table 4 are predominantly driven by the data for projected future impacts, which concerns over 90% of the available data. When splitting the observed studies by those which analysed historical and future events, we find the main results to be consistently identified in the data for future impacts, while data on historical impacts are insufficient to obtain significant parameter estimates (Appendix Table 7).

Table 4: Results from the WLS regression with both manually set and then optimised weights. The key results are in bold.

Variable	Coef.	Stand. error	t-stat.	Sign.	Variable	Coef.	Stand. error	t-stat.	Sign.
Year of impact	0.00018	0.0057	2.83	***	Sheep and lambs	0.037	0.0043	8.62	***
Year of study	0.0085	0.0034	12.4	***	Other agriculture and aquaculture	0.00066	0.0033	0.20	
Rain, Cyclone, Heat	0.037	0.0029	12.3	***	Oats, sorghum and other cereal grains	-0.020	0.0033	6.16	***
Drought	0.019	0.0025	7.30	***	Wheat	-0.020	0.0027	7.37	***
Flood	**-0.058**	**0.0020**	**28.50**	***	Barley	-0.020	0.0032	6.42	***
Bushfire	**-0.058**	**0.0021**	**27.10**	***	Rice	-0.020	0.0033	6.23	***
Rest of NSW	0.00031	0.012	0.059		Oilseeds	-0.020	0.0032	6.43	***
MDB region of NSW	0.000076	0.012	0.015		Legumes	-0.020	0.0032	6.40	***
Rest of VIC	-0.00015	0.13	0.027		**Beef cattle**	**0.082**	**0.0044**	**18.90**	***
MDB region of VIC	-0.00015	0.127	0.027		Mining and gas extraction	-0.0024	0.0035	0.70	.
Outback QLD	-0.00034	0.013	0.062		Manufacturing	-0.0020	0.0032	0.64	.
East Coast QLD	-0.00040	0.013	0.074		Electricity, water and waste management	-0.0025	0.0035	0.71	.
MDB region of QLD	-0.00057	0.013	0.11		Construction	-0.0024	0.0035	0.70	.
Outback SA	0.00049	0.013	0.083		Trade	-0.031	0.0060	5.18	***
Rest of SA	0.00051	0.013	0.088		Accommodation, and Food and Beverage Services	0.0287	0.0052	5.59	***
MDB region of SA	0.00073	0.013	0.13		Transport	-0.0024	0.0035	0.71	.
Outback WA	-0.0015	0.013	0.23		Communication and Information Services, Business Services	-0.0024	0.0035	0.69	.
Wheat Belt	-0.0015	0.013	0.25		Public Administration Services	-0.0025	0.0035	0.70	.
Bunbury	-0.0018	0.013	0.30		Private Administration Services	-0.0024	0.0035	0.70	.
West TAS	0.00027	0.013	0.041		Severity	0.0060	0.0033	5.43	***
East TAS	-0.00019	0.013	0.031		Constant	-0.024	0.0070	3.22	***

4. Discussion

It was expected that the OLS regression would generate a lower R^2 due to the equal weighting of values. In this regression method, the outliers can greatly impact the line of best fit as all the data points are of equal importance and reliability, and are therefore treated equally. This method assumes constant variance in the errors, or homoscedasticity. The OLS regression also presents average data over the study area, which may result in ignoring potentially important information on the spatial differences of the correlations and model success (Nazeer and Bilal, 2018). Combined manual and optimised weights resulted in the highest R^2 due to combining the benefits of both weighting methods.

Rain, cyclones and heatwaves cause above-average production losses. This is because rain and cyclones not only cause losses in agricultural output, but also result in further physical damages e.g., to property, infrastructure, transportation routes, and inhibit power generation and transmission. Droughts on the other hand, do not result in physical damage and therefore some economic sectors may not be affected. Heatwaves may have also resulted in above-average economic losses as they are precursors for, or exacerbate other climate disasters. For example, heatwaves can exacerbate bushfires and drought, and they can also be a precursor for cyclones (Berardelli, 2019). Our results are therefore consistent with the literature on the impacts of high temperatures on productivity in both agricultural and non-agricultural domains (Dasgupta et al., 2021). These results are supported by a study conducted by Deloitte (2021) who found cyclones to result in greater economic losses than bushfires. We explained this by bushfires being slower moving than cyclones, enabling people to relocate resources and minimise economic losses (Australian Government Geoscience Australia, 2023). Our results also indicate that bushfires have a relatively weak relationship with production losses. This finding is supported by the FAO (2021) stating that wildfires cause 1% of agricultural loss, and by a study conducted in the USA suggesting that since the 1980s, cyclones and storm/rain events, caused greater economic impacts than droughts (National Integrated Drought Information System, 2023). Our results, however, are challenged by the FAO which suggests that droughts are the most prominent reason for agricultural production impacts, followed by floods internationally (FAO, 2021). Some sectors can substitute commodities when a climate disaster occurs, however this does not apply to tourism, as the visitors are not substitutable. Kotz et al. (2022), however, challenges this finding through their study, which indicates that the services and manufacturing sectors will experience the greatest economic impact. Their study, however, only considers economic impacts from increases in the distribution of precipitation. Climate and natural disaster impacts can play a large role on tourism as seen i) by the 2019 Australian bushfires where tourism reduction resulted in a 4.5 AU$B loss by January 2020 (the fires extended beyond this date) (Thiessen, 2020, Reiner et al., 2024) and ii) by the eruption of Eyjafjallajökull, an Icelandic volcano, which resulted in a 30% decline in tourists and a revenue loss of 180 GB£m (Troxler). Our findings also reveal that livestock production is more affected by climate disasters than other cropping. This is understandable as livestock suffers from both heat stress and flood drownings, and additionally would experience spillover impacts of climate change-induced fodder crop shortages. Hughes et al. (2022) supports our results through their study of cropping and livestock responses to climate change, finding that livestock farms are more adversely impacted than cropping farms by climate. Another study by Malik et al. (2022), employed Input-Output analysis to determine vulnerable sectors and regions in Australia in response to extreme weather events and climate change. Malik et al. (2022) found that vegetables, fruit and livestock were the most vulnerable sectors. This study, however, explored the economic ripple effect down supply chains and therefore, not production percentage losses. The results may slightly differ due to different production impact proxies being used or because this study does not consider supply chain spillovers post-disaster. No region experiences significantly out-of-average production losses, suggesting that no location within Australia is spared from climate disasters.

Our results also indicate positive and significant relationships of production losses with change climate severity and both the year of study and the year of impact. Logically, the further into the future, the more severe climate change will be, and the higher we must expect production losses to be. However, interestingly, the more recently a study was conducted, the bleaker its outlook for the future. This indicates that with increasing knowledge and access to data, and the development of new methods and measurement techniques, climate change is being found to pose a more serious problem. These results are supported by the IPCC's 6th Assessment Report (2022), suggesting that risks and impacts "increase to high and very high at lower global warming levels" (Le Page, 2023), compared to previous assessments. Moreover, our results are also consistent with estimates of the social cost of carbon (a common metric for the economic impact of climate change) that have increased over time (Tol, 2023).

Some data examined for this study explored multiple climate disasters occurring simultaneously, making it difficult to determine which climate-induced production losses could be attributed to a specific disaster impact type. Limitations were additionally present during data collection: Most horticultural produce studies were not used because they expressed production impacts in units of growing degree days, rather than yield or production losses, thus introducing potential uncertainty during conversions. Other studies only provided disaster impact information for a specific small region, farm or town, which we only used if the climatic conditions for the respective locations were similar to the remainder of the region. The historical data from Ulubaşoğlu et al. (2019) may slightly skew the results as impact values are small for floods and bushfires, as the number of lives impacted rather than production loss is being measured.

5. Conclusions

Our study has generally found significant susceptibility for production losses for primary sectors. However, secondary (manufacturing) and tertiary (construction, trade, utilities, services) economic sectors are connected to primary sectors via complex supply chain networks, and will therefore clearly be affected indirectly (Lenzen et al., 2019). Multi-Regional Input-Output (MRIO) analysis, an economic tool that analyses the ripple effects of impacts both directly and indirectly along a supply chain (Leontief, 1936), provides a means to investigate such indirect ripple effects. MRIO analysis can capture spillovers into regions and sectors that are different from the directly hit locations. In addition, it would also prove interesting to examine the impact of climate disasters on government and state indebtedness on each region's state budget (Ulubaşoğlu et al., 2019). This is because government expenditure is required for assisting with climate disaster recovery and for supporting people impacted by climate disasters. A study conducted by Crellin and MacNeil (2023) highlights that in Australia, major bushfires generate the greatest longevity and significant attention by the public in media than other climate disaster impact types. This is concerning as we found bushfires to have a lower production loss impact than other climate disaster types. This paper focuses on production losses taken from commercial not residential services. The Australian population may be more interested in media that focuses on residential impacts due to the direct effects disasters would have on their immediate surroundings. Therefore, future research would work on improving 'climate literacy' in the public to work towards mitigating all climate disasters and their impacts. A final extension consideration would be to determine a way to convert growing degree day impacts into a production yield impact so that more data on horticultural production could be provided in the study.

Conducting research that consolidates fragmented data on Australian climate disasters, relationships and trends could assist in deriving overarching conclusions to bolster mitigation efforts against climate disaster impacts. This research is timely as the Australian Government has proposed a National Climate Disaster Fund, an independently administered fund aimed at decreasing the rising costs of disasters that Australia experiences due to climate impacts. This would be funded by a levy placed on fossil fuel production with $1 per tonne of carbon dioxide for all coal, gas and oil produced in Australia, estimated to have the ability to raise 1.5 AU$B per year (The Australia Institute, 2023). The goal of the fund is to allocate funding to the regions and sectors most affected by disasters. The findings from this work are directly relevant to the fund's objectives, as we show that most sectors have some correlation with production impacts resulting from climate disasters, highlighting the flow-on effects that climate disasters impose. Additionally, this study is significant as it assists in discerning the sectors that are most vulnerable, and with increasing estimates over time. It is important to note that whilst this study has quantified the impacts of production losses in Australia, there are many more impacts beyond this (such as psychological, ecological and social impacts). Disaster management planning and disaster impact assessment are complex topics and therefore are unable to account for all impacts with any single method.

Furthermore, this work highlights that the Australian Government and organisations should examine a range of climate disaster impact types, with an emphasis on droughts. Emphasis for government disaster management planning should also be placed on the agricultural sectors that are directly impacted such as livestock and cropping, and sectors that are unable to substitute commodities such as tourism. These are priority areas listed in the National Climate Disaster Fund. Our findings, therefore, assist in identifying to which sectors finance should be directed to reduce or compensate production impacts resulting from climate change. As many studies suggest, supported by our results, the severity and frequency of disasters increase over time, highlighting the urgency of disaster management, prevention strategies and research into resource allocation for climate disaster recovery (Hay and Mimura, 2010, Thomas and Lopez, 2015, UNDRR, 2022). The Australian Government has a responsibility to lead and facilitate investment in sector-specific reforms to improve adaptation measures and establish a safety net for future disasters. This requires information on sector- and region-specific production losses, and disaster severity, which this study provides. Such information is vital for effective resource allocation and for devising management strategies to alleviate the impacts of disasters. New policies could be introduced to encourage adoption and further research into drought-resistant crops and livestock breeds e.g., Droughtmaster cattle to reduce productivity losses through drought periods (Droughtmaster, 2024). Regions more vulnerable to disasters could have more climate resilient infrastructure implemented to withstand the effects of climate events such as cyclones and floods. An effective example of this is Brisbane's Flood Planning Area codes, for preventing and/or to regulate construction in flood prone areas across (Brisbane City Council, 2014). Similar planning codes should be implemented in other regions to reduce physical losses in high-risk areas. Financial incentives such as grants or tax breaks for sectors and businesses that adopt climate adaptation measures could be provided. Finally, sectoral impact assessments such as the analysis that this study has conducted, should be updated regularly so that vulnerability assessments can provide reliable analysis to inform policies based on evolving climate scenarios.

This study assessed misaligned Australian climate disaster data, drawing connections that can assist in improving the response of Australia to climate change. Whilst efforts are being made to make Australia more resilient to reduce the impact of climate change, the severity and production impact of each climate disaster has increased beyond what initial studies indicated. These climate disasters will result in economic stress in regions and sectors, potentially necessitating government intervention to stabilise the economy. This work highlights possible future research avenues of MRIO analysis and areas for government investment. This work highlights possible future research avenues of MRIO analysis and areas for government investment, in particular the livestock and tourism sectors.

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7. Appendix

7.1 Regional and sectoral classification used in this study

Appendix Table 1: Regions selected for this study.

Rest of NSW
MDB region of NSW
Rest of VIC
MDB region of VIC
Outback QLD
East Coast QLD
MDB region of QLD
Outback SA
Rest of SA
MDB region of SA
Outback WA
Wheat Belt
Bunbury
West TAS
East TAS
NT

Appendix Table 2: Australian sectors elected for the study.

Sheep and Lambs
Shorn Wool
Oats, Sorghum, and Other Cereal Grains
Wheat
Barley
Rice
Oilseeds
Legumes
Beef Cattle
Untreated Milk
Dairy Cattle
Pigs
Poultry
Eggs
Vegetables
Fruit
Plant Nurseries
Flowers
Grapes for Wine
Horses
Deer
Animal Breeding
Sugar Cane
Unginned Cotton
Grass Seed, Forage and Hay
Skins
Ginned Cotton and Cotton Seed
Sheep Shearing
Aerial Agriculture
Other Agriculture
Forestry and Logging
Agriculture, Forestry and Fishing Support Services
Rock Lobsters
Prawns
Raw Fish
Shellfish etc
Aquaculture
Coal Mining
Oil and Gas Extraction
Iron Ore Mining
Non-Ferrous Metal Ore Mining
Non-Metallic Mineral Mining
Exploration and Mining Support Services
Meat Products
Fresh Meat
Offal, Hides, Skins, Blood Meal
Poultry, Slaughtered
Dairy Products
Cheese
Butter Oil
Butter
Vegetable Product Manufacturing
Fruit Product Manufacturing
Oils and Fats
Rice Products
Flour Mill Products
Gluten and Tapioca
Breakfast Foods
Pasta
Pies, Cakes, Biscuits
Bread and Bread Rolls
Confectionery
Food Products
Sugar
Fish
Lobster
Processed Seafoods
Animal Food
Soft Drinks
Beer and Malt
Spirits
Wine
Tobacco
Wool Scouring and Natural Fabrics
Human-Made Fibres
Textile Products and Finishing
Knitting Mill Products
Clothing
Footwear
Leather Products
Superphosphate
Mixed Fertilisers
Chemical Fertilisers
Cement, Lime
Basic Chemicals
Pesticides and Insecticides
Chemical Products
Plastic and Rubber Products
Paper and Wood Manufacturing
Petroleum and Coal Product Manufacturing
Glass, Ceramic, Cement, Lime, Ready Mixed Concrete, Plaster and Concrete and Other Non-Metallic Mineral Product Manufacturing
Basic Iron and Steel
Basic Non-Ferrous Metal
Fabricated Metal Products
Transport and Transport Equipment Manufacturing
Equipment and Machinery
Furniture and Miscellaneous Manufacturing
Fossil Electricity Generation, Transmission, Distribution, On-Selling and Electricity Market Operation
Renewable Energy
Gas Supply
Water Supply, Sewerage and Drainage Services, Waste Collection, Treatment and Disposal Services
Construction and Construction Services
Wholesale Trade
Retail Trade
Accommodation and Food and Beverage Services
Road Transport
Rail Transport
Water, Pipeline and Other Transport
Air and Space Transport
Postal and Courier Pick-up and Delivery Service and Transport Support Services and Storage
Communication and Information Services
Business Services
Public Administration Services
Private Administration Services

7.2 Justification of region selection

7.2.1 Murray Darling Basin (NSW, QLD, SA, VIC)

The Murray Darling Basin (MDB) was selected for this study as it is a large food-producing region, often titled the 'Food Bowl of Australia', accounting for 40% of the Australian food supply (Koehn et al., 2020). The MDB covers 14% of Australia's mainland and comprises approximately 40% of Australian farms (Murray-Darling Basin Authority, 2020). This region is known for the production of horticulture, wool and dairy (Murray-Darling Basin Authority, 2020) (Holland et al., 2015, Murray-Darling Basin Authority, 2020). In 2011-2012, the region accounted for 94% of cotton, 100% of rice, 60% of hay, 74% of grapes, and 59% of livestock and sheep production in Australia (Dinh et al., 2017). With an average agricultural production gross value of 14,991 AU$m in 2009, the MDB accounted for 39% of Australia's national value (Holland et al., 2015, Murray-Darling Basin Authority, 2020). Around 60% of the food produced in this region is exported (Holland et al., 2015, Murray-Darling Basin Authority, 2020). The MDB additionally has the largest river system in Australia, supplying a population of approximately 2 million with fresh water and 65% of Australia's irrigated land (Loch and Adamson, 2015). In this study, the MDB region was divided into four regions according to the four states it spans: the MDB region of New South Wales, the MDB region of Queensland, the MDB region of Victoria and the MDB region of South Australia. The SA2 regions allocated to the MDB region in this study were based on the map illustrated on official Murray Darling Basin Authority website (Murray-Darling Basin Authority, 2020).

Climate disasters are likely to prove a challenge for food production in the MDB. A particular concern is water availability. The MDB is anticipated to become 0.3-1.28°C warmer and have an annual rainfall reduction of 2-5% by 2030, which will harm agricultural productivity in the area (Hughes, 2015). It is believed that a 29% reduction in water availability will decrease irrigated agricultural product's gross value by approximately 15% at a baseline scenario (ABARES, 2019). Farmers will struggle in the future as it is estimated that crop water use will have to decrease by 2-50% (Kang et al., 2015). Loch and Adamson (2015) surveyed farmers within the MDB and found that roughly half of the surveyed farmers advised they were likely to leave farming in the coming 5-10 years, with drought being one of their top four reasons, highlighting their lack of confidence in long-term future water supply. Furthermore, a decline in spring and winter rainfall by 2030 is anticipated, with some increases in the northern end of the MDB and the largest decreases in the south (Evans and McCabe, 2010). Agricultural production in the MDB is also sensitive to climatic variations, as evident from a study that found almost a 20% reduction between the La Nina year 2001 and the El Nino year in 2002 (Evans and McCabe, 2010). Livestock heat stress is expected to rise, and there will be a change to the distribution of weeds and pests (Crimp et al., 2010). Pasture productivity and quality are expected to decline by 8-40% in the west and 15% in the east (Crimp et al., 2010).

7.2.2 New South Wales Regions

Two regions were selected in NSW: the MDB region of NSW and the other labelled as the Rest of NSW. The MDB region of NSW, as described above, is a vital region to examine as it covers most of the state (75%) (Murray-Darling Basin Authority, 2020). The Rest of NSW region (15%) mainly comprises the east coast of NSW. These regions include Coffs Harbour, Southern Highlands and Shoalhaven, Greater Sydney, Hunter Valley, Mid North Coast and Tweed (ABARES, 2019). The future climate of the East Coast of NSW will have fewer cold nights on the southern coast of NSW. Bushfires are expected to increase on the mid-coast of NSW, particularly around the Greater Sydney Region (New South Wales Environment Climate Change & Water, 2010). The high to extreme fire-risk frequency is likely to grow by 10-50%, with the fire period likely to stay within the present ranges (New South Wales Environment Climate Change & Water, 2010). Average annual rainfall is expected to increase on the north coast of NSW (Office of Environment and Heritage 2016). Severe winds from ex-tropical cyclone systems will have a low impact on most of the NSW regions, with the northern coast of NSW being most affected. Some modelling projections have suggested a rise in category 3-5 cyclones; this, however, will depend on greenhouse emission levels, upper atmosphere circulation alterations and the change of sea surface temperatures (New South Wales Environment Climate Change & Water, 2010). Drought is expected to increase in southern coastal NSW (Williams, 2016). Crop growth will be limited by a short growing season and cool winter temperatures. With an increase in temperatures, this is likely to reduce this constraint (Williams, 2016). Despite this potential improvement, areas suitable for crop production may be reduced, as rising sea levels will challenge managing water table levels, increasing acid sulphate soils (Williams, 2016). Urban heat is also expected to increase by 0.7°C by 2030 around the Greater Sydney Region (Office of Environment and Heritage, 2016). The cool season is predicted to decrease in temperature due to a slight reduction in moderate East Coast Lows (New South Wales Environment Climate Change & Water, 2010). Finally, NSW is expected to experience a rise in climate disasters such as wind, fire, lightning, hail, riverine flooding, flash flooding, heatwaves, coastal erosion and inundation (New South Wales Environment Climate Change & Water, 2010). Pests such as cattle ticks are expected to rise in northern NSW, resulting in increased chemical usage, unless more resistant breeds are introduced (White et al., 2003).

7.2.3 Queensland Regions

All of Queensland was divided into three regions: the MDB region of Queensland, Outback Queensland and East Coast Queensland. Agriculture currently covers 88.4% of Queensland, producing 19.87 AU$B Gross Value Product (Department of Agriculture and Fisheries, 2018). The MDB covers 15% of Queensland and is an important food bowl as discussed above (Murray-Darling Basin Authority, 2020).

The East Coast of Queensland includes the coastal area from Cairns down to the Gold Coast. The East Coast has a large variation in agricultural commodities, including bananas, sugarcane, avocados, cattle and calves, cotton, mandarins, poultry, strawberries, mushrooms and macadamias (ABARES, 2019). This region was selected due to its high-climate-induced disaster risks, such as fires, flooding, and severe storms (Queensland Government et al., 2017). Severe flooding is anticipated to increase in this region, resulting in the inundation of low-lying areas, particularly around the coast, resulting in the loss of fertile soil and crops. This flooding will be caused by events such as tropical cyclones. Whilst cyclones are anticipated to reduce in quantity, they are expected to become more intense, particularly in the northern part of the East Coast of Queensland (Queensland Government, 2019b). Cyclones result in great devastation, as seen by the 2006 Cyclone Larry that damaged 90% of northern Queensland's banana crops, impacting supply for nine months, with a price inflation of 500% (Hughes, 2015). Furthermore, flooding will increase as the sea level is anticipated to rise by 0.8 metres above current levels by 2100 (Queensland Government, 2019b). This flooding is alarming as the 2010-2011 Queensland floods resulted in a 1.6 AU$B loss of agriculture due to harvest disruption, as well as quality loss and transportation issues (IBISworld, 2011). The southern East Coast of Queensland is expected to warm between 0.6-1.3°C by 2070 (Queensland Government, 2019b). Further up the coast towards Townsville, however, more drastic temperature changes predicted. This includes a predicted temperature increase of 1.0-3.6°C by 2070 (Queensland Government, 2019c). This temperature rise will result in warmer and more frequent hot days, a reduction in frost-risk days and the risk of fire. This will prove challenging to many industries, such as the peanut industry, which has decreased production rates by up to 7% in the last 25 years, mainly as a result from a decrease in summer rainfall (Department of Agriculture Water and the Environment, 2019). The southern East Coast of Queensland will become more desirable for livestock due to the increased risk of heat stress across the rest of Queensland (Cobon, 2017). Livestock production, however, will still prove challenging as a 2.7°C increase will increase the heat stress of livestock by 30%, further impacting agricultural output (Cobon, 2017). Heat stress in livestock reduces conception, fertility, follicle development and peripartum survival (Cobon, 2017). Rising day temperatures will increase water turnover and heat loss through evaporation, resulting in a decreased rate of foraging by livestock. Finally, cereal production is expected to decline by 7-15% by 2030 (Potgieter et al., 2013).

Appendix Table 3: Examples of climate disasters in the East Coast Queensland region:

Scenario	***Impact***
Cyclone	Cyclone Larry destroyed 90% of **banana crops**, resulting in price inflations of 500% and impacting banana supply for 9 months (Hughes, 2015).
Flooding	The sea level is anticipated to rise 0.8 metres above current levels by 2100 (Queensland Government, 2019b). This is alarming as the 2010-11 floods resulted in a 1.6 AU$B loss of agriculture output due to disrupting to harvest, quality loss and transportation issues (IBISworld, 2011).
Temperature increase	The **peanut industry** has had a decrease in production rates by 7% in the last 25 years resulting mainly from a reduction in summer rainfall (Department of Agriculture Water and the Environment, 2019).
Heatwaves	A 2.7° C increase will increase the heat stress of **livestock** by 30%, further impacting agriculture (Cobon, 2017). This is evident as heat stress in livestock reduces conception, fertility, follicle development and peripartum survival (Cobon, 2017).
Rainfall	**Cereal** production is expected to decline by 7-15% by 2030 (Potgieter et al., 2013).
Carbon dioxide and climate change	Wheat yield in Emerald, Queensland is expected to rise 12% to 29% (Howden S.M, 1999).
Cyclone	Damage to Queensland's **sugar** industry is expected to cost 150 AU$m (Lenzen et al., 2019). Most of these costs lie in Mackay and Proserpine.
Cyclone	Cyclone Debbie caused Bowen's **vegetable** industry to have a loss of approximately 100 AU$m, accounting for about 20% of the season's crop (Lenzen et al., 2019).
Temperature increase	**Strawberries** decrease in weight by approximately 4.5g from every degree Celsius above a mean daily temperature of 16° C (Menzel, 2019).
Carbon dioxide increase	**Sugarcane** yields could increase by 4% in Ayr (Burdekin region) (Linnenluecke et al., 2020).
General climate change	By 2030, there is an estimated positive impact to **sugarcane** production in Maryborough of 4-7% (Sugar Research and Development Corporation, 2008). By 2070, in Maryborough, however, there the potential impact of an 8% increase or 47% decrease (Sugar Research and Development Corporation, 2008).
Cyclone	Cyclone Yasi in 2011 resulted in a 500 AU$m **sugarcane** loss (Climate Council, 2016).
Cyclone	Cyclone Yasi in 2011 resulted in 20% loss of **avocado** crops (Climate Council, 2016).

The final region of Queensland is called Outback, based on a large portion of the 'Outback' agricultural region described in the ABARES '*about my region'* map (ABARES, 2019). This area extends from the western part of Queensland from the boarder of NSW, along the border of the Northern Territory, stretching up to the tip of Cape York (ABARES, 2019). The Outback region produces around 2.3 AU$B, accounting for 18% of the state's total gross agricultural production (ABARES, 2019). The primary agricultural commodities produced in this region include cattle and calves, wool and mangoes (ABARES, 2019). This area is likely to experience more days of drought, fire, temperature increases and downpours, as well as less frequent, but more intense cyclones around Cape York (Queensland Government, 2019a, Queensland Government, 2021). It is predicted some crops will no longer productively grow in their current locations due to a reduction in maturing and chilling time (Queensland Government, 2021). Additional risks include waterlogging of crops such as sugarcane, resulting from increased rain in the north, reducing yields. This is of concern as the 2012 floods across southwest, central and western Queensland are estimated to have resulted in a loss of 70 AU$m from livestock and crop losses alone for primary producers (Queensland Government, 2021). Reductions in rainfall are also expected to cause a 12% loss in total crop production and decrease veal and beef available for export (Hughes, 2015).

7.2.4 South Australia Regions

South Australia was broken into three regions: South Australian Outback, the MDB region of South Australia and the Rest of South Australia. The MDB comprises 8% of South Australia and was discussed above in Section 7.2.1 (Murray-Darling Basin Authority, 2020).

The Outback of South Australia includes the Eyre Peninsula and the northern part of the state, based on the ABARES *'about my region'* map (ABARES, 2019). The key industries within this region are tourism, defence, mining and agriculture (RDA Far North SA, 2016). Agricultural land occupies around 50% of the region, which mainly comprises of native vegetative grazing (ABARES, 2019). The main commodities produced in the area include wheat, barley and wool (ABARES, 2019). Other commodities produced in the region include canola, sheep and lambs, pulses, cattle and calves, oats, hay and milk (ABARES, 2019). This region is expected to experience rainfall declines, with a 4.9% decrease at baseline conditions between 2030-2070. There is uncertainty about how rainfall intensity will change in the region (RDA Far North SA, 2016). There is a temperature projection of a 1.8°C increase by 2070 (RDA Far North SA, 2016). By 2030, Port Augusta is anticipated to experience a change from 43 days per year over 35°C, to 61 days by 2070 (RDA Far North SA, 2016). In Marree, days over 35°C are expected to grow from 95 days per year to 108 by 2030 and will further increase to 122 by 2070 (RDA Far North SA, 2016). Fire weather in Woomera is expected to increase by 31%, with a baseline of 17.7 to 23.2 days a year by 2030 (RDA Far North SA, 2016). This is likely to result in reduced vegetation availability and heat stress in livestock.

The Rest of South Australia region covers the Barossa, Yorke- Mid North, Adelaide, and some of south-eastern South Australia. The main commodities produced in this region include wine grapes, wool, potatoes, wheat, barley, and pulses. This region is likely to experience less rainfall, a trend which has occurred since 1970 (Climate Council, 2012). Drought is anticipated to become more intense, leading to the dehydration of soils and detrimental impacts on South Australia's agriculture (Climate Council, 2012). Heat will reduce wine grape quality by changing the acid and sugar levels in the grapes, creating a higher alcohol content and result in a lower quality wine (Mozell and Thach, 2014). It is expected that by 2050, 70% of wine-producing regions with a Mediterranean climate, such as the Barossa Valley, will no longer be suitable for grape production (Hughes, 2015).

7.2.5 Western Australia Regions

Western Australia was divided into three regions: Western Australian Outback, Wheatbelt and Bunbury based on the ABARES agricultural region map of Australia (ABARES, 2019). The Bunbury region comprises 7,100 km^2 of agricultural land, representing 29% of the region. The region produces 852 AU$m of gross value agricultural product, representing 8% of Western Australia's agricultural production. The main commodities produced in the region are milk (166 AU$m), cattle and calves (101 AU$m) and avocados (80 AU$m) (ABARES, 2019). These three commodities equate to 41% of the regions total agricultural production. Other commodities produced in the area include potatoes, wine grapes, carrots, apples, wool, hay and onions (ABARES, 2019). Bunbury is anticipated to experience drier and hotter weather and a rise in sea level (State Greenhouse Action Committee and Morgan, 2006). The southwest, where Bunbury is located, is experiencing a decrease in annual average rainfall by 6% (Bureau of Meteorology and CSIRO, 2019). This rain reduction has occurred in the early winter months and in the autumn. Summer rain has been unreliable; however, winter rain has been reliable, and a reduction of spring frosts has occurred. Temperatures have been rising (Bureau of Meteorology and CSIRO, 2019), which is expected to affect the horticulture industry as increased temperatures will alter seasonal aspects of climate. Fruit crops have specific growing temperatures ranges required for budding, flowering, colouring and productivity. New research may need to be conducted to examine low-chill varieties of fresh produce as a reduction in chilling time may occur (State Greenhouse Action Committee and Morgan, 2006).

The Wheat Belt is a highly productive area, covering 8% of Western Australia (197,300 km^2), with 63% of the region being covered by agricultural land (ABARES, 2019). This region produces a farming output of 6.5 AU$B, accounting for 60% of total gross value of Western Australia's agricultural production (total of 10.7 AU$B) (ABARES, 2019). The main agricultural activity in this region is dryland cropping. The main commodities produced include wheat (2.1 AU$B), barley (1.3 AU$B), and wool (801 AU$m) (ABARES, 2019). These three commodities represent 65% of Western Australia's gross agricultural product (ABARES, 2019). Other commodities produced in the region include sheep and lambs, canola, oats, hay, cattle and calves, eggs, and pluses. The Wheat Belt is expected to experience average rain reductions by 25% (around 85mm) (Wheatbelt Natural Resource Management), heat stress (disrupting wind and soil moisture), increased temperature, less frost, less winter and spring rain, higher intensity rainfalls, increased evaporation, reduced humidity in spring and winter, and harsher fire weather (Bureau of Meteorology and CSIRO, 2019, Department of Agriculture and Food, 2016, Wheatbelt Natural Resource Management, 2015).

The final region selected for Western Australia was the Outback, combining the ABARES *'about my region'* 'Outback North' and 'Outback South' together (ABARES, 2019). This region accounts for 91% of the state's area, with 40% of the land used for agriculture (ABARES, 2019). This area produces 2.93 AU$B gross value of agricultural production, equating to 28% of the gross value of agricultural production in Western Australia (10.7 AU$B) (ABARES, 2019). The main agricultural commodities produced in the region include wheat, canola and barley in the southern area, and cattle and calves, melons and maize in the northern part of the region (ABARES, 2019). Temperatures in this region are expected to rise:1.3-2.7°C around the Kimberley and 2.6-4.2°C in the southwest of the region under a high emission scenario (Department of Primary Industries and Regional Development, 2020). By 2090, in a high emission scenario, rain will decrease by 5-35% in the south-west, 2% in the Pilbara and 8-18% in the Kimberley throughout the dry winter and spring months, with unchanged rain levels in the summer rain (Department of Primary Industries and Regional Development, 2020). By 2070, drought is expected to increase by 80% (Department of Primary Industries and Regional Development, 2020), with a study suggesting a 66% greater probability that southern Western Australia will be affected twice as often by drought by 2030 (Department of Primary Industries and Regional Development, 2020). The frequency of tropical cyclones is expected to decline by 50% by 2090, with a 23% rainfall intensity increase within 200 km of the storm centre (Department of Primary Industries and Regional Development 2020). By 2090, in a high emission scenario, evaporation is expected to grow by 10.3% in the Pilbara, 6.5% in the interior of the region and 12.4% in the Kimberley (Department of Primary Industries and Regional Development, 2020). Wind speed is generally expected to remain constant. Fire risk is likely to increase over most of Western Australia due to the combination of drier, warmer weather (rainfall dependent). The Kimberley is estimated to have an unchanged fire risk, with the Pilbara and northern range lands at the most significant threat (a 50-517% increase in fire risk at Carnarvon by 2090 and 27-331% change at Port Hedland by 2090) (Department of Primary Industries and Regional Development 2020). Finally, frost is expected to decrease due to temperature rise (Department of Primary Industries and Regional Development, 2020).

7.2.6 Tasmanian regions

Studies suggest that the climate impacts in Tasmania are predicted to be more stable than in the rest of Australia (ACE CRC, 2010). This may be the result of the Antarctic Ocean being estimated to have the smallest warming rate compared to other oceans internationally (Holz et al., 2010, ACE CRC, 2010). Therefore, small changes are projected for Tasmania as the Antarctic Ocean will likely store much of this heat, moderating the climate of Tasmania (Holz et al., 2010, ACE CRC, 2010). Tasmania was divided into two regions: North-West and East Tasmania. The North-West represents the 'West Tasmania' and 'North West Tasmania' regions on the ABARES *'about my region'* map, and 'East Tasmania' represents the combination of 'Launceston and North East', 'South East' and 'Greater Hobart' region (ABARES, 2019).

The North-West Tasmania region covers 33% of Tasmania (22,400 km^2), with agricultural land occupying 61% of the area (ABARES, 2019). This region produces 631 AU$m of agricultural output, contributing to 37% of the gross value of Tasmania's agricultural production (ABARES, 2019). The main agricultural commodities produced within the region are milk (248 AU$m), cattle and calves (152 AU$m) and potatoes (65 AU$m) (ABARES, 2019). Other commodities include onions, apples, hay, strawberries, mushrooms, beans and cherries. This region is expected to have an increase in the number of growing days. Pasture growth is expected to rise due to a variety of reasons, such as a reduction in temperature limitation and rising carbon dioxide fertilisation (Regional Development Australia, 2015). Frost days will reduce, and there will be a reduction in chill hours, which may impact the growth of fruits, berries and nuts; an increase in drought frequency, evaporation rise and rainfall is expected to decrease by 18% in the summer and 15% in the winter (ACE CRC, 2010). Tasmania is the only state where dairy production is not expected to decline (Hughes et al. 2015).

East Tasmania accounts for 66.28% of Tasmania. This region produces 1.03 AU$B of agricultural output, reflecting 64% of Tasmania's gross value of agricultural product (1.6 AU$B). In the northern part of East Tasmania, the primary commodities are wool, cherries, sheep and lamb. Around the Hobart region, the main commodities are eggs, wine grapes and lettuce. In Southeast Tasmania, the main commodities are milk, cattle and calves, and potatoes (ABARES, 2019). It is believed there will be a rise in rainfall by 20-30% along the coast of East Tasmania (Tasmanian Institute of Agriculture and Tasmanian Government, 2012, Tasmanian Institute of Agriculture, 2012). This will result in a slightly warmer south than the west and more rain in East Tasmania than in North-West Tasmania. This will increase crops such as rye grass during spring and later winter, with yields rising from around 4.2 t/ha to 6.7 t/ha, depending on the location (Tasmanian Institute of Agriculture, 2012). The flowering and maturation of wheat will occur earlier by 13-18 days throughout this century (Tasmanian Institute of Agriculture, 2012). This region is additionally likely to experience a higher rate of fruit flies (ACE CRC, 2010).

7.2.7 Northern Territory

The whole of the Northern Territory, commonly titled the 'Food Bowl' of Asia, is classified as a single region (ABARES, 2019). This is because the Northern Territory produces little agricultural output, comprising of only 1% of Australia's agricultural production (ABARES, 2019). It currently produces 649 AU$m through forestry, fishing and agriculture, generating 2.5% of the region's gross product. Various weather systems impact the climate of the Northern Territory. The Northern Territory is predicted to endure an increase in extremely hot days resulting from climate change, estimated to reduce cattle exports in 2030 by 19.5% and 33.2% in 2070 (Northern Territory Government, 2020). The surrounding sea is additionally projected to suffer ocean acidification whilst increasing in height by 0.17 metres by 2030 and 0.85 meters by 2090 compared to the sea levels present between 1986-2005 (Northern Territory Government, 2020). The ocean temperature is also estimated to rise from 0.4-1.1°C by 2100. The coastal waters are estimated to rise from 0.3-1.6°C under low emissions and 2.2-4.1°C under high emissions (National Environmental Science Program Earth Systems and Climate Change Hub, 2020). As a result, fishery production is expected to drop by around 40% by 2055 (Hughes, 2015). Furthermore, it is estimated that the Northern Territory will experience warmer days, heat waves will be more apparent, rainfall events will be heavier, and drought periods may increase (National

Environmental Science Program Earth Systems and Climate Change Hub, 2020). Due to the heavy summer rains, peanut production is currently being considered to shift from Queensland to the Northern Territory (Department of Agriculture Water and the Environment, 2019). Finally, tropical cyclones will be less common however, more intense. Evaporation is predicted to increase, and fire weather is estimated to be harsher (National Environmental Science Program Earth Systems and Climate Change Hub, 2020).

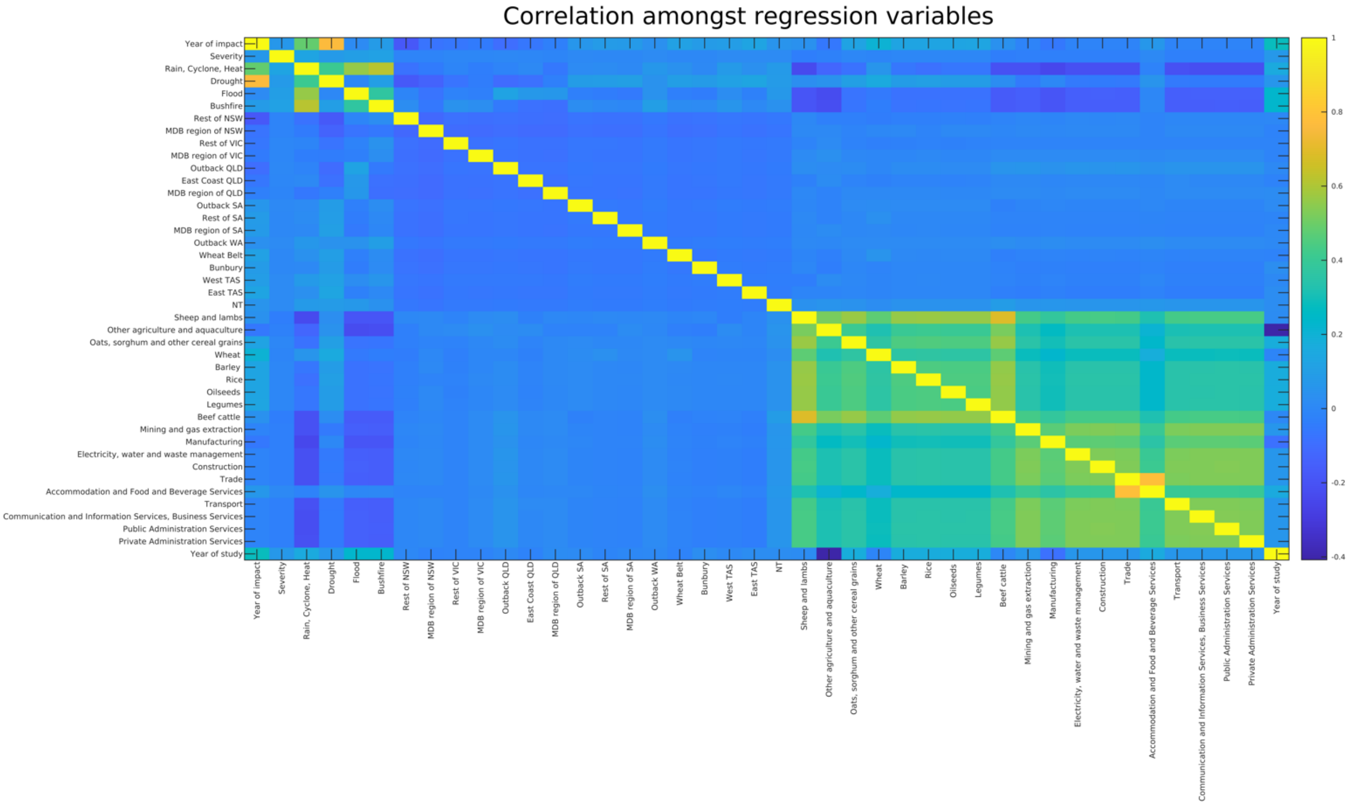
7.2.8 Victorian Regions

Victoria is a very agriculturally productive state, exporting 12.8 AU$B annually, accounting for 23.4% of Australia's total agricultural production (Victorian State Government, 2018). Victoria was divided into two regions: The MDB region of Victoria and Rest of Victoria. The MDB covers 50% of Victoria as outlined previously.

The remaining 50% of Victoria, the Rest of Victoria comprises of Barwon, Gippsland, the Great South Coast and the southern half of the Central Highlands (Agriculture Victoria, 2021). It additionally holds Melbourne's food bowl, which generates enough food to meet the food requirements of 41% of the Greater Melbourne population (Sheridan, 2015). The Rest of Victoria region produces a variety of commodities, including dairy, beef, poultry, horticulture, sheep meat and lamb (Agriculture Victoria, 2021). This region is expected to suffer numerous climate impacts. The region is anticipated to have a temperature increase ranging from 0.8-1.8°C (Victorian State Government, 2019). This is detrimental as heat stress in this region on dairy cows is anticipated to decrease milk yield by 10-25% and even up to 40% in extreme conditions (Hughes, 2015). If a 3°C increase occurs, there will be a 4% gross value loss in the wool, sheep and beef sectors (McKeon et al., 2009). The production of grasslands is estimated to decrease by 14% by 2070 due to increased temperatures (Moore and Ghahramani, 2014). Rainfall is expected to be variable. In the long term, however, there is an anticipated decline in spring and winter rain (medium-high confidence) (Victorian State Government, 2019). Extreme rain events are projected to be of greater intensity (Victorian State Government, 2019). By 2050, the climate of Colac is likely to be like that of Wodonga, and Geelong that of Shepparton. The climate of Bairnsdale is likely to become that of Cowra (NSW), and the climate of Traralgon is like that of Bairnsdale. The climate of Warrnambool is expected to become like that of Benalla and the climate of Hamilton is expected to become like that of Warrnambool (Victorian State Government, 2019). Frosts are anticipated to become less common over time; however, some regions are predicted to experience increased frost risk (Victorian State Government, 2019). Fire seasons are expected to become longer and commence earlier (Victorian State Government, 2019). These fires are likely to increase the destruction of produce and cause blockages along transportation routes. Finally, wheat production has been shown to have production gains in southwest Victoria (Wang et al., 2018).

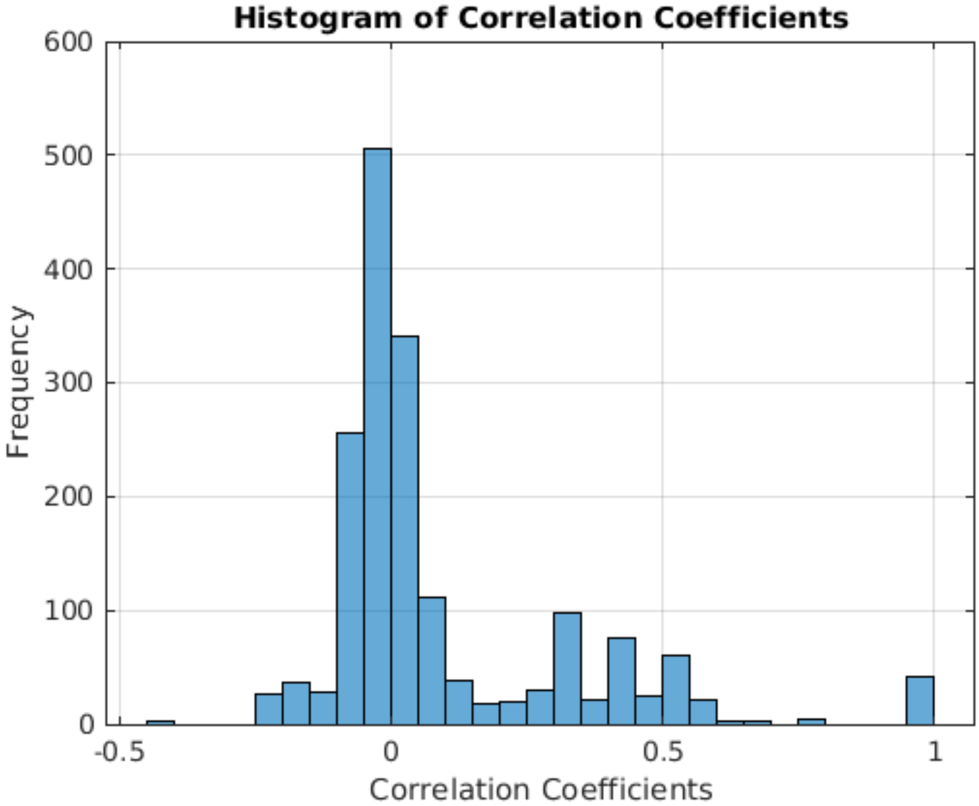
7.3 Multicollinearity of explanatory variables

Correlation between regression variables can be seen through a Pearson's correlation matrix, represented here by a heatmap (Appendix Figure 1). Negative correlations, displayed by values being close to -1, signify that as one variable increases, the other decreases. Positive correlations, indicated by values being close to 1, signify that the variables decrease or increase together. Dark blue and yellow colours indicate a strong correlation, whilst light blue and green indicate a weaker correlation. Variables should not be distinguished individually and are therefore aggerated in the regression analysis. The distribution of correlation coefficients can be seen in Appendix Figure 2.



Appendix Figure 1: Pearson's correlation between explanatory variables.

To minimize overcrowding when visualising results such as in the Pearson's correlation heatmap (Appendix Figure 1) and in the results of the main regression paper (Table 4), we aggregated the sector names and then abbreviated the sector names (Appendix Table 4).



Appendix Figure 2: The distribution of correlation coefficients after conducting the Pearson's correlation analysis.

Appendix Table 4: The aggregation of variable names used in the results.

Disaggregated variable names	***Aggregated variable names***	***Abbreviated names for results***
Year of Study	*Year of Study*	*Year of Study*
Year of Impact	*Year of Impact*	*Year of Impact*
Severity	*Severity*	*Severity*
Rain	*Rain, Cyclone, Heat*	*Rain, Cyclone, Heat*
Cyclone		
Heat		
Drought	*Drought*	*Drought*
Flood	*Flood*	*Flood*
Bushfire	*Bushfire,*	*Bushfire*
Rest of NSW	*Rest of NSW*	*Rest of NSW*
MDB region of NSW	*MDB region of NSW*	*MDB region of NSW*
Rest of VIC	*Rest of VIC*	*Rest of VIC*
MDB region of VIC	*MDB region of VIC*	*MDB region of VIC*
Outback QLD,	*Outback QLD,*	*Outback QLD*
East Coast QLD,	*East Coast QLD,*	*East Coast QLD*
MDB region of QLD,	*MDB region of QLD,*	*MDB region of QLD*
Outback SA	*Outback SA*	*Outback SA*
Rest of SA	*Rest of SA*	*Rest of SA*
MDB region of SA	*MDB region of SA*	*MDB region of SA*
Outback WA	*Outback WA*	*Outback WA*
Wheat Belt	*Wheat Belt*	*Wheat Belt*
Bunbury	*Bunbury*	*Bunbury*
West TAS	*West TAS*	*West TAS*
East TAS	*East TAS*	*East TAS*
NT	*NT*	*NT*
Sheep and Lambs	*Sheep and lambs*	*Sheep and Lambs*
Shorn Wool	*Shorn wool, Untreated milk, Dairy cattle, Pigs, Poultry, Eggs, Vegetables, Fruit, Plant nurseries, Flowers, Grapes for wine, Horses, Deer, Animal breeding, Sugar cane, Unginned cotton, Grass Seed, Forage and Hay, Skins, Ginned cotton and cotton seed, Sheep shearing, Aerial agriculture, Other Agriculture, Forestry and Logging, Agriculture, Forestry and Fishing Support Services, Rock lobsters, Prawns, Raw Fish, Shellfish etc, Aquaculture*	*Other Agriculture and Aquaculture*
Untreated Milk		
Dairy Cattle		
Pigs		
Poultry		
Eggs		
Vegetables		
Fruit		
Plant Nurseries		
Flowers		
Grapes for Wine		
Horse		
Deer		
Animal Breeding		
Sugar Cane		

Unginned Cotton		
Grass Seed, Forage and Hay		
Skins		
Ginned Cotton and Cotton Seed		
Sheep Shearing		
Aerial Agriculture		
Other Agriculture		
Forestry and Logging		
Agriculture, Forestry and Fishing Support Services		
Rock Lobsters		
Prawns		
Raw Fish		
Shellfish etc		
Aquaculture		
Oats, Sorghum and Other Cereal Grains	*Oats, Sorghum and Other Cereal Grains*	*Oats, Sorghum and Other Cereal Grains*
Wheat	*Wheat*	*Wheat*
Barley	*Barley*	*Barley*
Rice	*Rice*	*Rice*
Oilseeds	*Oilseeds*	*Oilseeds*
Legumes	*Legumes*	*Legumes*
Beef Cattle	*Beef Cattle*	*Beef Cattle*
Coal m4Mining	*Coal Mining, Oil and Gas Extraction, Iron Ore Mining, Non-Ferrous Metal Ore Mining, Non Metallic Mineral Mining, Exploration and Mining Support Services*	*Mining and Gas extraction*
Oil and Gas Extraction		
Iron Ore Mining		
Non-Ferrous Metal Ore Mining		
Non-Metallic Mineral Mining		
Exploration and Mining Support Services		
Meat Products	*Meat products, Fresh meat, Offal, Hides, Skins, Blood Meal, Poultry, Slaughtered, Dairy Products, Cheese, Butter Oil, Butter, Vegetable Product Manufacturing, Fruit Product Manufacturing, Oils and Fats, Rice Products, Flour Mill Products, Gluten and Tapioca, Breakfast Foods, Pasta, Pies, Cakes, Biscuits, Bread and Bread Rolls, Confectionery, Food products, Sugar, Fish, Lobster, Processed Seafoods, Animal Food, Soft Drinks, Beer and malt, Spirits, Wine, Tobacco, Wool Scouring and Natural Fabrics, Human-Made Fibres, Textile Products and Finishing, Knitting Mill Products, Clothing, Footwear, Leather Products, Superphosphate, Mixed Fertilisers, Chemical Fertilisers, Cement, Lime , Basic Chemicals , Pesticides and Insecticides, Chemical Products, Plastic and Rubber Products, Paper and Wood Manufacturing, Petroleum and Coal Product Manufacturing, Glass, Ceramic, Cement, Lime, Ready Mixed Concrete, Plaster and Concrete and Other Non-Metallic Mineral Product Manufacturing, Basic Iron and Steel, Basic Non-Ferrous Metal, Fabricated Metal Products, Transport and Transport Equipment Manufacturing, Equipment and Machinery, Furniture and Miscellaneous Manufacturing*	*Manufacturing*
Fresh Meat		

Offal, Hides, Skins, Blood Meal

Poultry, Slaughtered

Dairy Products

Cheese

Butter Oil

Butter

Vegetable Product Manufacturing

Fruit Product Manufacturing

Oils and Fats,

Rice Products

Flour Mill Products

Gluten and Tapioca

Breakfast Foods

Pasta

Pies, Cakes, Biscuits

Bread and Bread Rolls

Confectionery

Food Products

Sugar

Fish

Lobster

Processed Seafoods

Animal Food

Soft Drinks

Beer and Malt

Spirits

Wine

Tobacco

Wool Scouring and Natural Fabrics

Human-Made Fibres

Textile Products and Finishing

Knitting Mill Products

Clothing

Footwear

Leather Products

Superphosphate

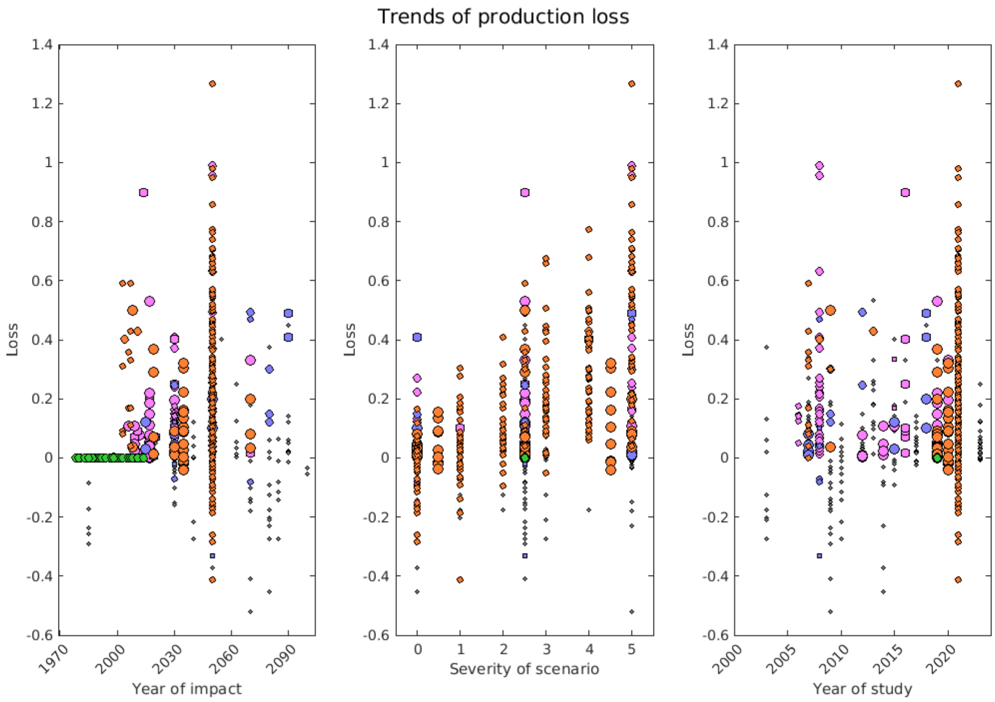
Mixed Fertilisers

Chemical Fertilisers

Cement, Lime

Basic Chemicals		
Pesticides and Insecticides		
Chemical Products		
Plastic and Rubber Products		
Paper and Wood Manufacturing		
Petroleum and Coal Product Manufacturing		
Glass, Ceramic, Cement, Lime, Ready Mixed Concrete, Plaster and Concrete and Other Non-Metallic Mineral Product Manufacturing		
Basic Iron and Steel		
Basic Non-Ferrous Meta		
Fabricated Metal Products		
Transport and Transport Equipment Manufacturing		
Equipment and Machinery		
furniture and miscellaneous manufacturing		
Fossil Electricity Generation, Transmission, Distribution, On Selling and Electricity Market Operation	*Fossil Electricity Generation, Transmission, Distribution, On Selling and Electricity Market Operation, Renewable Energy, Gas Supply, Water Supply, Sewerage and Drainage Services, Waste Collection, Treatment and Disposal Services*	*Electricity, Water and Waste Management*
Renewable Energy		
Gas Supply		
Water Supply, Sewerage and Drainage Services, Waste Collection, Treatment and Disposal Services		
Construction and Construction Services	*Construction and Construction Services*	*Construction*
Wholesale Trade	*Wholesale Trade, Retail Trade*	*Trade*
Retail Trade		
Accommodation and Food and Beverage Services	*Accommodation and Food and Beverage Services*	*Accommodation and Food and Beverage Services*
	Road Transport, Rail Transport, Water, Pipeline and Other Transport, Air and Space Transport, Postal and Courier Pick-up and Delivery Service and Transport Support Services and Storage	*Transport*
Road Transport		
Rail Transport		
Water, Pipeline and Other Transport		
Air and Space Transport		
Postal and Courier Pick-up and Delivery Service and Transport Support Services and Storage		
Communication and Information Services	*Communication and Information Services, Business Services*	*Communication and Information Services, Business Services*
Business Services		
Public Administration Services	*Public Administration Services*	*Public Administration Services*
Private Administration Services	*Private Administration Services*	*Private Administration Services*
Constant	*Constant*	*Constant*

7.4 Production loss trends



Appendix Figure 3: Trends of fractional production loss for the variables of year of impact, disaster severity and year of study.

7.5 Robustness tests for multiple regression

*Appendix Table 5: Comparison of regression variable results between 8 different regression methods. Through conducting a student t-test, the levels of significance are determined by comparing the examined data sets means in relation to their standard deviation to ascertain the likelihood that the data sets are different (Ibinson and Vogt, 2017). This is explained in the probability values p of the test. If p ≤0.01, p ≤0.05, p≤0.1, p≤0.33, then the results are recorded as '***', '**', '*', '.', respectively, where the level of statistical significance decreases the greater the p. When there is no significance present between variables, no '*' or '.' is recorded.*

Variable	OLS	Sig	WLS OPT	Sig	WLS MAN	Sig	WLS MAN OPT	Sig	LOG OLS	Sig	LOG WLS OPT	Sig	LOG WLS MAN	Sig	LOG WLS both MAN & OPT	
Year of impact	0.0011	***	0.00034	***	0.001	***	0.00018	***	0.086	***	0.011	**	0.061	***	0.0045	.
Severity	0.044	***	0.0025	***	0.053	***	0.0033	***	0.044	***	0.0026	***	0.053	***	0.0031	***
Rain, Cyclone, Heat	-0.034	***	0.011	***	-0.023	**	0.037	***	-0.024	**	0.047	***	-0.0086	.	0.043	***
Drought	0.061	***	0.025	***	0.055	***	0.019	***	0.07	***	0.021	***	0.069	***	0.025	***
Flood	-0.079	***	-0.025	***	-0.086	***	-0.058	***	-0.085	***	-0.053	***	-0.093	***	-0.059	***
Bushfire	-0.072	***	-0.024	***	-0.08	***	-0.058	***	-0.077	***	-0.053	***	-0.088	***	-0.059	***
Rest of NSW	-0.054	***	0.0029	.	0.011	.	0.00031		-0.13	***	-0.052	***	-0.11	***	-0.1	***
MDB region of NSW	-0.062	***	0.0032	.	0.0017		0.000076		-0.13	***	-0.052	***	-0.12	***	-0.1	***
Rest of VIC	-0.081	***	0.0013		-0.015	.	-0.00015		-0.16	***	-0.053	***	-0.14	***	-0.1	***
MDB region of VIC	-0.078	***	0.0015		-0.013	.	-0.00015		-0.15	***	-0.052	***	-0.14	***	-0.1	***
Outback QLD	-0.051	**	0.0015		0.0096	.	-0.00034		-0.13	***	-0.053	***	-0.11	***	-0.1	***
East Coast QLD	-0.056	***	0.0015		0.0077		-0.0004		-0.13	***	-0.053	***	-0.12	***	-0.11	***
MDB region of QLD	-0.048	**	0.002		0.015	.	-0.00057		-0.12	***	-0.053	***	-0.11	**	-0.11	***
Outback SA	-0.062	***	0.002		0.0038		0.00049		-0.13	***	-0.051	***	-0.12	***	-0.1	***
Rest of SA	-0.075	***	0.0022		-0.0097		0.00051		-0.15	***	-0.052	***	-0.13	***	-0.1	***
MDB region of SA	-0.076	***	0.0022		-0.013	.	0.00073		-0.15	***	-0.051	***	-0.13	***	-0.1	***
Outback WA	-0.067	***	-0.00012		-0.0035		-0.0014		-0.14	***	-0.053	***	-0.13	***	-0.11	***
Wheat Belt	-0.016	.	0.0011		0.059	***	-0.0015		-0.088	**	-0.051	***	-0.06	.	-0.11	***
Bunbury	-0.032	.	0.0012		0.037	*	-0.0018		-0.11	**	-0.052	***	-0.084	**	-0.11	***
West TAS	-0.1	***	0.00016		-0.04	*	0.00027		-0.17	***	-0.053	***	-0.16	***	-0.1	***
East TAS	-0.081	***	0.00075		-0.014	.	-0.00019		-0.15	***	-0.052	***	-0.13	***	-0.1	***
NT	-0.059	**	0.0015		0		0		-0.13	***	-0.053	***	-0.12	***	-0.1	***
Sheep and Lambs	0.051	***	0.058	***	0.049	***	0.037	***	0.052	***	0.067	***	0.049	***	0.038	***
Other Agriculture and Aquaculture	-0.0098	.	-0.011	***	-0.019	*	0.00066		-0.01	.	-0.011	***	-0.022	**	-0.00077	
Oats, Sorghum and Other Cereal Grains	-0.01	.	-0.025	***	-0.0065	.	-0.02	***	-0.011	.	-0.024	***	-0.0074	.	-0.02	***
Wheat	-0.026	***	-0.023	***	-0.022	**	-0.02	***	-0.022	***	-0.02	***	-0.018	**	-0.019	***
Barley	-0.0097	.	-0.025	***	-0.0066	.	-0.02	***	-0.011	.	-0.024	***	-0.0068	.	-0.021	***
Rice	-0.0056	.	-0.026	***	0.0019		-0.02	***	-0.0066	.	-0.024	***	0.0016		-0.02	***
Oilseeds	-0.008	.	-0.025	***	-0.0033		-0.02	***	-0.009	.	-0.024	***	-0.0036		-0.021	***
Legumes	-0.013	.	-0.025	***	-0.012	.	-0.02	***	-0.014	.	-0.024	***	-0.012	.	-0.021	***
Beef cattle	0.042	***	0.1	***	0.029	**	0.082	***	0.045	***	0.084	***	0.031	**	0.082	***
Mining and gas extraction	0.00087		0.00019		0.00038		-0.0024	.	0.00099		-0.0015		0.00048		-0.0023	.
Manufacturing	-0.038	***	-0.0023	.	-0.033	***	-0.002	.	-0.04	***	-0.0038	.	-0.035	***	-0.0022	.
Electricity, Water and Waste Management	-0.00028		-0.000015		-0.00094		-0.0025	.	-0.000086		-0.0014		-0.00074		-0.0023	.
Construction	0.0011		0.000027		0.001		-0.0024	.	0.0015		-0.0014		0.0016		-0.0023	.

Trade	-0.065	***	-0.022	***	-0.066	***	-0.031	***	-0.063	***	-0.025	***	-0.064	***	-0.031	***
Accommodation and Food and Beverage Services	0.068	***	0.022	***	0.069	***	0.029	***	0.065	***	0.024	***	0.067	***	0.028	***
Transport	-0.0006		-4.30E-05		-0.0015		-0.0024	.	-0.00056		-0.0014		-0.0016		-0.0023	.
Communication and Information Services, Business Services	0.0016		-3.90E-05		0.0018		-0.0024	.	0.0022		-0.0014		0.0025		-0.0023	.
Public Administration Services	0.002		6.60E-06		0.0023		-0.0024	.	0.0026		-0.0014		0.0031		-0.0023	.
Private Administration Services	0.00094		-4.30E-05		0.00074		-0.0024	.	0.0013		-0.0014		0.0012		-0.0023	.
Year of Study	-0.0023	**	0.00019	.	-0.0027	***	0.0034	***	-0.044	*	0.063	***	-0.046	*	0.11	***
Constant	0		0		-0.082	***	-0.024	***	0		0		0		0	
R^2	**0.491**		**0.534**		**0.531**		**0.563**		**0.487**		**0.528**		**0.526**		**0.559**	

Appendix Table 6: Comparison of regression results across four specifications using robust standard errors clustered by Region, Region and Disaster Type, Region and Sector, as well as Region, Disaster Type and Sector. All regressions are conducted using the combined manual and optimally assigned weights. In this case, regional dummy variables are implemented as fixed-effects and the coefficients for the remaining variables are reported. Within R^2 reports the variance explained within the units of the fixed effects (i.e. within the regions).

Variable	*Coef.*	*Standard error*	*Coef.*	*Standard error*	*Coef.*	*Standard error*	*Coef.*	*Standard error*
Year of Impact	0.0000907***	-0.0000202	0.0000907	0.0000432	0.0000907**	0.0000283	0.0000907	0.0000418
Severity	0.0028***	0.0002	0.0028*	0.0005	0.0028***	0.0002	0.0028*	0.0005
Year of Study	0.0032***	0.0002	0.0032**	0.0005	0.0032***	0.0003	0.0032**	0.0005
Rain Cyclone Heat	0.0431***	0.0011	0.0431***	0.0009	0.0431***	0.0014	0.0431***	0.0009
Drought	0.0216***	0.0007	0.0216***	0.0012	0.0216***	0.0011	0.0216***	0.0013
Flood	-0.0568***	0.0008	-0.0568***	0.002	-0.0568***	0.0009	-0.0568***	0.0017
Bushfire	-0.0569***	0.0007	-0.0569***	0.0022	-0.0569***	0.0008	-0.0569***	0.0019
Sheep	0.0386***	0.0013	0.0386***	0.0015	0.0386***	0.0015	0.0386***	0.0015
Beef	0.0810***	0.0008	0.0810***	0.0028	0.0810***	0.001	0.0810***	0.002
Other Agriculture and Aquaculture	-0.0007	0.0021	-0.0007	0.0023	-0.0007	0.0031	-0.0007	0.002
Grains	-0.0202***	0.0006	-0.0202***	0.0006	-0.0202***	0.0009	-0.0202***	0.0007
Wheat	-0.0188***	0.0005	-0.0188***	0.0006	-0.0188***	0.0006	-0.0188***	0.0006
Barley	-0.0205***	0.0004	-0.0205***	0.0006	-0.0205***	0.0008	-0.0205***	0.0007
Rice	-0.0205***	0.0005	-0.0205***	0.0006	-0.0205***	0.0008	-0.0205***	0.0006
Oilseeds	-0.0203***	0.0006	-0.0203***	0.0007	-0.0203***	0.0009	-0.0203***	0.0008
Legumes	-0.0207***	0.0007	-0.0207***	0.001	-0.0207***	0.0009	-0.0207***	0.001
Mining and Extraction	-0.0021***	0.0002	-0.0021**	0.0003	-0.0021***	0.0001	-0.0021**	0.0002
Manufacturing	-0.0024***	0.0003	-0.0024**	0.0003	-0.0024**	0.0007	-0.0024*	0.0005
Electricity, Water and Waste Management	-0.0022***	0.0002	-0.0022**	0.0003	-0.0022***	0.0001	-0.0022**	0.0002
Construction	-0.0022***	0.0002	-0.0022**	0.0003	-0.0022***	0.0001	-0.0022**	0.0002
Trade	-0.0262***	0.0006	-0.0262***	0.0008	-0.0262***	0.001	-0.0262***	0.0009
Tourism	0.0241***	0.0006	0.0241***	0.0009	0.0241***	0.0011	0.0241***	0.001
Transport	-0.0022***	0.0002	-0.0022**	0.0003	-0.0022***	0.0001	-0.0022**	0.0002
Communication, Information and Services	-0.0022***	0.0002	-0.0022**	0.0003	-0.0022***	0.0001	-0.0022**	0.0002
Public Administration Services	-0.0022***	0.0002	-0.0022**	0.0003	-0.0022***	0.0001	-0.0022**	0.0002
Private Administration Services	-0.0022***	0.0002	-0.0022**	0.0003	-0.0022***	0.0002	-0.0022**	0.0003
Fixed effects:	Region		Region		Region		Region	
S.E.: Clustered	Region		Regin + Disaster Type		Region + Sector		Region + Disaster Type + Sector	
Observations	3,392		3,392		3,392		3,392	
Within R2	0.96		0.96		0.96		0.96	

7.6 Historical and predicted disaster results

We chose to separate the regression results for the historical and predicted climate disaster variables in order to check the robustness of the results (Appendix Table 7).

*Appendix Table 7: Results for the WLS regression with optimised and manually assigned weights comparing historical and predicted climate disaster variables. This regression uses a fixed-effect for the region, which still employs dummy variables, however, it suppresses the output for them. The levels of significance are determined by comparing the examined data sets means in relation to their standard deviation to ascertain the likelihood that the data sets are different (Ibinson and Vogt, 2017). This is explained in the probability values p of the test. If p ≤0.01, p ≤0.05, p≤0.1, p≤0.33, then the results are recorded as '***', '**', '*', '.', respectively, where the level of statistical significance decreases the greater the p. When there is no significance present between variables, no '*' or '.' is recorded.*

	All data		*Future data*		*Historical data*	
Variable	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error
Year of Impact	0.0000907***	-0.0000202	0.0001***	0.0000247	0.0000012	0.00000117
Severity	0.0028***	-0.0002	0.0029***	0.0002		
Year of Study	0.0032***	0.0002	0.0031***	0.0002		
Rain Cyclone Heat	0.0431***	0.0011	0.0421***	0.0012		
Drought	0.0216***	0.0007	0.0209***	0.0008		
Flood	-0.0568***	0.0008	-0.0562***	0.0007	-0.00000123	0.00000118
Bushfire	-0.0569***	0.0007	-0.0566***	0.0008		
Sheep	0.0386***	0.0013	0.0383***	0.0014	-0.000000707	0.000000793
Beef	0.0810***	0.0008	0.0806***	0.0009		
Other Agriculture and Aquaculture	-0.0007	0.0021	-0.0004	0.0021		
Grains	-0.0202***	0.0006	-0.0201***	0.0006		
Wheat	-0.0188***	0.0005	-0.0188***	0.0006		
Barley	-0.0205***	0.0004	-0.0205***	0.0005		
Rice	-0.0205***	0.0005	-0.0204***	0.0005		
Oilseeds	-0.0203***	0.0006	-0.0203***	0.0006		
Legumes	-0.0207***	0.0007	-0.0206***	0.0007		
Mining and Extraction	-0.0021***	0.0002	-0.0021***	0.0002	0.0000417	0.0000225
Manufacturing	-0.0024***	0.0003	-0.0024***	0.0004	0.000000305	0.000000908
Electricity, Water and Waste Management	-0.0022***	0.0002	-0.0022***	0.0002	-0.000000707	0.000000793
Construction	-0.0022***	0.0002	-0.0022***	0.0002	0.0000168	0.00000927
Trade	-0.0262***	0.0006	-0.0265***	0.0007	-0.000000433	0.000000486
Tourism	0.0241***	0.0006	0.0243***	0.0007		
Transport	-0.0022***	0.0002	-0.0022***	0.0002	0.0000115	0.00000694
Communication, and Information	-0.0022***	0.0002	-0.0022***	0.0002	0.0000117	0.00000637
Public Administration Services	-0.0022***	0.0002	-0.0022***	0.0002	-0.000000706	0.000000793
Private Administration Services	-0.0022***	0.0002	-0.0022***	0.0002		
Fixed-Effects:	Region		Region		Region	
S.E. clustered by	Region		Region		Region	
Observations	3,392		3,042		320	
R2	0.96197		0.96158		0.25495	
Within R2	0.96004		0.95943		0.1448	

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Spillover economic losses due to an outbreak of Fusarium Wilt TR4 in the Philippines

Abstract

In 2015, the Davao region in the Philippines experienced a severe outbreak of Fusarium wilt TR4, a disease fatal to the Cavendish banana cultivar, also known as Panama disease. Once a single specimen is infected, the entire crop must be destroyed to reduce further transmission. This outbreak impacted 15,000 ha of productive land, resulting in a loss of 296 US$m in export revenue. Economic impacts can be felt directly or indirectly due to the ripple effects of a disaster given the highly interconnected web of supply chains, including industries involved in providing inputs for banana production, distribution or consumption. In this report, Multi-Regional Input-Output (MRIO) analysis was used as an economic modelling tool to quantify the spillover economic impacts of this outbreak in other geographic regions and industry sectors. We determined that direct and indirect spillover effects resulted in an economic loss of 134 US$m. The most significant regional spillover effects were felt by Asia and Oceania (excluding Japan, China and South Korea) (52.8 US$m), the Middle East (27.05 US$m), and Europe (16.49 US$m). The greatest sectoral losses were experienced by services (35.63 US$m), manufacturing (excluding food and beverages) (35.2 US$m) and construction (13.66 US$m). These results can be scaled up to predict which regions and sectors would likely suffer flow-on economic impacts associated with similar disease outbreaks in a given country. These findings can then aid in the development of disaster recovery plans.

1. Background

Fusarium wilt is a destructive plant disease affecting banana cultivars worldwide. The soil-borne fungus *Fusarium oxysporum f. sp. cubense* infects the roots of plants and blocks vascular transport of nutrients and water, eventually resulting in death (Beckman, 1987). Once a plant is affected by Fusarium wilt, the fruit is no longer harvestable. To prevent further spread of the disease, the infected plant and any neighbouring, potentially exposed, banana plants are destroyed, including the fruits. Fusarium wilt likely originated in Southeast Asia (Ploetz and Pegg, 1997) and was first reported in Australia in 1874 (Bancroft, 1877). The worldwide spread of the disease in the first half of the 20th century virtually annihilated the 'Gros Michel' banana, a once-popular monoculture cultivar produced in Central America, Jamaica and Martinique, that was exported to North America and Europe (Stover, 1962). This resulted in an estimated worldwide trade loss equivalent to 2.3 US$B to date (Aquino, 2013). By the 1960s, major exporters had transitioned to the then disease-resistant 'Cavendish' cultivar as the primary export banana (Ploetz, 2005).

Fusarium wilt first infected the Cavendish cultivar in Taiwan in 1976. It was not until 1977, however, that the pathogen was identified as a new tropical race 4 (TR4). By this time, more than 1,200 ha of Cavendish banana fields had been infected by Fusarium wilt TR4 in Taiwan (Su, 1997). The subsequent spread of Fusarium wilt TR4 throughout Asia saw the destruction of commercial plantations in Malaysia, Indonesia and Australia in the 1990s (Buddenhagen, 2009, Walmsley, 2019). The spread of Fusarium wilt TR4 to the Philippines was confirmed in 2008 (Molina, 2008). It has since spread to other parts of Asia and the Middle East (García-Bastidas et al., 2014, Ordoñez et al., 2016). In 2019, Fusarium wilt TR4 was confirmed to have spread to Colombia (García-Bastidas, 2020), the third largest exporter of bananas in the Americas and fourth in the world (FAO, 2019a).

Fusarium wilt TR4 spreads via infected plants or soil. The movement of contaminated material between plantations can occur due to human activity or through run-off and flooding (Queensland Government, 2021). Cavendish bananas are a highly susceptible monoculture, thus, no plants are resistant to the disease once infected (Su, 1997). This means management of the disease within a jurisdiction following the first outbreak is virtually impossible without drastic eradication measures, such as burning all potentially contaminated plant matter. To ensure disease eradication, the contaminated areas cannot be used to grow Cavendish bananas for many years following infection (IICA, 2021). This level of eradication can have severe impacts on the production volume of Cavendish bananas for years following the outbreak, substantially impacting the local banana economy. Since the discovery of Fusarium wilt TR4 in Australia's Northern Territory in 1997, it has lost 90% of its commercial banana enterprises (Walmsley, 2019). It is projected that between 1.26 million and 1.7 million ha of global Cavendish banana production area could be infected by TR4 by 2040, with as much as 70% of the production area affected in countries that are already managing outbreaks of this high-burden disease (Scheerer et al., 2018).

1.1 The banana economy

In 2019, worldwide banana exports totalled 14.2 US$B. The top five exporters, Ecuador, the Philippines, Costa Rica, Guatemala and Colombia, were estimated to be responsible for over 60% of the export value (OEC, 2021). The top five banana importers are the United States, China, Japan, Germany and the Netherlands, which together account for over 44% of banana consumption (OEC, 2021). The Cavendish banana variety accounts for almost all banana exports (FAO, 2003). In 2019, banana exports from the Philippines were valued at 1.72 US$B, making the Philippines the second highest global exporter of bananas after Ecuador (OEC, 2021). Bananas are the Philippines' largest agricultural export and accounted for 1.41% of the Philippines total export revenue in 2019 (Harvard University Centre for International Development, 2021). Exports to Japan, China and South Korea make up over 80% of the total value of banana exports from the Philippines. Other major export destinations include Saudi Arabia, Iran, Hong Kong and United Arab Emirates (Harvard University Centre for International Development, 2021).

1.2 Philippines case study

Fusarium wilt TR4 was first observed in a Cavendish banana plantation in the Philippines in 2002 (Molina, 2008). Further outbreaks of the disease occurred on commercial Cavendish farms in 2004 and 2005 (Molina, 2008). Each episode resulted in the complete clearance of land containing the infected plants, as well as the surrounding hills, to prevent further spread of the disease (Molina, 2008). By 2013, Fusarium wilt TR4 was continuing to spread through small independent farms in the Mindanao region of the Philippines (Aquino, 2013). In 2015, a substantial drop in the volume of bananas exported from the Philippines was recorded (FAO, 2021). This loss coincided with a severe Fusarium wilt TR4 outbreak in the Davao region, a region responsible for 36% of total banana production (Republic of the Philippines, 2018) and more than half of the Cavendish cultivar (Montiflor et al., 2019). This volume decrease resulted in more than a 60% reduction in the export value of bananas between 2014 and 2015 (FAO, 2021). The Philippine banana export market has since recovered with the 2018 export value of 1.5 US$B, surpassing the previous maximum reached in 2014 of 1.1 US$B. In 2019, this export value further increased to 1.9 US$B (FAO, 2021).

In 2020, export volumes decreased by 14% in comparison to 2019 due to lower production levels and logistical challenges created by restrictions implemented to manage the COVID-19 pandemic (Arcalas, 2021). This reduction may have been impacted by external factors such as the effects of the COVID-19 pandemic on production, supply chains, and trade negotiations. There have been, however, numerous reports of expanding outbreaks of Fusarium wilt TR4 in the Mindanao region throughout 2020 and 2021 (Cayon, 2020, Gomez, 2021). These outbreaks are yet to be officially confirmed. Continued unmonitored spread of Fusarium wilt TR4 through the major banana regions could result in further significant drops in production in the future. Banana exports from the Philippines in 2022 reached 1.41 US$B (OEC, 2022b).

1.3 Assessment of direct impact

In 2015, 15,500 ha of Cavendish banana farms in the Davao region of the Philippines were infected by the TR4 strain of Fusarium wilt (Montiflor et al., 2019). In the Philippines, Cavendish bananas are predominantly produced for international export (Republic of the Philippines, 2018). The banana cultivar Lakatan dominates the domestic fresh banana market, while Saba and Cardaba bananas are the main cultivars used for cooking and processed foods such as banana chips and catsup (Republic of the Philippines, 2018). The domestic Cavendish banana market in the Philippines is negligible (Republic of the Philippines, 2018). Thus, all direct financial impacts from this outbreak are assumed to have occurred in the export market. The Philippine's fresh banana export market is made up exclusively of the Cavendish variety (Arado, 2018). Data on Philippine banana production, especially Cavendish bananas, is non-existent as most banana data were collated into categories called 'bananas and plantains (fresh and dried)'. Therefore, this study is unable to estimate the impact attributable to bananas alone, nor the impact of the Fusarium wilt TR4 on Cavendish bananas specifically. The direct impacts are thus measured on the whole Philippine banana sector.

The direct and spillover economic impacts from Fusarium wilt TR4 outbreaks are dependent on the type of Cavendish banana market supported by the country experiencing an outbreak. The Philippines, Costa Rica and Colombia produce Cavendish bananas for export. The Philippines predominantly supplies Asian countries such as Japan, China and South Korea, whereas Costa Rica and Colombia supply Northern America and Europe (Harvard University Centre for International Development, 2021). The direct economic impacts of a loss in Cavendish banana production would be felt within the country experiencing the outbreak, but the spillover effects from supply chain disruption would predominantly occur in the regions importing the bananas, producing banana-related value-added products or providing services further along the supply chain.

Notably, previous studies have considered both the documented historic (Aquino, 2013) and predicted local economic impacts (Cook et al., 2015) of Fusarium wilt TR4 outbreaks in regions that support commercial banana production. However, the important spillover economic impacts across different regions and sectors have not been included in the analysis. This study aims to develop a comprehensive estimate of the economic spillover impacts of the 2015 Fusarium wilt TR4 outbreak in the Davao region in the Philippines into different sectors and regions using MRIO modelling. In this study we (1) Explore how MRIO analysis can be used to determine the spillover disaster impacts of the 2015 Fusarium wilt TR4 outbreaks in the Philippines, (2) Provide an overview of the spillovers resulting from this disaster, (3) Examine how the spillovers identified from the outbreak impact policy decisions, and (4) Propose how recognising and estimating the spillovers can be used to inform disaster management plans.

2. Materials and methods

2.1 Input-Output analysis calculations

Numerous analysis methods can be adopted to quantify the impact of disasters. Computable General Equilibrium modelling, involving long-run optimisation-based equilibrium analysis, is often employed (Okuyama and Santos, 2014). Advantages of this method include the ability to incorporate price changes post-disaster and consider supply constraints and import substitutions. However, such modelling can be labour intensive and too optimistic when considering market flexibility (Okuyama and Santos, 2014). Many other quantitative disaster methods do not consider the effects that may be experienced outside administrative boundaries, which is vital to examine due to economic flows between countries and regions (Koks and Thissen, 2016). Faturay et al. (2020) suggests, however, that there is no perfect disaster analysis method, as each disaster requires its own approach.

Input-Output (IO) techniques can also be considered as a quantitative disaster analysis method. Wassily Leontief developed IO analysis in 1936 (Leontief, 1936). IO analysis is a macro-economic method that can be used as an economic scenario modelling tool, which utilises inter-industry datasets to provide a holistic examination of direct and indirect disaster impacts on different production layers along supply chains (Alsamawi et al., 2014, Okuyama and Santos, 2014, Tukker and Dietzenbacher, 2013). Today, over 100 national statistics agencies around the world contribute to the development and maintenance of IO databases (Tukker and Dietzenbacher, 2013). Most studies that quantify the impact of disasters do not consider economic spillovers into different sectors within a supply chain web, making IO analysis an easy-to-interpret tool (Malik et al., 2018). Economic spillovers occur when the economic impact of an event spreads to regions and sectors where the disaster does not have an immediate impact. For example, abattoirs are impacted when there is a drought that reduces livestock production. Various studies have built on Leontief's work through the adoption of MRIO analysis, allowing examination of the economic inter-industry flow between various sectors and regions (Koks and Thissen, 2016). MRIO has been employed for research, public policy (Rose and Miernyk, 1989) and informing Life Cycle Assessment (Boylan et al., 2020). By 2013, numerous global MRIO databases had been developed, distinguishing more than 10,000 unique products and industries.

IO disaster analysis can be conducted by Schulte in den Bäumen et al.'s (2014) IO method, which uses IO databases to examine how an economy changes with sector impacts. This method assumes that production output decreases due to disaster damage (Faturay et al., 2020). The analysis first considers supply shocks by using a concept called an event matrix, which isolates the decrease in production capabilities. This method assumes production capacity is fully employed at 100% capability, which forms immediate output levels post-disaster (Faturay et al., 2020). The disadvantage of this method, however, is that the sum of intermediate inputs (inputs needed to generate post-disaster output) and final demand can be greater than post-disaster outputs (i.e. demand is greater than supply), resulting in the economy not being able to self-reproduce (Faturay et al., 2020).

The present study will use a modification of Schulte in den Bäumen et al.'s (2014) IO method, following Faturay et al.'s (2020) variation. In this method, it is assumed that, i) production capacity is decreased due to disaster damages and does not assume that production capacity is at 100% capacity. Instead, Faturay et al. (2020) suggests that outputs are not greater than production capacity (Equation 1). This method also assumes, ii) that intermediate demands are not negative, which is achieved through starting calculations from given final demands (Equation 2). These assumptions generate a set of feasible solutions for output levels that maximise the sum of outputs (Faturay et al., 2020). Determining the maximum sum of post-disaster output is achieved through employing a linear programming method (Faturay et al., 2020). Schulte in den Bäumen et al.'s (2014) method focuses on one year and disregards post-disaster dynamics.

A MRIO table comprises of a $\mathbf{T}$, $\mathbf{y}$ and $\mathbf{x}$ matrix. The $\mathbf{T}$ matrix, is the 'intermediate demand' matrix with the size $N \times N$, holding information on inter-industry transactions between all countries (Fry et al., 2018). Within supply chains, demand can occur between industries or can arise from final consumers. The $\mathbf{y}$ represents the 'final demand' matrix which holds information on demand from final consumers such as governments and households. $\mathbf{x}$ represents the 'total output' matrix. In IO analysis, an $\mathbf{A}$ matrix is also formed which reflects the amount of inputs required to produce \$1 of output. The $\mathbf{A}$ matrix is also known as a direct coefficients matrix or production recipe of an economy (Faturay et al., 2020) and is calculated through $\mathbf{A}_{ij} = {\mathbf{T}_{ij}}/{\mathbf{x}_{\mathrm{ij}}}$. IO analysis often uses an identity matrix $\mathbf{I}$ with the size $N \times N$, which is populated by 1's in the diagonal of the matrix, and 0's are placed everywhere else (Faturay et al., 2020). IO analysis assumes Leontief's fundamental accounting identity displayed by $\mathbf{y} = (\mathbf{I} - \mathbf{A})\mathbf{x} = \mathbf{x} - \mathbf{T} \Leftrightarrow \mathbf{T} + \mathbf{y} = \mathbf{x}$ (Leontief, 1936).

Schulte in den Bäumen et al.'s (2014) IO method can determine post-disaster output by maximising the total output based on two conditions:

i) $\tilde{\mathbf{x}} \leq (\mathbf{I} - \mathbf{\Gamma})\mathbf{x}_0$ (1)

ii) $\mathbf{y_1} \geq \mathbf{0}$ (2)

Here, $\mathbf{\Gamma}$ is an $N \times N$ event matrix, comprising of a set of diagonal fractions representing production losses in those sectors that are directly impacted (Faturay et al., 2020). For example, a value of 0.3 represents a 30% output decrease post-disaster. $\tilde{\mathbf{x}}$ represents the potential maximum post-production, $\mathbf{y}_1$ represents consumption possibilities post-disaster (Lenzen et al., 2019), and $\mathbf{x}_0$ represents total output pre-disaster. In this method, the $\mathbf{A}$ matrix is assumed constant (i.e. the quantity of inputs required to produce \$1 of output does not differ post-disaster), thus the economic structure is unchanged. Therefore, it is assumed that industries in the short term are unable to restore their original production abilities through substitution of inputs. An example of the spillover calculation process and an illustrative example from Steenge and Bočkarjova (2007) with an altered event matrix can be found in the paper by Faturay et al. (2020).

2.2 Data

The $\mathbf{T}$ and $\mathbf{y}$ matrices are populated using data from the Global IELab so that both the direct $\mathbf{\Gamma}$ and indirect impacts of a disaster to be explored. The Global Industrial Ecology Virtual Laboratory (IELab) (Lenzen et al., 2017a) contains data that are used to determine the spillover effects along sectors and regions from the 2015 Fusarium wilt TR4 outbreak in the Philippines. The data contained within the IELab includes data from state accounts, IO tables, economic accounts, information on agricultural commodities and inter-regional trade (Lenzen et al., 2017b). It additionally has an in-built data updating function so that recent social and economic data are considered to provide current disaster predictions in a cost-effective manner (Lenzen et al., 2019).

Regions and sectors were selected for the study through regional and sectoral groupings customised to the economic context of the Philippine banana industry. A total of 25 regions were chosen, including countries that are major banana industry trade partners of the Philippines. These include Japan, China, South Korea, Hong Kong, Iran, United Arab Emirates, Saudi Arabia, Kuwait, Singapore and New Zealand (Harvard University Centre for International Development, 2021). The remaining countries in the world are sorted into sub-continent geographical regions (Appendix Table 1). For the 26 sectors, the agriculture sector is disaggregated into two sectors: ‘Bananas including plantains (fresh or dried)’ and ‘Rest of agriculture’, so that the spillover impacts of the outbreak on the rest of the agricultural sector can be identified (Appendix Table 2). The remaining sectors are an aggregation of sectors to reflect those within a standard national economy. To reduce overcrowding when visualising the spillover effects on all 26 sectors and 25 regions on a figure, a condensed dataset for both regions and sectors is developed (Appendix Tables 3 & 4).

We developed an MRIO table in the Global IELab (version 2.7) (Lenzen et al., 2017a) using the 26 sectors and 25 regions defined above. The primary data underlying the construction of the MRIO in the Global IELab stem from the Asian Development Bank (2021) MRIO database with the following data feeds: ADB MRIO, food and agriculture statistics from FAO STAT (FAO, 2019c), Balancing, Engineering (Lenzen et al., 2022), Fisheries and Aquaculture Statistics (FAO, 2018), industrial statistics from the INDSTAT database (UNIDO, 2020a), mining and utilities statistics from the MINSTAT database (UNIDO, 2020b), Inter-Country Input-Output Tables (OECD, 2018), global trade statistics from the UN Comtrade database (UN and COMTRADE, 1990), UNSNAMA (USDA, 2011), World Bank database (World Bank, 2021), World Bank HES database (World Bank, 2017) and from the Main Aggregates database (UNSD, 2020). 2015 is selected as the study year as this was the year of the Fusarium wilt TR4 outbreak in the Philippines.

To determine the direct and indirect impacts of the 2015 Fusarium Wilt outbreak in the Philippines, the IO table output was cross-checked against further region-specific data from the published literature to validate the results. Primary sources of information about production and export were sought from the Philippines government and banana industry groups where possible. These include primary economic data on total banana output from the Philippines, production value, final demand of each country and export data. Data were collected from the FAO and the Philippine Statistic Authority (FAO, 2021) (Philippines Statistics Authority, 2015). This data collection ensures as much data is used as possible and hence increase validity of the results and their derivation from values consistent in research. The values of intermediate exports $\mathbf{T}$ and final demand $\mathbf{y}$ of each country selected in the regional aggregator (Tables 1 & 2) are firmed up with export data. Firming up the data is achieved by averaging banana export values from published evidence. Philippine banana export value estimates included 658 US$m (Philippines Statistics Authority, 2015) and 440 US$m (FAO, 2021) to provide an average Philippine banana export value of 548.9 US$m. A portion of this export value is then allocated to different export countries according to their respective export percentage from the Philippines Statistics Authority (2015). A comparison of literature values and MRIO table values are seen in the figure (Appendix Figure 1). The disaster variables are then prepared.

2.3 Event matrix

The event matrix $\mathbf{\Gamma}$ as previously defined, was formed by using primary data statistics on the impact of each sector/region and dividing these by the gross output in the MRIO (Schulte in den Bäumen et al., 2014). The non-diagonal cells within the matrix are filled with 0s (Schulte in den Bäumen et al., 2014). Post-disaster production possibilities $\mathbf{y}_1$ are the result. An event matrix was therefore used to determine the spillover impacts of the 2015 Fusarium wilt TR4 outbreak in the Philippines.

As of 2015, regions that had recorded cases of TR4 strain of Fusarium wilt are Northern Mindanao (Bukidnon), Central Mindanao (Sarangani) (Fruitnet Staff, 2009) and the Davao Region (Molina, 2012). The outbreak in Bukidnon has since been brought under control, limiting spread (Balane, 2012), and beyond 2009 there were no further reports of infection in Sarangani. Therefore, the cases observed in the Davao region in 2015 were assumed to account for all the cases of Fusarium wilt TR4 for the whole of the Philippines for that year. Thus, 100% production volume loss was assumed for the 15,500 ha infected hectares reported in the 2015 outbreak. Based on the literature, the percentage loss of Cavendish bananas due to the Fusarium wilt TR4 outbreak in the Philippines was calculated as follows:

the production volume of Cavendish bananas in 2014 is estimated to be 4.5 Mt, with a production area of 84,000 ha (Republic of the Philippines, 2015). Therefore, the production volume in 2014 can be assumed to be 53 t/ha. As it has been estimated that there was a 15,500 ha production area lost to Fusarium wilt TR4 in 2015 in the Davao region (Montiflor et al., 2019), it can be assumed that the production volume loss due to Fusarium wilt TR4 was 822,000 t/ha. Banana output for 2015 can therefore be extrapolated to 3,670,000 t, making the percentage loss of Cavendish banana output in the Philippines due to Fusarium wilt TR4 18.5%. Alternatively, the economic trade loss due to the Fusarium wilt TR4 outbreak on Cavendish bananas can be calculated. The total quantity of bananas exported from the Philippines in 2015 was 1.22 Mt with a total export value of 548.9 US$m based on averaging exports from the FAO and Philippines Statistics Authority (Philippines Statistics Authority, 2015) (FAO, 2021). This gives an export price per tonne of Cavendish Bananas of 448.77 US$ in 2015. Hence, the total direct financial loss in exports due to the impact of TR4 on Cavendish bananas in the Philippines in 2015 is estimated to be 369 US$m, or a 32.8% economic export loss.

3. Results

3.1 Direct impacts and spillover overview

Our results indicate that every region or sector examined in this study was affected by the 2015 Fusarium wilt TR4 outbreak on Cavendish bananas in the Philippines (Figure 1, Figure 2 and Table 1). The direct and indirect spillover impacts due to the outbreak were estimated to be 134 US$m. The direct impacts of the Fusarium wilt TR4 outbreak highlight a 1.6 US$m economic loss in the Philippines study region (Figure 1). Broadly, there are direct spillovers evident in the countries that import bananas from the Philippines (Japan, China and South Korea). Spillover effects, however, are also evident in regions not directly impacted by the Fusarium wilt TR4 2015 outbreak, such as the Rest of Asia and Oceania (52.8 US$m), the Middle East (27.05 US$m) and Europe (16.49 US$m) (Figure 1). This is because production loss in the Philippine banana sector affects sectors in regions that rely on either demand bananas (e.g., hospitality, tourism and food manufacturing), or are sectors that supply resources to banana crop production (e.g., fertilisers and fuel for agricultural machinery). These sectors also experience a downturn when banana production decreases. Such ripple effects down the supply chain do not finish there, as impacts proceed to high-order upstream and downstream sectors, including the manufacture of basic chemicals for fertilisers, manufacture of agricultural machinery, construction of storage facilities, transport, insurance, catering and ancillary services to hospitality. Thus, the ripple effect along the supply chain extends into sectors (e.g., construction and services) that - at first sight - appear not be linked to banana production. Frequently, these higher-order sectors are situated in regions that do not directly receive bananas, but may include manufacturing such as machinery and chemicals, or provide tourism services etc.

When the regional losses are disaggregated, the results highlight that the regions that felt the greatest impacts are Iran (9.68 US$m), Southern Asia (8.64 US$m), Southern Europe (6.59 US$m) and Central Asia (6.57 US$m). Additionally, further disaggregation of the sectors highlight that the main sectoral impacts are felt by hotels and restaurants (9.45 US$m), public administration (9.13 US$m) and other manufacturing (8.6 US$m) (Table 2). When regional and sector pairings are compared, it is evident that within the Rest of Asia and Oceania, the greatest sectoral spillovers were felt within the sectors of manufacturing, services and construction (Table 2). In the Middle East, the greatest losses were felt within the sectors of services, manufacturing and trade (Table 2). Within Europe, the greatest economic sectoral losses were experienced within manufacturing and services (Table 2). The top 20 region-sector pairings highlight that a diversity of sectors was impacted across many regions resulting from trade dependencies along supply chains (Table 2). When the services sector is disaggregated into different services, it is evident that most impacts are felt by public administration (9.13 US$m), domestic services (6.96 US$m), and services from extraterritorial organizations and bodies (6.24 US$m) (Table 3 and Figure 3). Whilst the Philippines appears to have sustained a minor economic impact from the outbreak, it is only because it has a small economy compared with other regions selected within the study. The economic impact on the Philippines as a percentage of GDP is relatively small (smaller than 10^{-3}%).

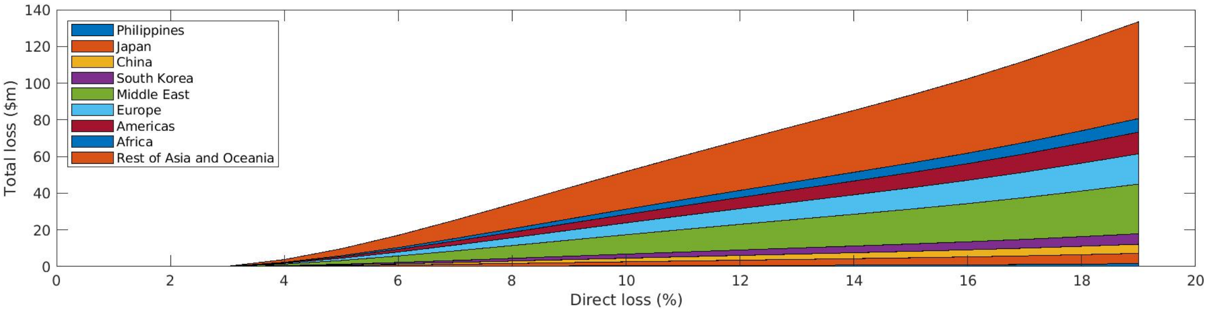

Figure 1: Regional economic spillover loss measured in US$ resulting from the 2015 Fusarium wilt outbreak in the Philippines. An economic spillover range is shown from 0-19% for reference should other outbreaks occur.

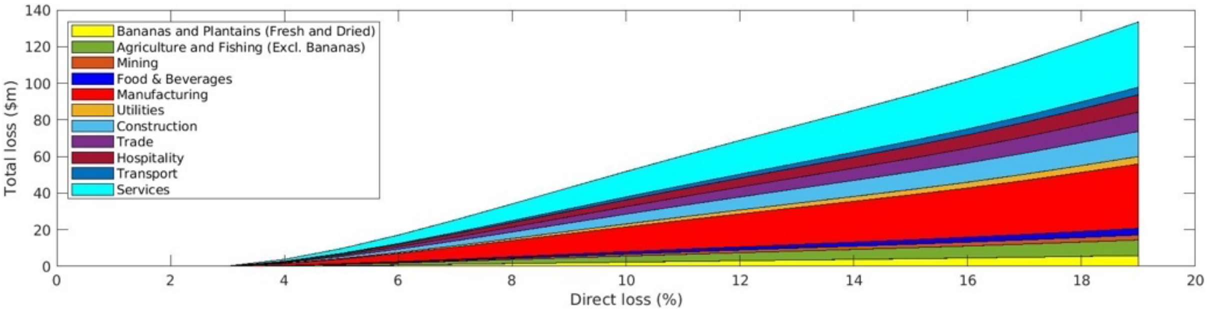

Figure 2: Sectoral economic spillover loss measured in US$ resulting from the 2015 Fusarium wilt outbreak in the Philippines. An economic spillover range is shown from 0-19% for reference should other outbreaks occur.

Table 1: Sectoral and regional economic spillover losses measured in US$ resulting from the 2015 Fusarium wilt outbreak in the Philippines

Sector	***Loss (US$m)***	***Region***	***Loss (US$m)***
Services	35.63	Rest of Asia and Oceania	52.8
Manufacturing	35.2	Middle East	27.05
Construction	13.66	Europe	16.49
Trade	10.57	Americas	11.83
Hospitality	9.45	Africa	7.43
Agriculture and fishing (excl. bananas)	8.55	South Korea	5.74
Bananas and plantains (fresh and dried	5.89	Japan	5.6
Transport	4.18	China	4.95
Utilities	4.05	Philippines	1.60
Food and beverages	3.63		
Mining	2.67		

Table 2: Top 20 ranked regional losses and their corresponding sector paring due to the Fusarium wilt TR4 outbreak in the Philippines in 2015.

Country	***Sector***	***Loss (US$m)***
Rest of Asia and Oceania	Manufacturing	15.62
Rest of Asia and Oceania	Services	14.09
Middle East	Services	6.94
Middle East	Manufacturing	6.50
Rest of Asia and Oceania	Construction	5.10
Europe	Manufacturing	5.02
Europe	Services	4.34
Rest of Asia and Oceania	Hospitality	3.75
Rest of Asia and Oceania	Trade	3.74
Middle East	Trade	3.04
Americas	Services	3.03
Americas	Manufacturing	3.01
Rest of Asia and Oceania	Rest of Agriculture and Fishing	2.78
Middle East	Construction	2.74
Africa	Manufacturing	2.47
Rest of Asia and Oceania	Bananas Including Plantains, Fresh or Dried	2.31
Africa	Services	2.11
South Korea	Services	1.77
Middle East	Rest of Agriculture and Fishing	1.74
Middle East	Hospitality	1.74

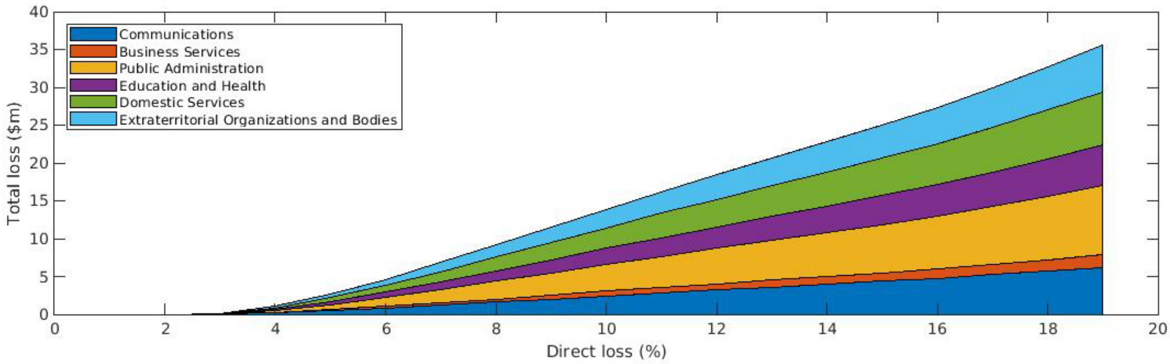

Figure 3: Disaggregation of the economic loss experienced by the services sector in US$ due to the Fusarium wily TR4 outbreak in the Philippines in 2015. An economic spillover range is shown from 0-19% for reference should other outbreaks occur.

Table 3: Disaggregation of the economic loss experienced by the services sector due to the Fusarium wily TR4 outbreak in the Philippines in 2015.

Sector	Loss (US$m)
Public Administration	9.13
Domestic Services	6.96
Extraterritorial Organizations and Bodies	6.24
Communications	6.22
Education and Health	5.46
Business Services	1.63

4. Discussion

4.1 Discussion of results

The economic spillovers of Fusarium wilt TR4 are - at least in a global context and compared with countries' GDP - relatively small. It is likely that such economic effects cannot be directly observed, as they would be swamped by general macroeconomic variability of a larger magnitude. Another consequence of the small impact magnitude is that the impact numbers presented in Table 1 and 2 are relatively uncertain, as they are comparatively small entries amongst many larger MRIO transactions. Small transactions are disproportionately affected by variability during MRIO table construction (Lenzen et al., 2013).

The foreign banana sector directly and indirectly depends on the Philippine banana sector. This may result from trade loss of banana seedlings due to infected seedlings being destroyed. The agriculture and fishing (excluding bananas) sector was negatively impacted as the banana sector is relied on for the production of banana meal, one of the most popular alternatives to traditional animal feed for livestock production. Banana meal is sold by numerous companies such as Food and Beverage Online (Food & Beverage Online, 2022), Lance Infinity Enterprises and Shouri Jai Enterprises (List Company, 2022). The FAO suggests that between 12-15 Mt of bananas may be available for livestock feed use per year internationally (Babatunde, 1992). Mining underpins many supply chain activities as it can provide products such as coal for electricity. The international mining sector is therefore impacted by the outbreak as a decline in banana supply results in a decline in operations along the supply chain which may require electricity for operation such as banana sorting machines. Another reason for economic loss experienced in the international mining sector includes a potential demand decrease for mined metal to produce machinery and agricultural tools resulting from a decline in banana production. Economic spillovers into the food and beverages sector is apparent due to increased wholesale prices. An increase in wholesale prices due to Fusarium wilt TR4 outbreak is further supported by studies that indicate that an increase in Fusarium wilt TR4 outbreaks will result in a rise of 3.2% in retail prices of bananas by 2028 in developed countries (FAO, 2019b). The food and beverage manufacturing sector loss, however, was only 3.63 US$m (Table 2). This small loss can be attributed to bananas mainly being consumed as a fresh product, rather than a value-added product such as banana chips, baby food, catsup and fabric fibres made from banana waste (Bannatex, 2022). This assumption is supported by research that indicates that typically only 5% of total production (the second grade bananas) are sold as baby food puree, animal feed or disposed (Calderon and Rola, 2003). Furthermore, the trade (retail and wholesale) and transport sectors are adversely impacted by a decrease in traded product in the banana and plantain, and agriculture and fishing sectors.

When the services sector is disaggregated, it is apparent it is affected in manifold ways. The education and health sector is adversely impacted due to a decline in banana and banana-related products provided to school canteens and hospitals, such as leaves for packing school lunches (Pornel, 2019). Within the domestic services sector, it is currently estimated there are 1.4 million Filipinos employed as kasambahays (working at a residence) according to a survey conducted by the Department of Labor and Employment and the Philippine Statistics Authority (Department of Labor and Employment, 2020). The domestic services sector (including cooking and cleaning) is additionally negatively impacted from the outbreak as less bananas are available for home cooking. There are around 5.6 million smallholder farmers that rely on banana production for employment and income (Calderon and Rola, 2003). When work cannot be conducted due to disease outbreak, less domestic activities would be outsourced to conserve income and families would complete the tasks themselves. Business services are impacted as catering and events services have a reduction in banana supply. Services provided by extraterritorial organizations and bodies can be attributed to aid provided to assist with the Fusarium wilt outbreak, as an indirect impact. This is evident as 30 organisations including the Food and Agriculture Organisation have developed an international plan to combat the Fusarium wilt TR4 spread, costing 47 US$m in 2015 (The Guardian, 2015). Additionally, ACIAR, since 1990 has provided $3.3 AU$m into research to mitigate the Fusarium wilt TR4 spread upon commercial producers and smallholder farmers (Australian Centre For International Agricultural Research, 2018).

The remainder of the sectors are likely to be indirectly impacted by the Fusarium wilt TR4 outbreak in the Philippines in 2015. These sectors include manufacturing, construction, utilities and amongst the services sector; communications, and public administration. An economic spillover into manufacturing sectors (excluding food and beverages) is felt due to an indirect impact resulting from a decreased demand for industries that provide goods and services to banana-related food and beverage manufacturing businesses such as plastic for packaging. The construction industry may have experienced economic spillovers due to a decrease in those investing in building infrastructure that aid in banana production, such as storage sheds and sorting facilities, as projects may get delayed due to contaminated areas becoming unusable for years, thus decreasing cash-flow for investment. Economic spillovers into the utilities sectors could be explained by a decrease in water usage for irrigation as farmers cannot produce crops on the 15,500 ha production of contaminated land (Montiflor et al., 2019), and a reduction in electricity usage resulting from fewer industry operations along the supply chain such as ethylene ripening rooms and refrigerated transport. Losses experienced by the public administration services sector are felt due to losses experienced in: foreign economic aid related services, resources used for unemployment compensation benefit schemes, family and child allowance programs, and services related to the distribution of catering trades, restaurants and hotels, construction, and manufacturing related services. These sectors do not directly depend on the supply of bananas are but are likely to reduce operations because the sectors discussed above have a ripple effect impact. These sectoral losses are supported by Australian Banana Growers Council (2021), as they suggest Fusarium wilt TR4 is typically discovered close to or at time of harvest. Therefore, suggesting that most economic impacts will occur downstream in supply chains, not upstream in the supply of agricultural and farming tools. Thus, most economic impacts occurred downstream in the supply chain through diminished banana trade, not upstream in the supply of inputs from the agricultural sector to aid in the management of banana plantations.

Our results indicated that the downstream regions such as the Rest of Asia and Oceania and the Middle East experienced greater economic spillover losses than major Cavendish trade regions. It is important to note, however, that due to the drop in the supply of Cavendish bananas from the Philippines, the major export destinations of China and Japan increased their demand from Ecuador so that domestic demand could be met (FAO, 2017). This would suggest that the main importing countries would not appear to have large economic losses compared to other regions. Substitution of commodities, however, is not in the scope of this type of IO analysis. The regions within Europe and North America are indirectly affected by the Fusarium wilt TR4 outbreak as they are the recipient of much of China and Japan's exports, and thus experience economic impacts due to the ripple effect of disasters along supply chains. This trade reliance is evident as China and Japan exported 409,979 US$m (partner share 18.03%) and 126,387 US$m (partner share 20.23%) to the United States respectively, and 456,000 US$m and 78,400 US$m (OEC, 2022a) to Europe respectively in 2015 (World Integrated Trade Solution, 2022). The spillovers into regions contained within Europe and North America are less than that of the Middle East and the Rest of Asia and Oceania as there are fewer sectors that are dependent on trade from the Philippines. This is evident as in 2015 the Rest of Oceania relied on the Philippines for 12.55% of their total imports and the Middle East region relied on the Philippines for 0.53%, compared to Europe and the United States which relied on the Philippines for 0.52% and 0.85% respectively (OEC, 2022b) (Appendix Table 5).

4.2 Limitations and extensions

It is important to note that the results for the indirect impacts are acquired from a model of international trade and thus can only approximate the impact that occurred in different sectors and regions (Lenzen et al., 2019). There is limited available data on banana production in the Philippines. Most data collected was in categories that included bananas and plantains (fresh and dried) varieties, and therefore this study cannot separate the impact on the banana sector alone or the Cavendish banana variety alone. Additionally, data were often categorised into production periods from 2014-2015. There was a drought in 2014, reducing the availability of data where the Cavendish banana yield loss can be entirely attributed to the Fusarium wilt TR4 outbreak alone as the drought may have had adverse effects on production output (FAO, 2017). Banana producers may have also failed to report losses, or their losses may not be considered, as data are often underrepresented in developing countries (Behrens et al., 2017). Finally, Schulte in den Bäumen et al.'s (2014) disaster analysis method used to determine the supply chain impacts of the 2015 Fusarium wilt TR4 outbreak did not consider the substitution of commodities – for example, the Philippines may have traded a different variety of banana or the import countries may have obtained their bananas from another country (Okuyama and Santos, 2014). This method may also overestimate disaster impacts as it cannot model price changes post-disaster (Okuyama and Santos, 2014).

The work conducted in this study could be extended through a predictive application of MRIO modelling, where the findings of the 2015 case study are extrapolated to investigate the potential consequences of similar outbreaks in the Philippines or in other areas of the world. These could then be used to support industry cases for investment in disease mitigation and management initiatives. Future studies could consider dynamic CGE modelling, a more data-heavy approach in which price changes post-disaster can be considered. As a plantation cannot be used for many years post-infection, it would be interesting to compare the impact of production loss on different regions and sectors over this time. Prior to the Philippines' 2015 Fusarium wilt TR4 outbreak, India, the greatest producer of bananas internationally, mainly produced for a domestic market. In 2015, however, they expanded their export market by 47% due to expansion of areas harvested for traded varieties (FAO, 2017). India benefited from demand in Southeast Asia and the Gulf countries amid the Philippines' supply shortage, their greatest competitor (FAO, 2017). These bananas were additionally sold by India at a discount competitive price at 50% lower than that of the Philippines and Ecuador at the Dubai auction (FAO, 2017). Due to other countries being able to substitute the loss of the Cavendish bananas from the Philippines with supplies from other countries such as India, it would be interesting to quantitiatively analyse the economic disaster impacts of the Fusarium wilt TR4 outbreak, with the substitutions of commodities considered. A study has been conducted exploring the impact of Fusarium wilt in Colombia, the fifth greatest banana exporter, which highlighted that they would lose 800 US$m and 30,000 jobs each year if the disease is not quickly controlled (Daya, 2021). It could therefore, be beneficial to examine the impact of the 2015 Philippine Fusarium wilt outbreak on employment and value-added loss using satellite accounts in the IELab. The satellite accounts in the IELab allow a disaster impact to be examined through non-economic data such as carbon dioxide emissions, employment, consumption loss and wage reduction (Lenzen et al., 2017b). The use of satellite accounts would allow an even more holistic disaster analysis and further assist with disaster management plans. The study by Daya (2021) additionally did not consider the spillover effects of Fusarium wilt in Colombia, illustrating that spillover disaster analysis of Fusarium wilt has not been conducted previously. Finally, Cavendish banana producers can fall into one of two other categories, this includes an internal market, where products are produced and consumed in the same country, and a hybrid market, where products are both exported and consumed domestically in high numbers. In countries with a closed Cavendish banana market, such as Australia (Australian Banana Growers Council, 2021), both the direct and indirect impacts from a Fusarium wilt TR4 outbreak would be expected to occur predominantly within the single region. For a country that supports major domestic and export

Cavendish banana markets, such as China (FAO, 2021), it is expected that substantial supply chain spillover impacts would be observed both internally and externally. These two market types are out of scope for this study. The investigation, however, of case studies for each of these would support understanding the risk to the global Cavendish banana market from Fusarium wilt TR4.

5. Conclusions

5.1 Importance of disaster recovery plans and study importance

Disaster impact analysis is beneficial as it can assist in generating disaster recovery plans and assist in isolating areas that are more at risk of disasters. This aids development and investment decisions within a region. As the spillover impacts of 132.4 US$m are two orders of magnitude greater than the direct effects, it highlights the importance of exploring the ripple-effect of disasters. Therefore, the impacts determined in this paper are integral for predicting which sectors and regions could be impacted by another outbreak, either in the Philippines or elsewhere. It is vital the Philippines implement a management strategy to assist those involved in contract farming as they are currently contributing to the ongoing risk of Fusarium wilt TR4 outbreaks. Contract farming is a form of agreement between a farm owner and a marketing firm in which the farmer agrees to sell their produce at a pre-determined price to the firm, who will then coordinate the sale and distribution to external markets. This shifts the risk of investment in banana production to farm owners. A case study of 30 farms experiencing Fusarium wilt TR4 in the Davao region in the Philippines found that a substantial economic cost arises from outbreaks, not only in loss of revenue but also the cost of eradication (Aquino, 2013). In the Philippines, this cost is overwhelmingly borne by smallholder farm owners who are contracted by large multi-national corporations. An outbreak means a decline in money that can be invested in banana production, as well as the expected revenue from sales. On top of this substantial loss, farm owners are required to pay for the quarantine and eradication of the disease from all contaminated areas (Aquino, 2013). Farm owners are often unable to afford to use the necessary eradication and quarantine methods to manage the outbreaks. This creates opportunities for the contaminated matter to spread to other farms, preventing the eradication of the disease and leading to other outbreaks. If contract farming remains a core aspect of the Philippine banana economy, with the responsibility for disease eradication remaining with farmers, it is inevitable that the Philippines will experience another severe Fusarium wilt TR4 outbreak. Therefore, developing a disaster management plan to assist those in contract farming, could dramatically reduce the risk of economic spillover impacts and Fusarium wilt TR4.

Fusarium wilt TR4 has already spread to three of the five major Cavendish banana exporters. In addition to the Philippines, there have been outbreaks recorded in Costa Rica and Colombia, which are the third and fifth largest exporters, respectively (FAO, 2021). Colombia, which saw 866 US$m in revenue from cavendish banana exports in 2018, experienced their first outbreak of Fusarium wilt TR4 in 2019, and a national emergency was declared (Galvis, 2019). A Fusarium wilt TR4 outbreak was observed in 2021 in Costa Rica, where the Cavendish banana industry generates an estimated 1 US$B in export revenue annually and 140,000 jobs (Maxwell, 2020). Fusarium wilt TR4 is yet to reach Ecuador, the world's largest exporter. Outbreaks, however, have been reported in neighbouring Peru (World Banana Forum, 2021). Governments in South America and Central America have invested in substantial preventative measures, supporting enterprises as well as small and medium land owners in the quarantine and eradication of the disease (Maxwell, 2019) (Maxwell, 2020) (IICA, 2021). This investment has enabled containment of the disease with no substantial outbreaks yet reported. Therefore, the Philippines should consider the implementation of similar management plans.

5.2 Policy implications and suggestions

There is a growing risk of both direct and indirect global economic impacts resulting from severe Fusarium wilt TR4 outbreaks in countries that dominate the Cavendish banana export market. Policy interventions must be made across the banana supply chain to reduce this risk. Firstly, governments in countries that support Cavendish banana production should ensure all producers, from enterprises to smallholder farmers, are supported through education and financial assistance to manage and eradicate Fusarium TR4 outbreaks effectively. This can be achieved through direct government support or via market regulations that help to shift some of the eradication responsibility to enterprises engaging in contract farming practices to source Cavendish bananas (de la Cruz and Jansen, 2018). Secondly, importers should diversify their Cavendish banana supplier portfolio. While experiencing some economic impact due to an outbreak is likely, the expected level of impact will decrease as dependency on any single supplier is reduced. Thirdly, stakeholder countries, whether producers or consumers of Cavendish bananas, should invest in the development of a non-susceptible cultivar for major export. The continuing global spread of Fusarium wilt TR4 is inevitable and will continue if the TR4 susceptible Cavendish cultivar remains the dominant export banana. Thus, there will always be a risk of a Fusarium wilt TR4 outbreak and subsequent global economic impact from supply chain spillover. Research, however, is currently underway to develop a Fusarium wilt TR4 resistant cultivar that can replace the Cavendish cultivar as the dominant export banana (Dale et al., 2017). As the risk of a severe TR4 outbreak in a major Cavendish banana export country continues to increase, acceleration of this research through investment should be prioritised, and success in the development of a resistant cultivar will eliminate the risk.

5.3 Summary

As prior work exploring Fusarium wilt TR4 focuses on the biological aspects (e.g., mitigation strategies and disease resistance) or the direct agricultural impacts (such as yield loss) (Australian Centre For International Agricultural Research, 2020, Damodaran et al., 2020, Orr and Nelson, 2018), this study successfully fills a research gap by examining supply-chain-wide impacts. Exploring macroeconomic impacts such as through using IO analysis is rarely explored in plant disease assessment. The 2015 Fusarium wilt TR4 outbreak in the Philippines had the ability to cause economic supply chain disruption in all sectors and regions explored in this study. This study successfully adopted IO analysis to highlight the importance of considering the spillover effects disasters can induce as unexpected regional and sectoral impacts are apparent. The regional spillover effects felt by the Rest of Asia and Oceania (52.8 US$m), the Middle East (27.05 US$m) and Europe (16.49 US$m) and sectoral losses felt by services (35.63 US$m), manufacturing (excluding food and beverages) (35.2 US$m) and construction (13.66 US$m), demonstrate that major disruptions can occur on international economies due to the ripple effect disasters have along supply chains. It is increasingly important to analyse the impacts of Fusarium wilt TR4 outbreaks as banana varieties become less resistant, with 80% of global banana production under threat (Australian Government, 2020). As surface temperatures increase from climate change, it may further escalate the incidence of Fusarium wilt TR4, as studies have found that higher temperatures promote the growth of Fusarium wilt (Karangwa et al., 2016). This work offers an opportunity to enhance or update disaster management plans to reduce the impacts identified within this study, which will reduce the burden and increase resilience towards Fusarium wilt TR4.

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7. Appendix

Appendix Tables 1 & 2: Groupings used for the regional (left) and sectoral (right) concordances.

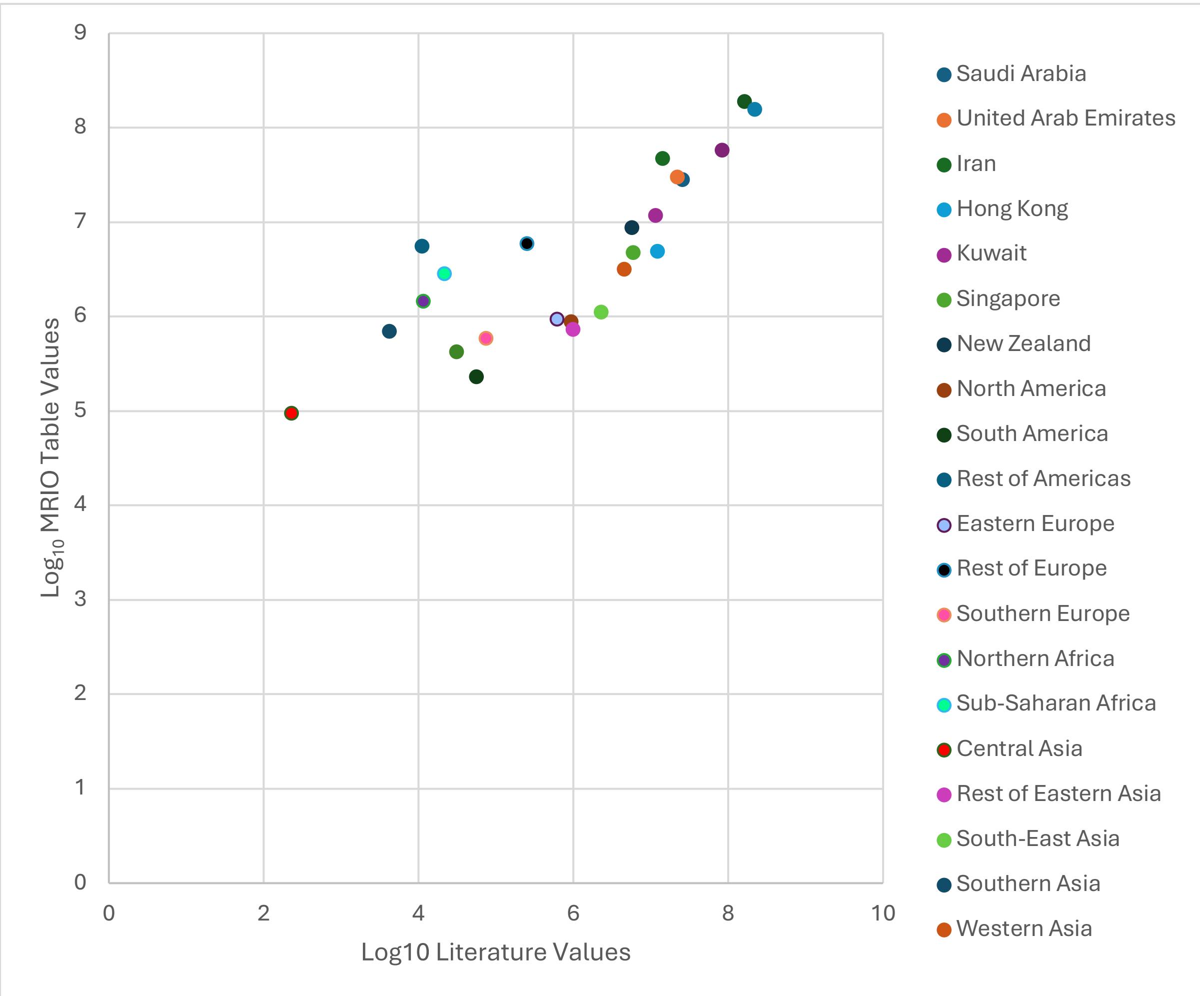
Philippines
Saudi Arabia
United Arab Emirates
Iran
Hong Kong
Kuwait
Singapore
New Zealand
North America
South America
Rest of Americas
Eastern Europe
Southern Europe
Rest of Europe
Northern Africa
Sub-Saharan Africa
Central Asia
Rest of Eastern Asia
South-East Asia
Southern Asia
Western Asia
China
Japan
South Korea
Rest of Oceania

Bananas Including Plantains, Fresh or Dried
Rest of Agriculture
Fishing
Mining and Quarrying
Food and Beverages
Textiles and Wearing Apparel
Wood and Paper
Petroleum, Chemical and Non-Metallic Mineral Products
Metal Products
Electrical and Machinery
Transport Equipment
Other Manufacturing
Recycling
Electricity, Gas and Water
Construction
Maintenance and Repair
Wholesale Trade
Retail Trade
Hotels and Restaurants
Transport
Post and Telecommunications
Financial Intermediation and Business Activities
Public Administration
Education, Health and Other Services
Private Households
Others

Appendix Tables 3 & 4: Region (left) and sector (right) aggregator labels.

Japan
China
South Korea
Middle East
Europe
Americas
Africa
Rest of Asia and Oceania

Rest of Agriculture and Fishing
Mining
Food & Beverages
Manufacturing
Utilities
Construction
Trade
Hospitality
Transport
Services



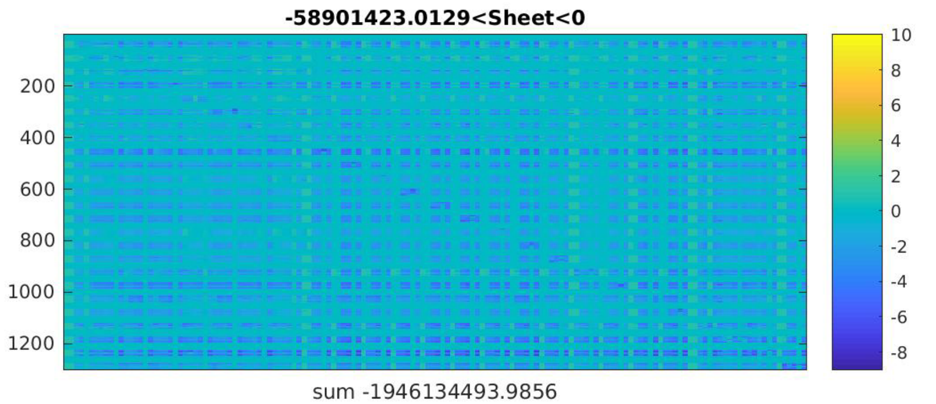
Appendix Figure 1: Comparison of banana export data from the Philippines to other regions between results generated through MRIO table production and data collected from the FAO (FAO, 2021) (Philippines Statistics Authority, 2015).

Appendix Figure 2 illustrates the trade flow between countries. The trade relationship between two regions is assigned a value for every sector, represented by the coloured squares of the matrix. For each matrix index, if the region on the x-axis predominantly imports the sector's goods and services from the region, the y-axis it will have a positive value. If the region on the x-axis predominantly exports the sector's goods and services to the region, the y-axis it will have a negative value. A greater magnitude of these values indicates either a large proportion of imports (green to yellow) or a large proportion of exports (blue to purple).

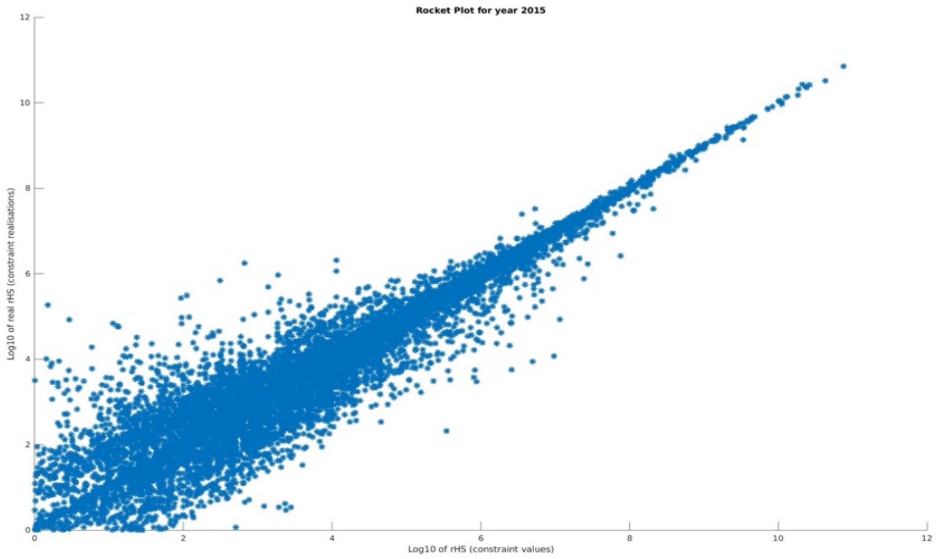
The regions are ordered as shown in Appendix Table 1. Saudi Arabia, United Arab Emirates, Iran, Kuwait fill positions two, three, four and six in the list respectively. These countries are importers of goods and services for the majority of the 26 sectors (Harvard University Centre for International Development, 2021). This is consistent with the repeating vertical green line with varying degrees of brightness in the heatmap that indicates major importers generally listed at the beginning of each sector. Darker blue vertical lines are generally observed at the end of each sector, most clearly observed in the final columns to the right of the heatmap. These represent regions such as China, Japan and South Korea. Each of these countries have large and diverse export markets (Harvard University Centre for International Development, 2021) so this pattern is also consistent with the expected negative values represented by the blue lines.

MRIO table reliability was determined through rocket and hockey plots created during MRIO table establishment. The reliability of the generated model base table was reviewed using a rocket plot visualisation. Appendix Figure 3 plots the constraint values against the constraint realisations. Stronger adherence is observed for larger constraint values indicating better preservation of the MRIO elements addressed through these constraints. Reliability reduces as values decrease, therefore adherence to the values is lower in the final MRIO. This trend is expected for the given data (Lenzen et al., 2012).

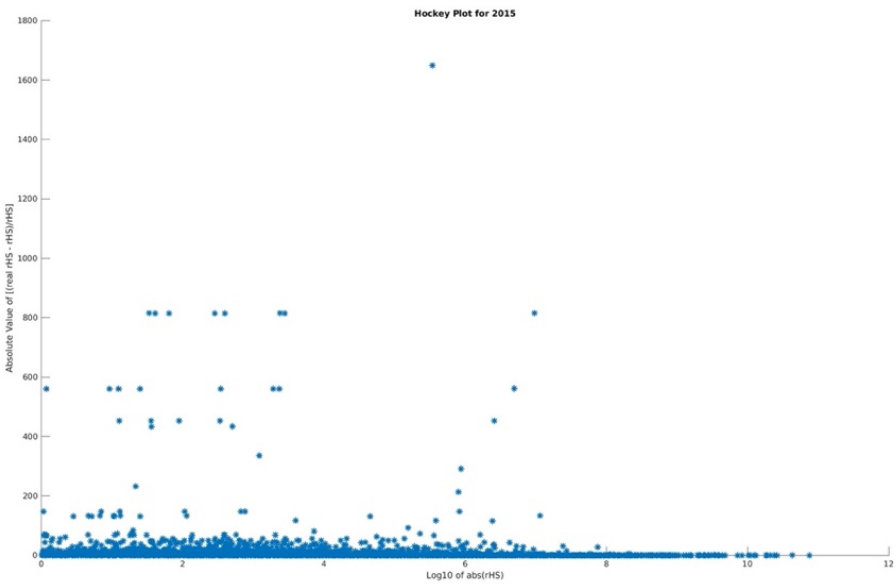
A hockey plot was generated to compare the magnitude of the computed values against the proportion of the variation between the real and computed values to the computed value. Appendix Figure 4 shows most plot points trend along the x-axis with some larger variations away from the axis for smaller computed values. This follows the expected trend and combined with the rocket plot validates the inputs to the model events matrix.



Appendix Figure 2: Heatmap of the trade relationship between each of the 25 defined regions for the 26 defined sectors. For each matrix index, values greater than zero represent the country on the x-axis imports from the country on the y-axis. Values less than zero indicate an export relationship.



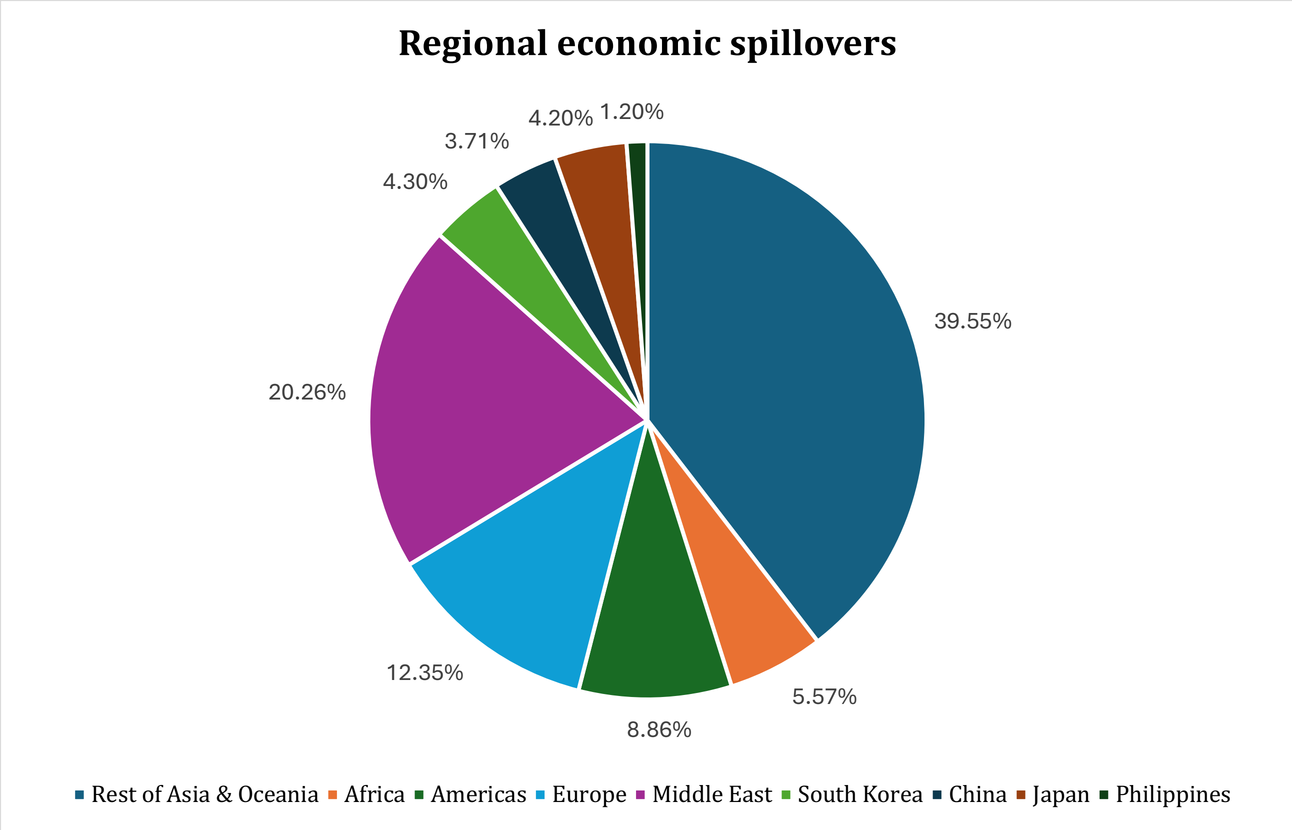
Appendix Figure 3: Rocket plot- constraint values are plotted against constraint realisations for the MRIO table generated for the year 2015.

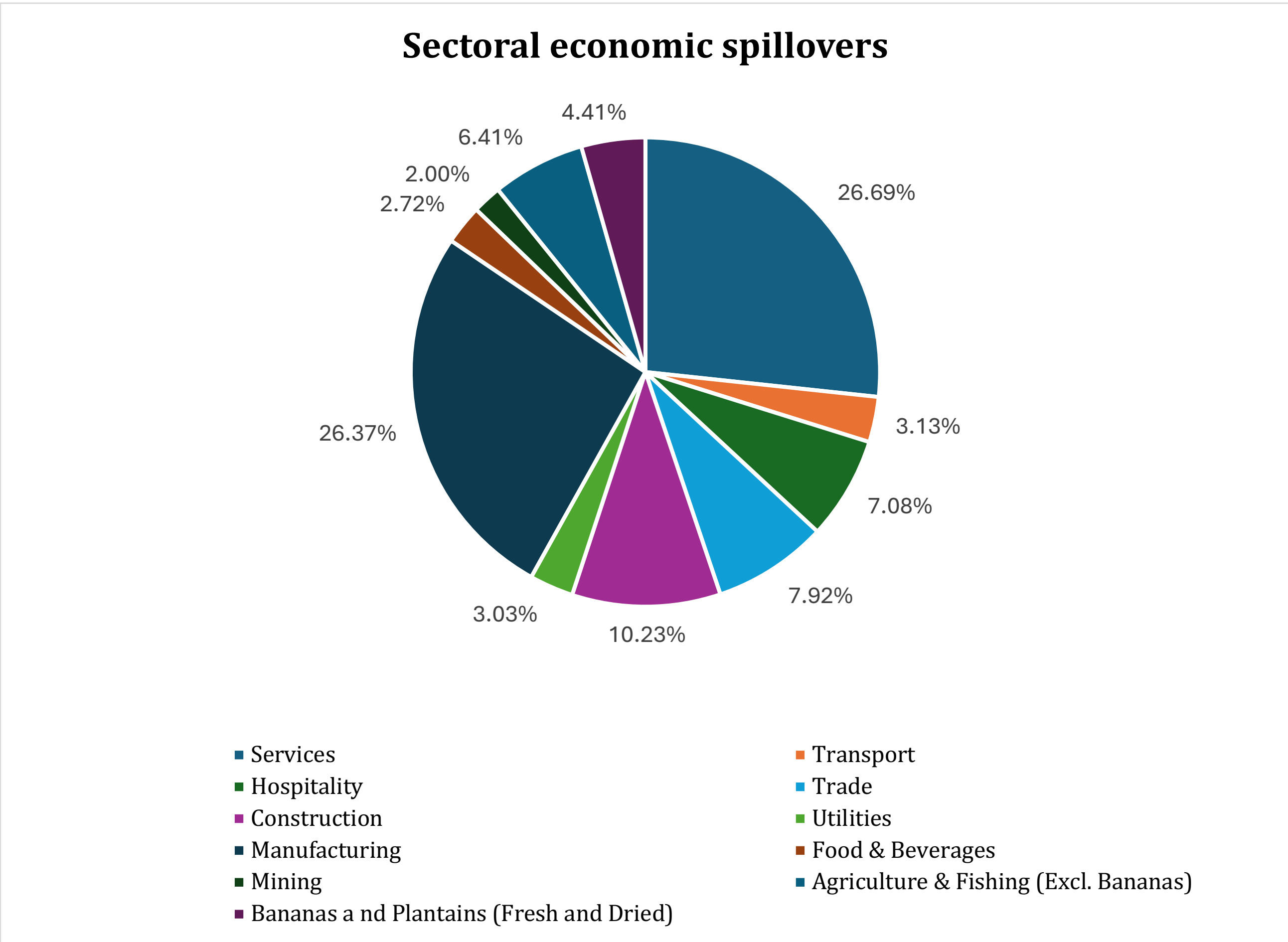


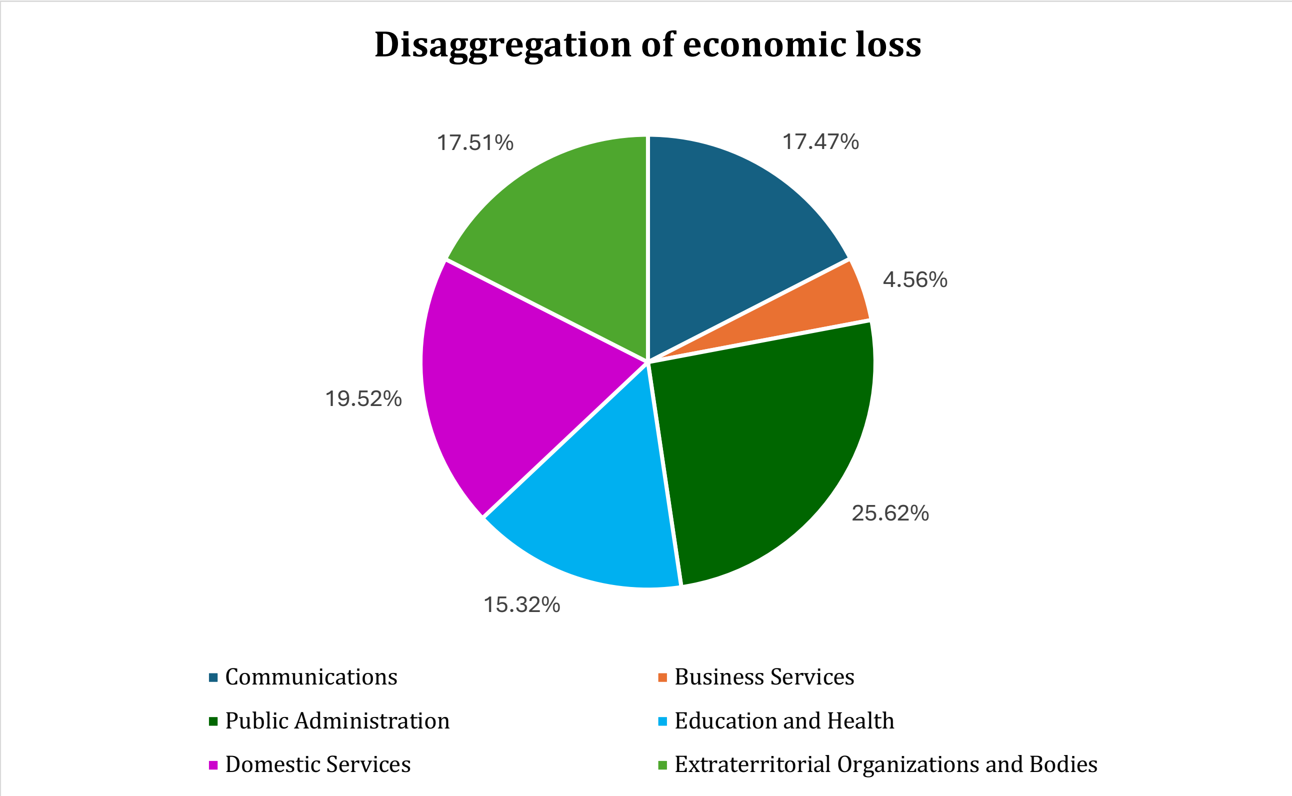
Appendix Figure 4: Hockey plot- for the MRIO generated for 2015 where the magnitude of the computed values are plotted against the proportion of the variation between the real and computed values to the computed value.

Appendix Table 5: 2015 import and export from the Philippines to regions within the Middle East and Rest of Oceania (OEC, 2022).

Country	Import from Philippines (US$m)	% of Philippines Import (70100 US$m)	Export to Philippines (US$m)	% of Philippines export (US$m)	Imports from each region (US$m)	Exports (US$m)	% of import to the region
Middle East							
United Arab Emirates	404	0.58	487	0.69	232000	182000	0.17
Iran	152	0.21	14.4	0.021	60600	70800	0.25
Saudi Arabia	186	0.27	1670	2.38	171000	192000	0.109
Total	742	1.06	2171.4	3.09	463600	444800	0.530
Rest of Oceania							
Australia	627	0.89	1250	1.78	192000	205000	0.33
New Caledonia	12.6	0.018	0.061	0.000087	2860	1490	0.44
Papua New Guinea	17.9	0.026	119	0.17	4740	9000	0.38
French Polynesia	2.95	0.0042	0.056	0.00008	1650	203	0.18
Solomon Islands	1.78	0.0025	11	0.016	491	514	0.36
Tonga	0.39	0.00055	N/A	N/A	169	11.7	0.23
Tuvalu	0.069	0.000098	N/A	N/A	53.6	38.3	0.13
Vanuatu	0.52	0.00074	0.82	0.0012	332	858	0.16
Samoa	1.1	0.0016	0.0052	0.0000074	439	81.8	0.25
Nauru Palau	0.0087	0.000012	0.0028	0.000004	70.7	29	0.012
Cook Islands	0.014	0.00002	N/A	N/A	129	24.4	0.011
Fiji	2.03	0.0029	0.88	0.0012	2510	1010	0.081
Federated States of Micronesia	5.58	0.008	0.065	0.000093	162	22.6	3.44
Kiribati	0.59	0.00084	2.86	0.0041	204	129	0.2897
Marshall Islands	247	0.35	2.22	0.0032	14700	567	1.68
Palau	7.79	0.011	0.00602	0.0000086	170	18.2	4.58
Total	927.32	1.32	1386.97	1.98	220680.3	218997	12.55
US	11800	13.6	7000	9.99	2210000	1390000	0.85
Europe	9540	16.83	7870	11.23	1840000	2020000	0.52


Regional economic spillovers
39.55%
5.57%
8.86%
12.35%
20.26%
4.30%
3.71%
4.20%
1.20%
Rest of Asia & Oceania
Africa
Americas
Europe
Middle East
South Korea
China
Japan
Philippines


Sectoral economic spillovers
26.69%
3.13%
7.08%
7.92%
10.23%
3.03%
26.37%
2.72%
2.00%
6.41%
4.41%
Services
Transport
Hospitality
Trade
Construction
Utilities
Manufacturing
Food & Beverages
Mining
Agriculture & Fishing (Excl. Bananas)
Bananas a nd Plantains (Fresh and Dried)



Appendix Figures 5, 6 & 7: Breakdown of economic losses in different regions, sectors and services.

Appendix Table 6: Comparison of economic losses felt in directly hit (in red) and indirectly hit (in black) regions and sectors measured in US$m.

	Bananas Including Plantains, Fresh or Dried	Rest of Agriculture and Fishing	Mining	Food & Beverages	Manufacturing	Utilities	Construction	Trade	Hospitality	Transport	Services
Philippines	0	0	0	0	668.44	0	448.23	0	0	0	484.25
Japan	288.11	599.72	0	284.69	1145.00	274.50	728.52	601.24	235.79	196.76	1248.73
China	335.85	347.59	213.48	0	67.60	82.70	819.66	912.01	336.62	223.99	1613.78
South Korea	311.34	574.98	0	251.25	698.41	107.99	767.49	617.57	417.77	223.73	1772.85
Middle East	447.23	1744.44	762.32	825.50	6503.21	1445.28	2744.62	3041.57	1743.96	850.08	6936.90
Europe	1111.13	1337.84	745.16	389.76	5015.96	406.00	628.64	532.97	1260.78	722.22	4344.50
Americas	745.11	714.05	143.42	19.40	3013.82	399.057	1634.88	926.85	953.33	249.70	3028.97
Africa	329.99	454.94	14.09	302.80	2466.91	0	790.32	189.06	753.99	16.34	2108.96
Rest of Asia and Oceania	2318.10	2780.15	789.74	1554.46	15620.24	1333.92	5097.99	3744.71	3748.05	1691.80	14091.73

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Nutritional and economic losses resulting from climate-induced disasters on traditional food sources in Tonga and Fiji

Abstract

The Pacific Island countries of Fiji and Tonga are highly sensitive to the impacts of climate disasters, given that their agricultural and fishing industries rely heavily on the natural environment. These climate disasters result in both economic spillovers and macronutrient losses. Tonga and Fiji rely on traditional food sources such as root crops (cassava, sweet potato, taro and yams) and fish to supply essential daily macronutrients of carbohydrates, fats and protein. In this paper, we project what dietary changes may occur in Fiji and Tonga as a result of climate disasters that impact fish and root crop production. We also conduct a regression analysis on 445 data observations from climate disaster research to explore relationships between production losses, different study and impact years, disaster severities, regions, sectors and type of disaster. The regression analysis focuses on disasters caused by cyclones, rain, drought, increased carbon dioxide, and heat. Input-Output analysis is employed as an economic scenario modelling tool so that the economic spillovers into regions and sectors resulting from climate disasters on root crops and fish production can be quantified. The results suggest all macronutrient availability will decline, with protein being the most significant loss in the fishing sector and carbohydrates in the root crop sector. Cyclones, rain increases and droughts appear to result in greater production losses than carbon dioxide emissions and heat. We find that the economic impacts are felt directly and indirectly due to the flow-on effect of disasters along complex supply chains. Economic impacts were more significant for the fishing sector than for root crops. The sectors that experienced the greatest losses were livestock, dairy, manufacturing and cropping. The regions that experienced the most significant losses were the main import regions – these being Asia, the United States and the Middle East. The results from this paper can assist in determining macronutrient and economic losses resulting from climate-induced production losses of Fijian and Tongan traditional food sources of root crops and fish. Our work highlights the potential impacts of future disasters on regions, sectors, and macronutrients, and can allow for better development of disaster management plans and post-disaster resource allocation.

1. Introduction

Climate disasters result in direct (at the site of impact) and indirect (flow-on effects) sectoral and regional impacts across supply chains. These impacts can include damage to infrastructure and also reduced food availability, income, market access, and potable water (IPCC, 2014). Climate disasters are increasing in both severity and frequency. Developing countries are expected to disproportionately experience their impacts (Mendelsohn et al., 2006), as 96% of disaster-related deaths occur in lower-economic regions (Abeygunawardena, 2009). Developing countries experience a 'double penalty' because, in addition to experiencing the disaster, their poverty makes them more vulnerable to disaster impacts such as recovery costs (Drabo and Mbaye, 2015). To reduce these effects, determining the economic spillovers into different regions and sectors is crucial for disaster management strategies. Quantifying economic spillovers into regions and sectors also helps isolate vulnerable areas so mitigation strategies can be employed specifically for each region and sector.

Most studies that explore climate disasters mainly focus on where the direct impact occurs, such as just the agricultural sector, instead of examining how these disasters impact other sectors and regions (Malik et al., 2022). These studies have oversimplified results as they do not provide a holistic assessment of disasters, as they neglect to account for complex supply chain systems, inter-industry transactions, employment and nutritional intake. Additionally, current climate disaster research in developing countries is inadequate compared to developed countries due to limited data availability from a lack of reporting and funds for collection (Dupraz-Dobias, 2022, Behrens et al., 2017). Therefore, results produced from developing countries are often unreliable and invalid, making research less conducive - creating a cycle where research is focused in developed countries. Subsequently, the impact of climate disasters in middle- and lower-income countries is underrepresented (Behrens et al., 2017).

In this study, we chose to focus on the economic and nutritional impacts of climate disasters in Tonga and Fiji. Tonga and Fiji were selected for this study as i) both countries have a decent population size when compared to other countries within the Pacific Islands (Pacific Community, 2020), making these regions vital to research as climate impacts will therefore be felt by more people and, ii) due to their size, these countries have a larger GDP than other countries within the Pacific Islands. Consequently, there is greater economic and nutritional data availability to conduct this study. iii) Both Tonga and Fiji are expected to be some of the most vulnerable countries globally (Barnett, 2011), and are anticipated to have an increased frequency of disasters such as episodes of heatwaves, droughts, storm surges, intense cyclones and severe flooding (Sisifa et al., 2016). Examples of these disasters include the 2003 Cyclone Ami, which resulted in a 35 US$m decline in crop profitability in Fiji (McKenzie et al., 2005). Flooding has also occurred in Fiji, such as at the Rewa and Wainibuka Rivers flooding in April 2004, with an estimated crop production decline of 50-70% (Fijian Government, 2004). In 2012, Fiji's largest island, Viti Levu, suffered from three climate disaster events: a category four cyclone, a one-in-25-year flood, and a one-in-50-year flood, resulting in estimated damages equal to 4.3% of their GDP (Simmons and Mele, 2013). The United Nations (UN) has isolated Tonga as one of the most susceptible countries to the harmful effects of climate change, with a particular sensitivity to rising sea levels (Gangopadhyay and Rai, 2021). Between 1960-2010, more than 80 cyclones hit Tonga, with a current average of two cyclones annually (Gangopadhyay and Rai, 2021). Currently, 75% of people in Fiji and Tonga experiencing poverty reside in rural areas and are dependent on agriculture directly or indirectly for their livelihoods (Shaun, 2017), which is alarming as the agricultural sector is estimated to be one of the most severely climate-impacted sectors in all regions of the Pacific Islands (Dun et al., 2023).

It is important to assess the impacts of climate disasters on Fijian and Tongan traditional staple foods as the subsequent production loss will negatively impact their dietary consumption of macronutrients. Traditionally, diets within the Pacific Islands consisted of 82% plant foods such as leafy vegetables and complex carbohydrates, with the remainder of their diet consisting of protein from fish, pigs, and poultry consumption (Connell, 2015, Gnecchi-Ruscone and Paini, 2017). Since the rise of trade liberalisation circa 1995, the Pacific Islands have increased their imported high-calorie, high-fat content, low-nutrient, highly-processed food quantities such as products of baked goods, rice and noodles (Charlton et al., 2016, Plahe et al., 2013). Imports of processed foods increased in the Pacific Islands by 9,246 US$m between 2003-2013 ('Ofa and Gani, 2017). Processed food consumption is now 52% of the Tongan diet based on household expenditure data and obesity data (Sahal Estimé et al., 2014). Recently, there has been a decline in the affordability and availability of traditional staple foods resulting from factors such as rising population and climate change (Cassels, 2006, Thow and Snowdon, 2010) and the prices of imported products have fallen, making them more readily accessible and desirable (Sahal Estimé et al., 2014, Ravuvu et al., 2017, Sievert et al., 2019, Thow and Snowdon, 2010). When climate disasters reduce staple food production, the staple foods are typically substituted with imported processed foods. When coupled with a more sedentary lifestyle, this diet change has increased non-communicable diseases, the double burden of malnutrition, obesity, nutrient deficiencies and diabetes (Davila et al., 2024). In the Pacific, non-communicable diseases are now the cause of 60-80% of deaths; resulting in a low life expectancy of 60 years (Davila et al., 2024). These health issues place an economic strain on Pacific Island governments (Anderson, 2013), with government expenditure on health nearly doubling in Tonga between 1995-2006 (Ofa and Gani, 2017).

We assess the impacts of climate disasters for the traditional food sources of fish and root crops (cassava, sweet potato, taro and yams). Root crops are important to the diets of Pacific Islanders, with the Food and Agriculture Organisation (FAO) estimating that they contribute 68% of dietary energy and 42% of dietary protein (FAO, 2008). The FAO in 2008 classified taro and cassava in the tropics as the fourteenth and third most prominent sources of carbohydrates respectively (Shaun, 2017) and over 90% of the Tongan population depend on root crops for survival (Pole, 1993). Fish is Tonga's largest export, comprising 21% of their exports in 2018, and Fiji's 2nd largest export, comprising 12.93% in 2018. Most fish are captured from lagoons, coral reefs and estuaries, and are an essential component of Pacific Islander diets (Charlton et al., 2016, Farmery et al., 2020). The fishing industry in the Pacific is located in a hotspot for marine heat waves, resulting in decreased lagoon health and coral bleaching, which impact marine health (Holbrook et al., 2022). An example of this impact is evident in 2016 in Fiji, where there were significant fish deaths due to decreased dissolved oxygen present in the water (Marra, 2021). Root crops and fish are interesting commodities to explore - as most root vegetables are consumed domestically, and fish are primarily exported, allowing the spillovers of both domestic and international markets to be compared.

We have three methodological components to this study, all focusing on the staple food types of fish and root crops (cassava, yam, taro, and sweet potato). We first run scenarios to model the economic spillovers into different regions and sectors in Tonga and Fiji that may arise should a climate disaster occur. Eight different regression analysis methods are then employed to determine trends between production loss and different climate disaster variables (disaster region, sector, severity, impact type, the year of study and year of impact), which has not been done before. Finally, we generate nutritional food balances for macronutrient consumption in various Pacific Island nations. The results of the nutritional food balances and the regression analysis are combined to model cyclone and carbon dioxide impacts on macronutrients over time. We then present our findings of all three methods. This study will help to bridge the research gap between developed and developing countries by contributing to the production of data on the impact of climate disasters within the Pacific Islands region.

2. Methods and data

First, we collect data on climate-induced production impacts in Tonga and Fiji on fishing and the root crops of cassava, yam, taro, and sweet potato. Trends and relationships between studies are hard to determine as they have misaligned information such as different production loss units, explore different impact types, regions and sectors, measure disaster severity differently, in different years of impact and study years. We organise and harmonise these variables so that the data can be analysed consistently, allowing trends and conclusions to be established. We then run eight regression analysis methods on the data to draw relationships between production loss attributes and climate change attributes. The production loss data is then used to generate economic spillover scenarios through Input-Output (IO) analysis to assess economic, regional, and sectoral spillovers after climate disasters alter fishing and root crop productivity. Finally, the changes to dietary macronutrients are assessed to determine how the production losses caused by cyclones and carbon dioxide on the staple food groups of root crops and fish translate into macronutrient loss over time.

2.1 Input-Output analysis

In this paper, we model upstream sectoral and regional spillovers resulting from root crop and fish production declines using Multi-Regional Input-Output (MRIO) analysis. IO analysis is an economic scenario modelling tool developed by Leontief in the 1930s (Leontief, 1936), and has since been extended to MRIO analysis to examine multiple regions within an economy. The methodology employs National Accounts data that display the economic interactions between sectors within an economy. This paper adopts the Global IELab, a computing platform that generates MRIO tables using economic data (IELab, 2023). The Global IELab delivers economic transaction data by populating three matrices. Firstly, the $\mathbf{T}$ matrix with $N \times N$ dimensions holds information on inter-sectoral transactions (Fry et al., 2018). This is followed by a value-added matrix $\mathbf{v}$, which holds information on the inputs required to create the goods and services. The last matrix is the final demand matrix $\mathbf{y}$ charting resources from sectors to final consumers.

As economic data availability in developing countries is limited, we used a previously developed MRIO table called GLORIA (IELab, 2023). The data feeds to create the MRIO table can be found in the Appendix. We used GLORIA's previously defined sectors and regions for this study, based on international trade dependencies in the Pacific Islands region. GLORIA contains 164 regions globally, with Fiji and Tonga aggregated into a larger region called the 'Rest of Asia' (IELab, 2023). We augmented this MRIO table by adding Tonga and Fiji as additional individual regions, creating 166 regions. Research was conducted to manually add and approximate Tongan and Fijian inter-regional transactions and construct the MRIO table for each sector (including imports and exports of each country), providing information for the $\mathbf{T}$, $\mathbf{y}$ and $\mathbf{v}$ matrix. The $\mathbf{T}$, $\mathbf{y}$ and $\mathbf{v}$ values were extracted as US$D for 2018 from the UN Main Aggregate data as control totals (UN, 2024) (Appendix Tables 3-5). The $\mathbf{T}$, $\mathbf{y}$ and $\mathbf{v}$ matrix values for Fiji and Tonga were subtracted from the sum of the 'Rest of Asia' values to remove Fiji and Tonga from being aggregated in this region. Information on how these values were derived can be found in the Appendix. The 120 sectors in GLORIA were then aggregated into 19 regions and 47 sectors, reflecting the leading sectors for which GDP in the Pacific Islands is situated (Appendix Tables 1 & 2).

To derive the economic spillovers, we used Faturay et al. (2020)'s variation of IO analysis where two constraints are identified: i) outputs cannot exceed production capacity, and ii) intermediate demands cannot be negative. These constraints are addressed by initiating calculations from given final demands, resulting in a range of feasible solutions for output levels that maximise the total outputs (Faturay et al., 2020). The maximum sum of post-disaster output is examined by applying a linear programming method (Faturay et al., 2020). To determine post-disaster production possibilities, we examine the total economic output $\tilde{\mathbf{x}}$ of different sectors $1, \ldots, N$.

We commenced by establishing an event matrix $\mathbf{\Gamma}$, also known as a production loss matrix. $\mathbf{\Gamma}$ is a diagonal matrix of fractions defining post-disaster production losses. $\mathbf{x}_1$ dictates the post-disaster production change. In this study, our post-disaster production possibilities ranged from 0-19%, producing a model of a hypothetical production loss scenario. We ran this production loss scenario on Fiji and Tonga's fish and root crop sectors by dividing the production loss scenario by the IO gross output (Schulte in den Bäumen et al., 2014).

$$\tilde{\mathbf{x}} \leq (\mathbf{I} - \mathbf{\Gamma})\mathbf{x}_0$$

Here, **I** is an identity matrix populated by 1s in the diagonal of the matrix and 0s elsewhere, with the same dimensions as **Γ** (Faturay et al., 2020).

Post-disaster consumption possibilities are dictated by $\mathbf{y}_1$. To determine the amount of input *i* required to produce $1 output *j,* an **A** matrix is used with the elements ij (Faturay et al., 2020). The **A** matrix is established from the intermediate transaction matrix as $\mathbf{A}_{ij} = {}^{\mathbf{T}_{ij}}/_{\mathbf{x}_{ij}}$, where **x** is an $N \times 1$ vector. It is assumed that the **A** matrix remains constant after the disaster, suggesting that the inputs needed to produce $1 of output remain the same post-disaster, assuming that sectors cannot recover to their former production level through input substitutions (Faturay et al., 2020). IO analysis assumes the basic equation: $\mathbf{y}_1 = (\mathbf{I} - \mathbf{A})\mathbf{x} = \mathbf{x}_1 - \mathbf{T}_1 \Leftrightarrow \mathbf{T}_1 + \mathbf{y}_1 = \mathbf{x}_1$ (Leontief, 1936).

2.2 Regression analysis

Data were collected from 445 observations on Tongan and Fijian climate-induced disaster production impacts on fish and root crops (cassava, taro, sweet potato and yam) from peer-reviewed literature, statistics and government reports. We collated information on the explained variable fractional production loss and the explanatory variables of economic sector, region, year of study, year of impact, type of impact and disaster severity.

2.2.1 Production impacts (explained variable)

Fish and root crops (cassava, sweet potato, taro, and yam) production impact data were collected for cyclone, heat, drought, rain increase, and carbon dioxide increase. We collected data from both historical and future predicted events. We used the assumptions that i) commodity prices remain the same and ii) the amount of land remains the same over time to produce the specific agricultural commodity in that region.

The units of measurement used to record and measure production impacts in the literature are inconsistent. Subsequently, different proxies are used, such as percentage production loss, area loss, change in growing season, and changes to t/ha. We converted all these different proxies into percentage production loss for analysis, so all data were in the same units.

Some regions used in this study were more aggregated than those in literature, such as specific villages in Tonga and Fiji. To overcome this, we applied sub-region weights to scale down the percentage loss:

$$sub - regional\ loss = \frac{total\ regional\ production}{100} \times total\ production\ of\ sub - region\ (e.g., Viti\ Levu)$$

2.2.2 Explanatory variables

We used the same regions and sectors in the regression analysis as those addressed in the IO disaster analysis. A disaster severity ranking was recorded with each observation, ranging from 0-5. A score of 1 reflected a low disaster severity and a score of 5 reflected a high severity score. For example, some studies provided scenarios with a ‘worst-case scenario’ and a ‘best-case’ scenario, so a score of 5 and 1 was allocated, respectively. A score of 2.5 was provided as a halfway point if no severity was indicated in the study.

2.2.3 Multiple regression

We employed ordinary least squares (OLS), logarithmically transformed OLS, weighted least squared (WLS) and logarithmically transformed WLS to the collected data to explore relationships between the explained and explanatory variables. These trends help to predict production impacts for various sectors in Tonga and Fiji under different climate scenarios. Logarithmic transformation was applied to the year of study and year of disaster as these are large numbers compared to the value of small variables, such as a severity of 2. Three types of WLS regression methods were applied to the data: WLS with optimally assigned weights, WLS with manually assigned weights and WLS with a combination of both optimised and manually assigned weights. Each production loss data point was allocated a weight between 0 (minimum) and 1 (maximum). When a score of 0 is applied, it removes the study from the regression analysis. In the optimised weighting method, Matlab software applies the weight by excluding outliers that are more significant than two standard deviations away from the average. Manually applied weights were derived through criteria we developed which can be found in the Appendix.

We formed eight regression equations where: β_i is the regression coefficient and y denotes the production impact. *E* holds information on the economic sector and *C* refers to the country (Tonga/Fiji). The year of impact and year of study are displayed by *I* and *Y*, respectively. *S* represents the disaster severity, β_6 is the constant, and the error term is shown by ε. The WLS with optimised weights is indicated by *wo* and *wm* conveys manually assigned weighting methods. When both manually and optimised assigned weighting occurs, this is denoted by *wmo*.

OLS: $y = \beta_1 E + \beta_2 C + \beta_3 I + \beta_4 Q + \beta_5 Y + \beta_6 S + \varepsilon$ (1)

Semi-logged OLS: $y = \beta_1 E + \beta_2 C + \beta_3\, log_{10}(I) + \beta_4\, log_{10}(Y) + \beta_5 S + \beta_6 + \varepsilon$ (2)

WLS, optimised weights wo: $y = wo(\beta_1 E + \beta_2 C + \beta_3 I + \beta_4 Y + \beta_5 S + \beta_6 + \varepsilon)$ (3)

WLS, manually set weights: $wm\, y = wm(\beta_1 E + \beta_2 C + \beta_3 I + \beta_4 Y + \beta_5 S + \beta_6 + \varepsilon)$ (4)

WLS, optimised manual weights: $wom\, y = wom(\beta_1 E + \beta_2 C + \beta_3 I + \beta_4 Y + \beta_5 S + \beta_6 + \varepsilon)$ (5)

Semi-logged WLS, optimised weights: $wo\, y = wo(\beta_1 E + \beta_2 C + \beta_3\, log_{10}(I) + \beta_4\, log_{10}(Y) + \beta_5 S + \beta_6 + \varepsilon)$ (6)

Semi-logged WLS, manual weights: $wm\, y = wm(\beta_1 E + \beta_2 C + \beta_3\, log_{10}(I) + \beta_4\, log_{10}(Y) + \beta_5 S + \beta_6 + \varepsilon)$ (7)

Semi-logged WLS, manual and optimised weights: $wmo\, y = wmo(\beta_1 E + \beta_2 C + \beta_3\, log_{10}(I) + \beta_4\, log_{10}(Y) + \beta_5 S + \beta_6 + \varepsilon)$ (8)

Both *C* and *E* are dummy variables (binary values). A 1 was denoted if a climate disaster occurred in Fiji, and a 0 was allocated if the climate disaster occurred in Tonga. As the inclusion of all dummy values would produce 1, and therefore result in collinearity, one of the *C* and *E* variables were removed from the results, and the inclusion of a constant means the regression coefficients are provided in relation to the population average.

We developed a correlation matrix to test for multicollinearity amongst all explanatory variables. Any variable pairing that had a correlation value greater than 0.9 was aggregated. This study has a sample size of 455, and 431 degrees of freedom. The significance levels were explored through a Student *t*-test by measuring the means of the examined data sets compared to their standard deviations to determine the probability of the data (*p)* sets being different (Ibinson and Vogt, 2017). We assume the relationship between variables reduces in statistical significance the greater the *p*. When $p \leq 0.33$, $p \leq 0.1$, $p \leq 0.05$, p

≤0.01, the results were respectively documented as '.'. '*', '**', '***'. If there was no significance between variables present, no '.' or '*' was reported.

An r-squared (R^2) value was determined to explore the amount of variance for the explained variable, allowing insight into how well the observations fit in the model (Table 2). Figures of climate-induced production loss were plotted against the year of impact, economic sectors, regions, year of study, and severity (Appendix Figure 1). Figures were then generated to plot production losses from carbon dioxide emissions and cyclones over time.

2.3 Nutritional losses

2.3.1 Inventory of food balances

Employing nutritional food balances as a data source to explore the effects of climate change on food systems has been adopted in previous studies. This includes a study by Li et al. (2024) which examines how to reduce climate change impacts through dietary changes, using FAO Food Balances on 140 food products in 139 countries. Zhao et al. (2024) used food balance data to determine how to achieve food security with the threat of climate change. Further studies include using Portuguese Food Balances to determine diet sustainability (Bôto et al., 2024), and adopting data from the FAO Food Balances to investigate how to reduce environmental impacts from food consumption in Asia (Lin et al., 2024).

Daily consumption data on food and the three main macronutrients of protein, fat, and carbohydrates in 2018 were collected from different countries in the Pacific Islands. Data from the FAO Food Balances were used to convert the values of kcal and g/day to MJ/day and kg/day (FAO, 2024). The FAO, however, does not contain data on Tonga. We decided to use consumption data from The Pacific Community (SPC), formerly the South Pacific Commission (Statistics for Development Division, 2020), which contains information on the Pacific Islands' average consumption of different food groups to supplement the missing information on Tonga. We used the same countries from FAO data in the SPC Pacific Islands Food Consumption database to ensure that the SPC could represent Tonga. Of these, 10 of the 22 countries used in the SPC database contained data in the FAO Food Balances database: Kiribati, Solomon Islands, Papua New Guinea, Vanuatu, Federated States of Micronesia, Samoa, Fiji, Nauru, French Polynesia and New Caledonia. The Federated States of Micronesia and Nauru did not have 2018 data, and therefore, we examined 2019 as it is close to 2018 and 2021 and it was the most up-to-date data.

2.3.2 Nutritional loss calculations

We combined the carbon dioxide and cyclone regression results with the nutritional balance tables of Fiji and SPC to represent Tonga to model the proportion of MJ/cap/day that taro, sweet potato, cassava, yam and fishing individually contribute to energy, carbohydrate, protein and fat consumption. We used a moderate severity score of 3. These models allow us to explore how diets would change when climate disasters reduce production levels. The results were plotted with the average from the regression shown, the standard deviation to one sigma displayed, and a dotted line expressing the maximum and minimum regression scores.

3. Results and analyses

3.1 Inventory of food balances

On average, most Pacific Islanders obtain their energy from grains, nuts and seeds, meat products and root vegetables respectively (Figure 1). General trends indicate that countries with higher GDP, such as New Caledonia, French Polynesia, Nauru, Fiji and Samoa (Figure 2), have a higher protein per-capita intake, resulting from higher meat, eggs and dairy consumption levels than other Pacific Island regions. These countries also obtain more fat from meat, eggs and dairy than other Pacific Island regions (Figure 3). Broadly, our results indicate that countries with lower GDP consume higher levels of carbohydrates than those with higher GDP (Figure 4). Grain consumption provides the greatest carbohydrate input compared to other food types, followed by root vegetables, sugar, and sweeteners. Compared to the FAO data, the processed foods in the SPC data are the most significant contributors to all macronutrients.

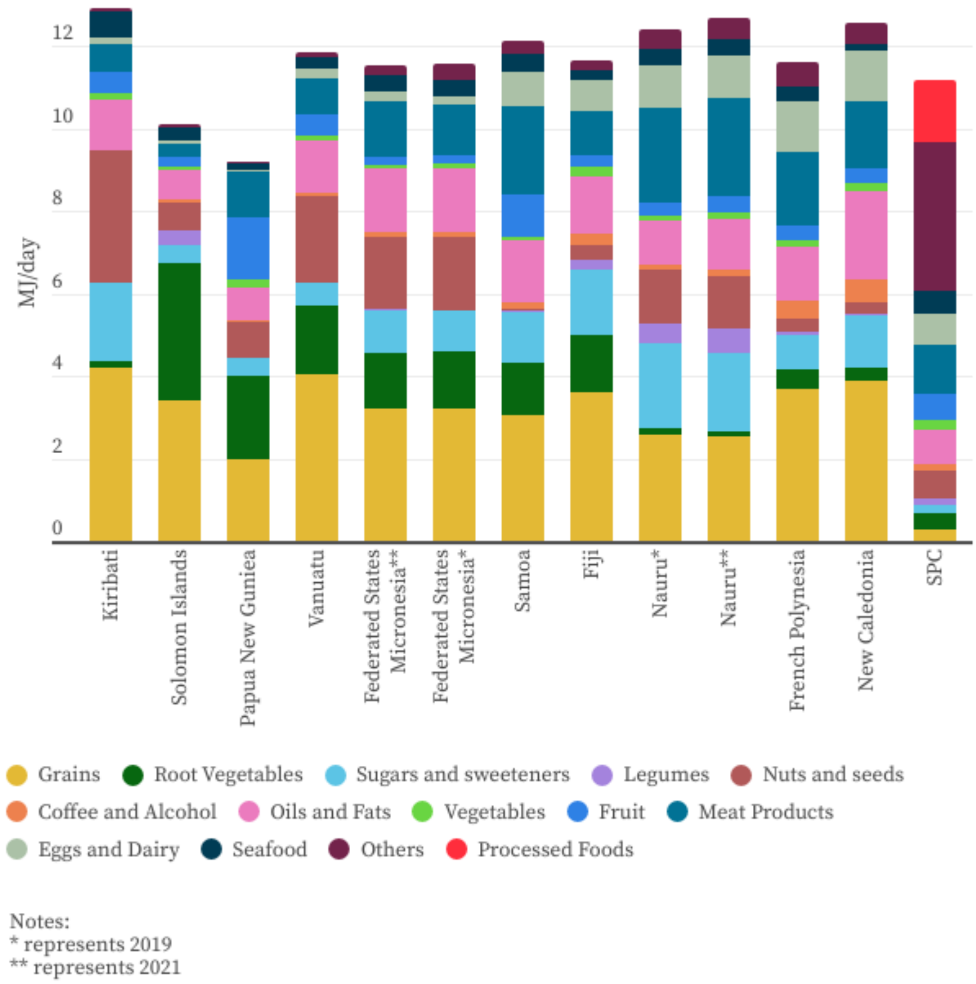


Figure 1: Food MJ/capita/day derived from different food sources across countries within the Pacific Islands, arranged by ascending GDP (FAO, 2024, SPC, 2015, World Bank Group, 2024).

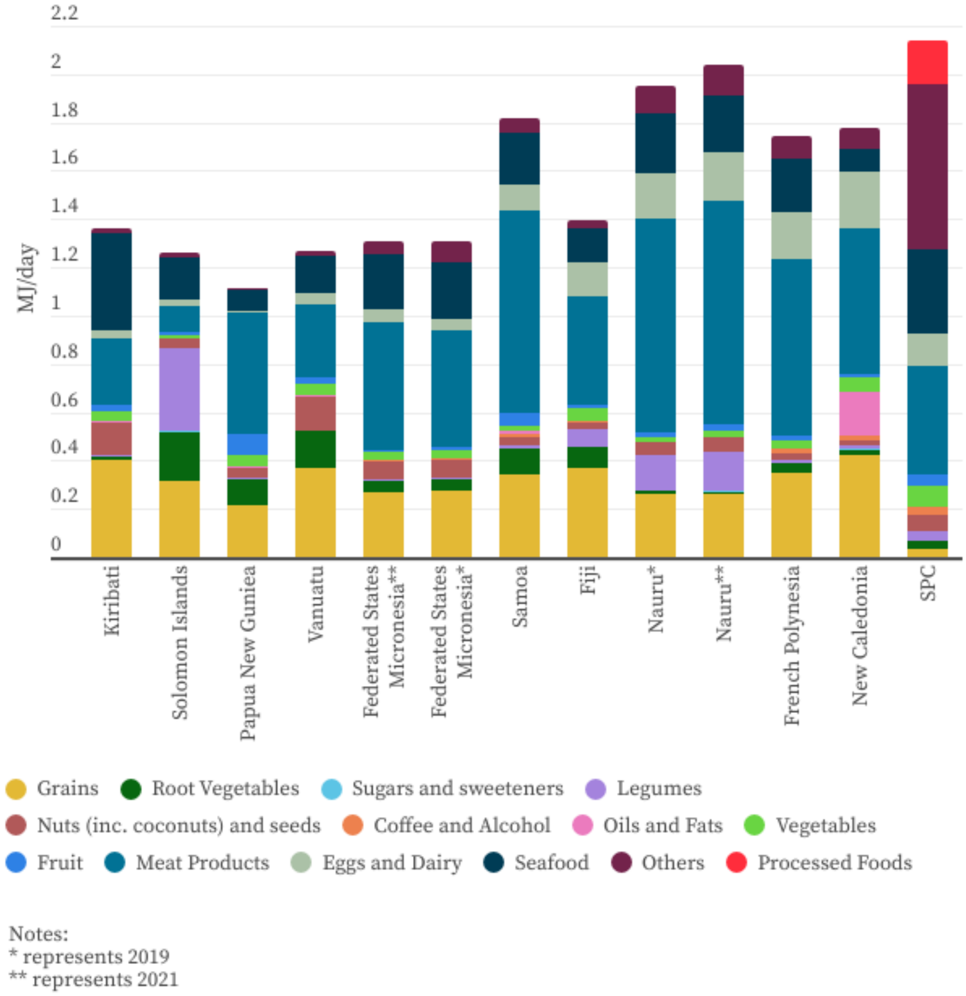


Figure 2: Protein MJ/capita/day derived from different food sources across countries within the Pacific Islands, arranged by ascending GDP (FAO, 2024, SPC, 2015, World Bank Group, 2024).

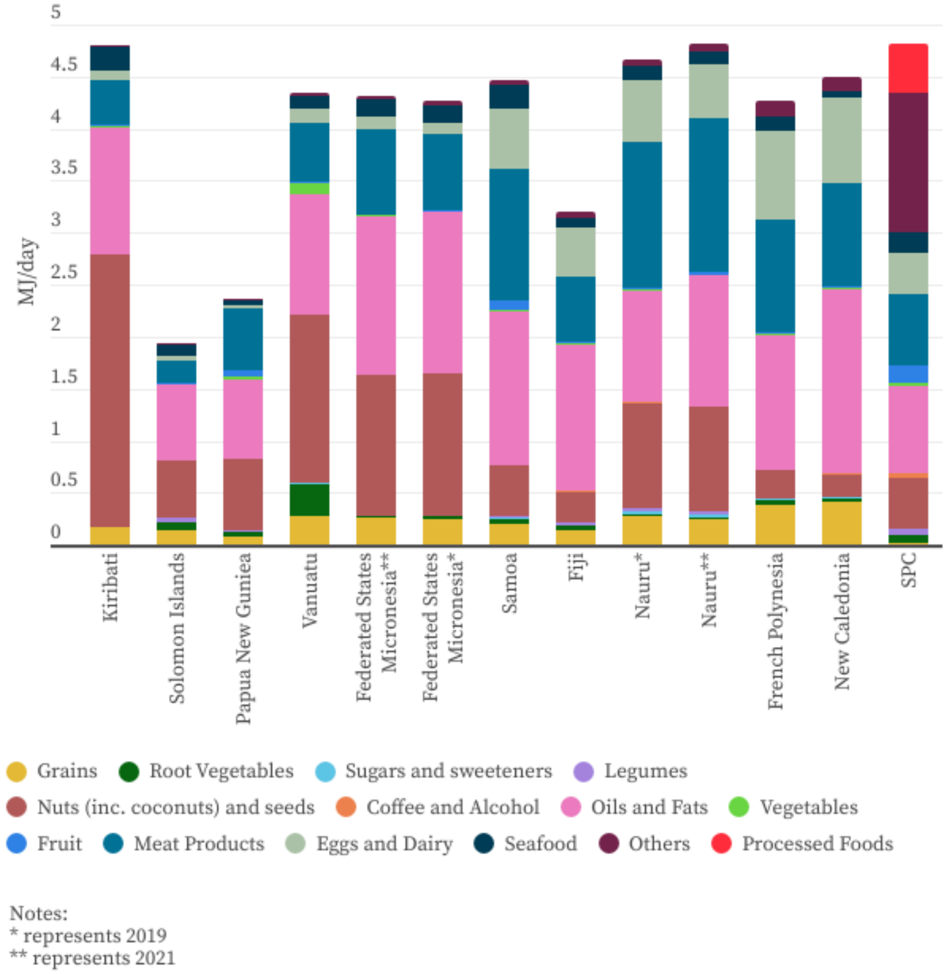


Figure 3: Fat MJ/capita/day derived from different food sources across countries within the Pacific Islands, arranged by ascending GDP (FAO, 2024, SPC, 2015, World Bank Group, 2024).

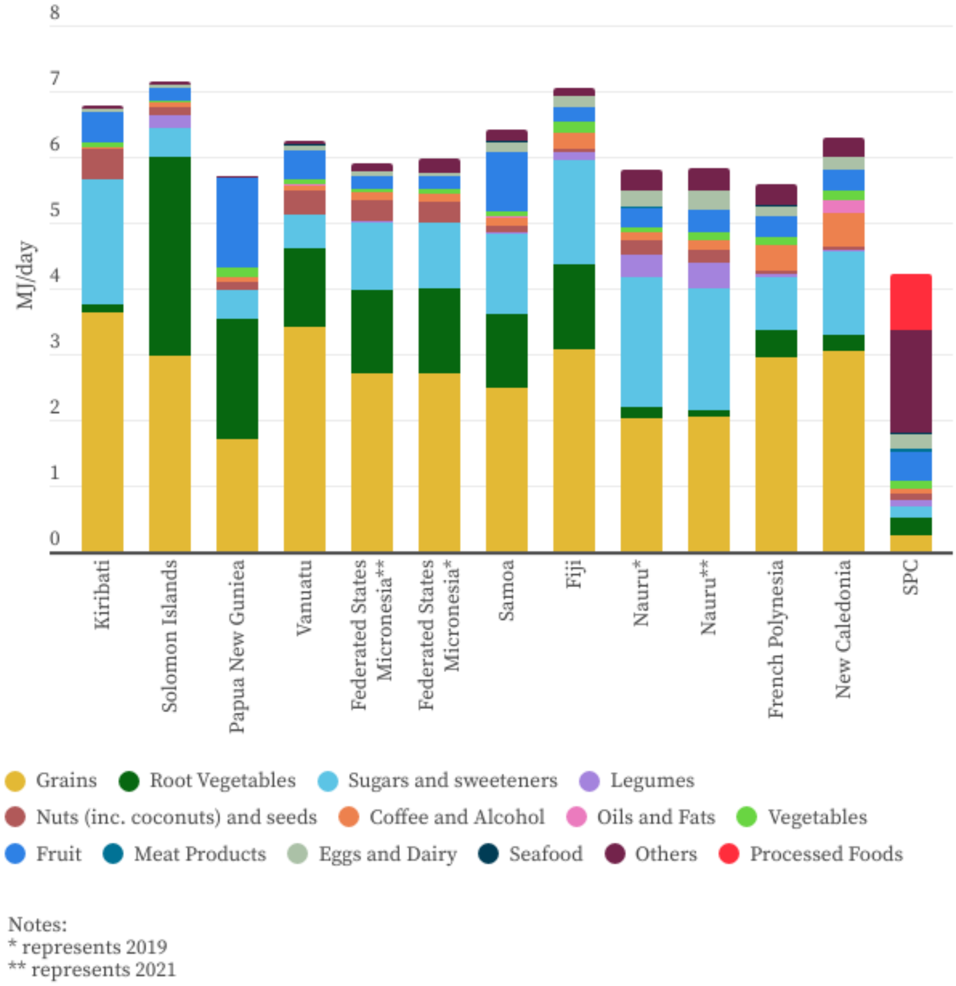


Figure 4: Carbohydrate MJ/capita/day derived from different food sources across countries within the Pacific Islands, arranged by ascending GDP (FAO, 2024, SPC, 2015, World Bank Group, 2024).

3.2 Spillover impacts

The modelled climate disaster production loss scenarios in Fiji and Tonga indicate that significant economic spillovers would occur across all sectors and regions. If fish catch were to decline for fishing communities, the combined direct and indirect sectoral economic losses would amount to 1.57 US$m for Fiji and 0.25 US$m for Tonga (Figures 5 & 6). In comparison, if root crop production were to decline, the losses would be less substantial, with losses of 0.061 US$m for Fiji and 0.05 US$m for Tonga. This disparity is due to greater fish exports than root crop exports, resulting in more substantial economic trade losses.

Economic spillovers in the Fijian fish sector would primarily be felt by Asia, the United States, Fiji, and the Middle East (Figure 6). These findings are supported as Fiji exports large quantities of fish, crustaceans, and molluscs to Asian markets, including 27.4% to China, 12.3% to Japan, 10.1% to Vietnam, 8.2% to Thailand, and 4.26% to Chinese Taipei (OEC, 2018a). The United States additionally receives 14.6% of Fijian fish, crustaceans and molluscs exports (OEC, 2018a). A direct loss to Fiji is logical as this is where the climate-induced impact occurred. Tongan spillovers would mainly be felt by their central export regions of Asia, North America, Fiji, the Middle East and Africa (Figure 5). In

2018, 27% of Tongan fish, crustaceans and molluscs were exported to Japan and 65.5% to North America (OEC, 2018b), which supports our findings. The IELab uses Comtrade data to develop the IO tables. These Comtrade data have gaps as they have done little data collection on the Middle East, so whilst Tonga and Fiji appear to have production losses in the Middle East, they are not reflected in their trade information.

A decline in fish production may impact the international cropping sector as fish, and fish-waste-based products such as fish hydrolysate, silage, meal, liquid fertiliser, compost and bone meal, are used to provide essential nutrients (e.g., nitrogen, phosphorous and potassium) for plant growth and development (Ahuja et al., 2020). In the Pacific Islands, only 40-60% of the fish's body is used in the final product (Bergé et al., 2014); 11% of the fish body is used for non-food purposes (81% to fishmeal and fish oil), bait, pharmaceutical use (collagen, peptides), pet food, and livestock raising (Coppola et al., 2021). This supports why the livestock, and, the meat and dairy product sectors, would subsequently experience economic losses; a decline in fish-based products used to directly feed livestock, combined with a decline in crop output (due to less fish-based fertiliser) for livestock feed, would therefore impact the livestock, meat and dairy product sectors. Around one-third of fish caught is estimated to be used for animal feed such as chickens, pigs, farmed fish, baiting fish and other livestock (Zabarenko, 2008, Johns Hopkins University Bloomberg School of Public Health, 2018). Economic spillovers into the manufacturing sector would be felt from a supply reduction in fish being converted into value-added products such as battered fish, fish-based goods (e.g., pies), fish flour, gelatine from bones and skin, and ready-to-eat convenience foods (e.g., frozen fish fillets, fish balls, fish stock, pickled/cured fish). The FAO (2022) states worldwide, 35% of fish is frozen, 44% is consumed fresh, 11% is prepared and preserved, and 10% is converted into fish-based products. As only 10% of fish is converted into fish-based products, it highlights why the food and beverage manufacturing sector would only experience a small economic loss.

The economic spillover effects from the Fijian root crop sector would be most significant for Asia, Fiji and North America (Figure 6). Export data shows that some of these countries are Fiji's main export regions for edible vegetables and tubers, explaining some of the spillovers: New Zealand (71.8%), Australia (11%), the United States (7.31%) and Kiribati (3.37%) (OEC, 2024). Tongan spillovers resulting from root crop production declines would be most felt in North America, Fiji and Latin America (Figure 5). The sectoral spillovers would be most significant in the meat and dairy products sector, and the cropping sector, which are an indirect loss. Losses in the cropping sector would be felt by Asia, the Middle East and Africa, and Europe. Losses in the meat and dairy products sector are primarily felt by Asia, Middle East and Africa, Europe and Latin America for all scenarios, except for fish declines in Tonga, where losses are felt by Australia and New Zealand, Asia and Latin America, and Europe (Appendix Tables 6-9). Root crops often serve as animal feed - a decrease in root crops results in a feed shortage for livestock within the meat and dairy product sectors. The manufacturing sector may feel economic losses due to a decline in the supply of root crops for value-added products such as chips and flour. The cropping sector may experience a financial impact as leftover root crops are frequently used as fertiliser.

The international fishing sector may experience losses from root crop declines due to the reduced availability of root starch, commonly used as a binding agent in aquaculture feed (FAO, 1987). Often, the by-products from old crops, including the old root, chopped leaves and the top of the mature corm, are used for green manuring or in fertiliser, explaining the losses to the cropping sector (Secretariat of the Pacific Community, 1999, FAO, 1996). Root crop output losses would result in economic disruptions to trade and transport exports as fewer products would be available for transport and trade. The livestock sector and meat and dairy products sectors would experience economic spillovers due to a decline in the supply of root crops used for animal feed. The stems and leaves of root crops are used in animal feed, as seen by a study conducted by the FAO that found that between 1984-86, 28% of cassava output was fed to animals (FAO, 1991). The manufacturing sector would also experience economic losses due to a decline in the supply of root crops that could be converted into value-added products such as chips, flour, and baked goods.

Mining is the backbone of many activities along the supply chain through its raw materials required for the development of electricity. Therefore, the international mining sector would suffer economic impacts from fish and root crop declines due to some sectors along the supply chain no longer requiring as much electricity for operation, such as packaging machines. The decline in electricity usage then negatively impacts the mining industry. The trade and transport sectors may experience economic losses due to decreased traded fish and root crop products. The services sector would experience losses due to foreign aid that may be paid from other countries to assist in climate disaster impacts; for example, Australia, at the 2023 United Nations Climate Change Conference, committed to providing the Pacific Islands 100 AU$m to the Pacific Resilience Facility and a further 50 AU$m to the Green Climate Fund (Wong, 2023). A decline in the services sector could also result from various factors, including insurance claims. Business services would also be impacted due to a decline in business support, such as food catering companies. Finally, utilities and construction would be adversely affected due to a decrease in disposable income that could be spent, for example, on new equipment and the construction of storage sheds, which would help in the production of root crops and fish.

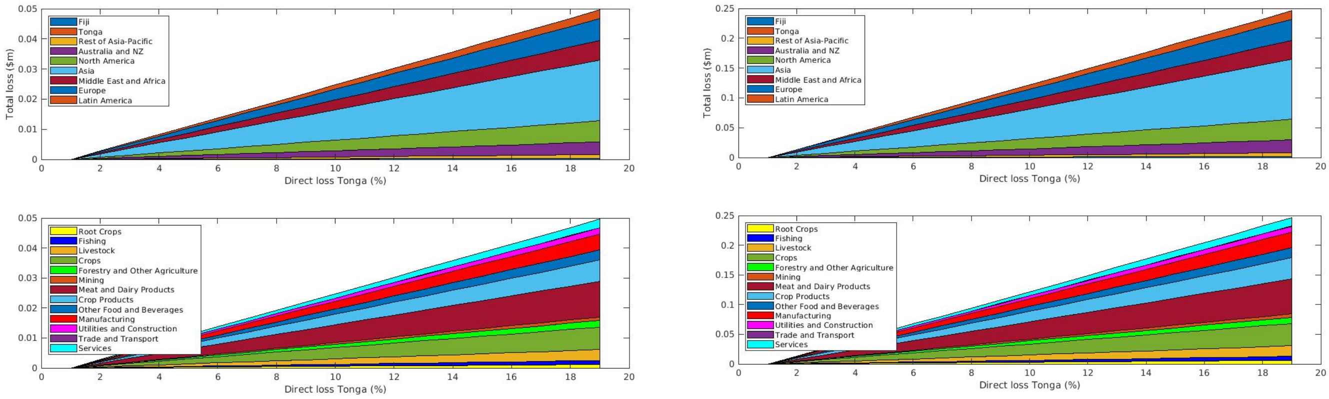


Figure 5: Regional and sectoral economic spillovers in $US from production losses on Tonga's root crops (left) and fishing (right).

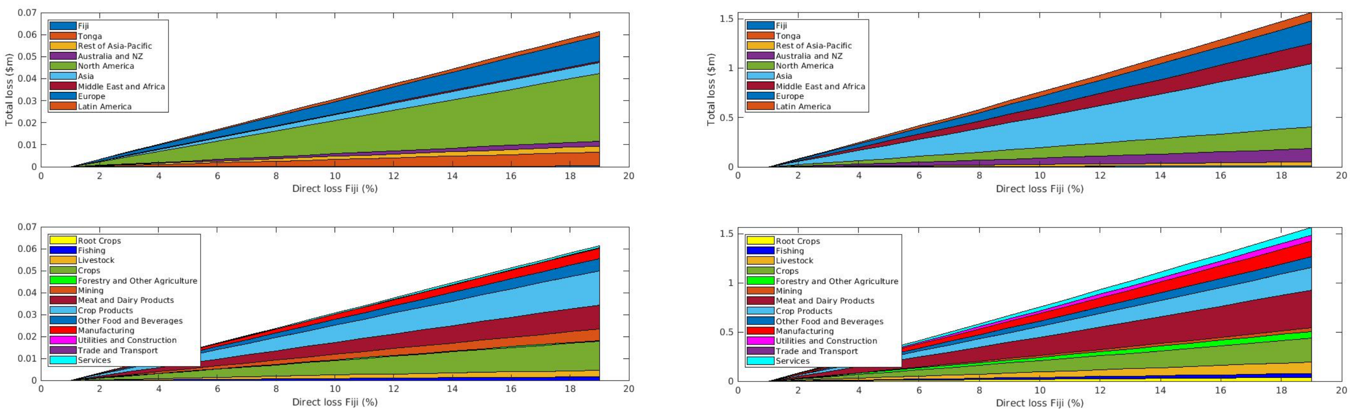


Figure 6: Regional and sectoral economic spillovers in $US resulting from production losses on Fiji's root crops (left) and fishing (right).

3.3 Regression results

3.3.1 Overview of data

Of the 445 observations collected, an increase in carbon dioxide was the most researched impact type (Figure 7). This focus may be attributed to the fact that studies often focus on carbon dioxide levels as a rise in carbon dioxide in the atmosphere heats the planet, causing the other impact types (NASA, 2024). A severity ranking of 5 was the most reported disaster severity. High severity scores in studies may result from climate disasters within the Pacific Islands regions being more severe than other locations or only severe impacts being reported due to their devastating effects. The data also suggests a trend where the later the disaster year, the greater the data availability by 2080. This may be because climate impacts are expected to heighten, leading to more research on the climate impacts anticipated in 2080. Most of the research on climate disaster impacts was conducted in 2012. Data availability was most significant for Fiji, which may be linked to Fiji having a larger population and economy (World Data, 2024). A larger economy suggests there is greater funding for climate disaster research, and a larger population is an incentive to conduct research as more lives will be impacted.

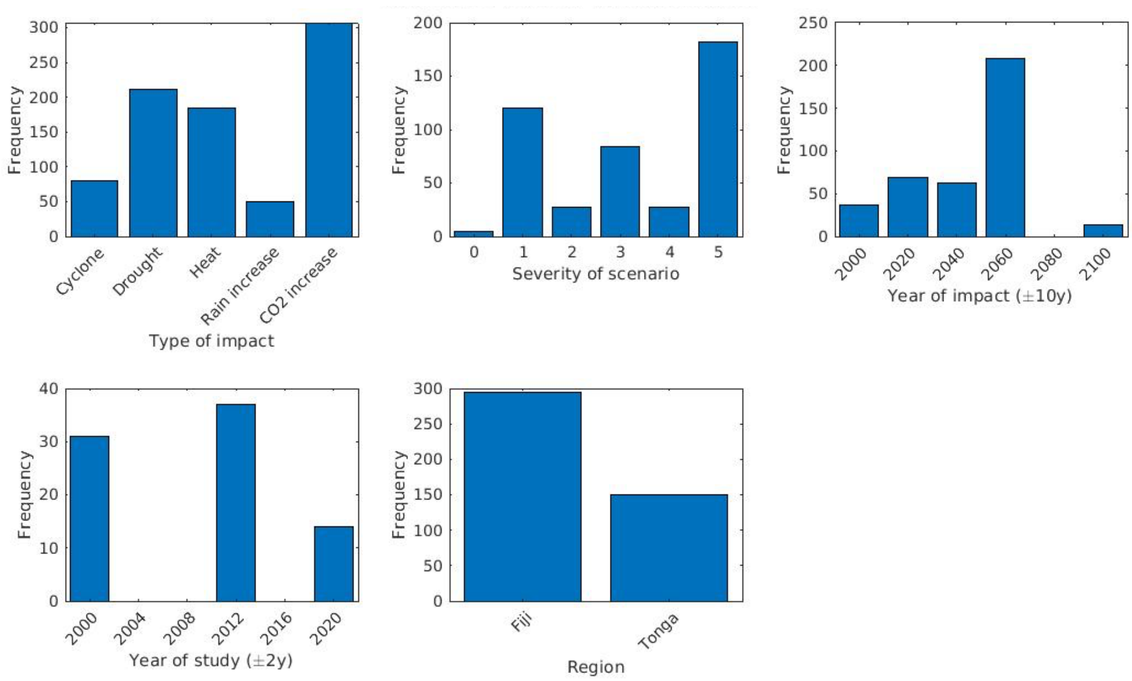


Figure 7: Attributes of regression data from 445 observations.

The OLS regression had the highest R^2 value compared to other regression types (Table 2). Due to the similar R^2 values, we chose to report on all regression methods to examine the relationships and trends between the explanatory variable and climate-induced production impacts. Note that the elimination of some dummy variables and the addition of a constant mean the regression coefficients explain the divergence from a production impact and other climate variables (e.g., sectors, regions, impact types, and years).

Table 2: R^2 value from the eight employed regression analysis methods.

Regression method	Equation	R^2
OLS	1	**0.252**
Log OLS	2	0.245
Log WLS manual	3	0.242
Log WLS optimised	4	0.238
Log WLS manual optimised	5	0.240
WLS manual	6	0.245
WLS optimised	7	0.231
WLS manual optimised	8	0.232

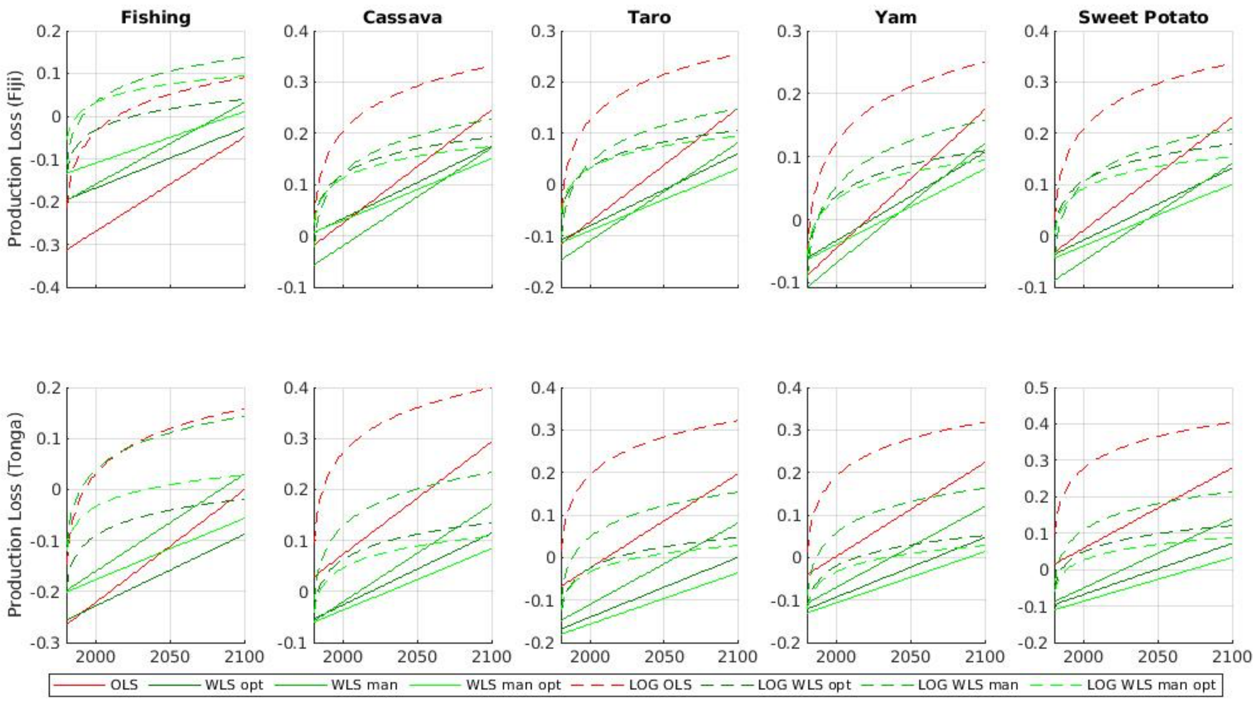
There is a significant relationship between the year of impact, disaster severity, year of study and all impact types (drought, cyclones, heat, rain and carbon dioxide increase) (Table 3). All regression types have a positive relationship between the year of impact, severity, cyclones, drought, rain and year of study, implying that production losses will increase over time. Out of all impact types, cyclones appear to cause the greatest losses. Cassava production is expected to experience the greatest decline. There is a negative relationship between the impact types of heat and carbon dioxide increase with production impacts. These results suggest that rises in carbon dioxide and heat result in below-average production impacts. Taro, yam and fish yield also have a negative relationship with production impacts, implying that these sectors will have below-average output losses as climate impacts grow.

When we modelled the impacts of carbon dioxide increase and cyclones, the results suggested the following: sweet potato production is expected to experience the most significant climate-induced production losses, followed by cassava, yam, taro and fishing respectively (Figure 8). Tonga will experience more substantial production losses than Fiji. In most scenarios, the OLS regression method suggested higher production losses, and the WLS, combined with manual and optimised weights, suggested lower production losses.

Table 3: Regression results from the eight employed analysis methods. Through completing a student t-test, significance levels are ascertained by comparing the examined data sets means in relation to their standard deviation to determine the likelihood that the data sets are different (Ibinson and Vogt, 2017). This is explained by the probability values of p of the test. If p≤0.33, p≤0.1, p ≤0.05, p≤0.01, then the results are documented as '.' '', '**', '***'. If there was no significance between variables present, no '.' or '*' was reported*

Variable	OLS	Sig.	WLS opt	Sig.	WLS man	Sig.	WLS man opt	Sig.	LOG OLS	Sig.	LOG WLS opt	Sig.	LOG WLS man	Sig.	LOG WLS man Opt	Sig.
Year of impact	0.0022	*	0.0014	**	0.0019	*	0.0012	**	0.17	.	0.096	.	0.14	.	0.083	.
Severity	0.0068		0.018	**	0.016	.	0.018	***	0.0078		0.019	**	0.017	.	0.018	***
Cyclone	0.29	*	0.2	***	0.24	**	0.19	***	0.31	*	0.25	***	0.28	**	0.25	***
Drought	0.14	.	0.058	.	0.12	.	0.059	.	0.15	.	0.063	.	0.12	.	0.061	*
Heat	-0.047		-0.05	.	-0.056	.	-0.054	.	-0.061		-0.066	.	-0.061	.	-0.067	*
Rain	0.12	.	0.062	.	0.12	.	0.049	.	0.14	.	0.072	.	0.13	.	0.062	.
CO2	-0.12	.	-0.073	.	-0.14	.	-0.067	*	-0.1	.	-0.056	.	-0.12	.	-0.049	.
Fiji	-0.048	.	0.06	**	0.0011		0.067	**	-0.068	.	0.058	*	-0.0057		0.066	**
Casava	0.014		0.042	.	-0.21	.	-0.24	***	0.081	.	0.083	*	-0.27	.	-0.32	***
Taro	-0.083	.	-0.072	.	-0.3	*	-0.36	***	0.0037		-0.0044		-0.35	*	-0.4	***
Yam	-0.056		-0.025		-0.26	.	-0.31	***	0		0		-0.34	*	-0.4	***
Sweet Potato	0		0		-0.24	.	-0.29	***	0.086	.	0.069	.	-0.29	.	-0.34	***
Fishing	-0.28	*	-0.16	**	-0.35	*	-0.38	***	-0.16	.	-0.07	.	-0.36	*	-0.4	***
Year of Study	0.005	.	0.0072	***	0.006	*	0.0077	***	-0.013		0.12	.	0.046		0.14	**
Constant	-0.18	.	-0.28	***	0		0		-0.27	.	-0.4	***	0		0	

Figure 8: Fractional production losses over time for fishing and root crops under the climate scenarios of CO_2 and cyclones.



3.4 Dietary changes

Cyclones and carbon dioxide increase reduce total macronutrient availability by decreasing the supply of fish and root crops. Notably, all macronutrients experience an increased loss over time as disaster frequency and production losses increase (Figures 9-13). Out of all macronutrients, the root crops of cassava, yam, taro and sweet potato reduce the availability of daily carbohydrates per capita the most. This is logical as cassava, taro, yam and sweet potato comprise of 34.7%, 24.2%, 24.1% and 27.3% carbohydrates respectively (FAO). The decline in the availability of macronutrients from all root crops is more significant in Fiji than in Tonga. Fiji is located in a region expected to suffer more from cyclone events than Tonga (Magee et al., 2020, The University of Newcastle), which reflects why our results indicate that macronutrient declines in root crops will be more significant in Fiji than in Tonga. Tonga, however, will experience a more substantial decrease in macronutrients from reduced fish production. Fish output declines are felt greatest in protein, followed by fat MJ/cap/day consumption, reflecting fish composition of protein typically between 13-20% (60-82% of the fish being water) (Weininger, 2024). Most regression methods were clustered together, resulting in the one-sigma standard deviation often being close to the minimum regression plotted line. Due to data gaps in the FAO nutrition database, no calculations for nutritional losses resulting from Fiji's taro climate-induced production decline can be produced.

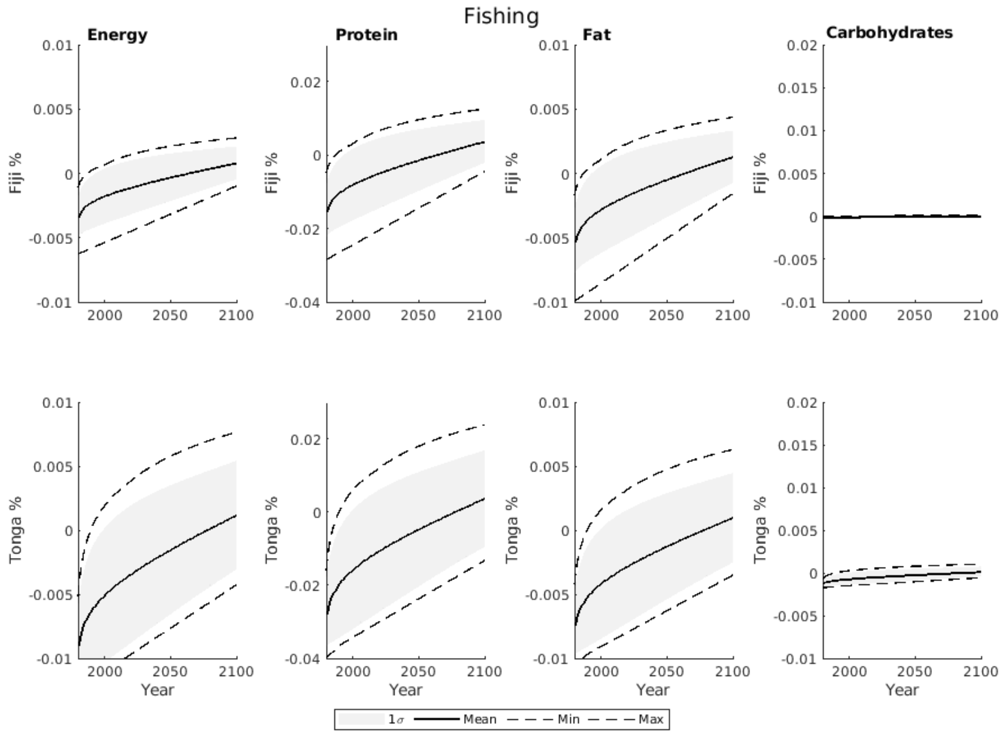


Figure 9: Estimated macronutrient losses due to production declines in the fishing sector over time in Tonga and Fiji resulting from cyclones and heat under a severity scenario of 3.

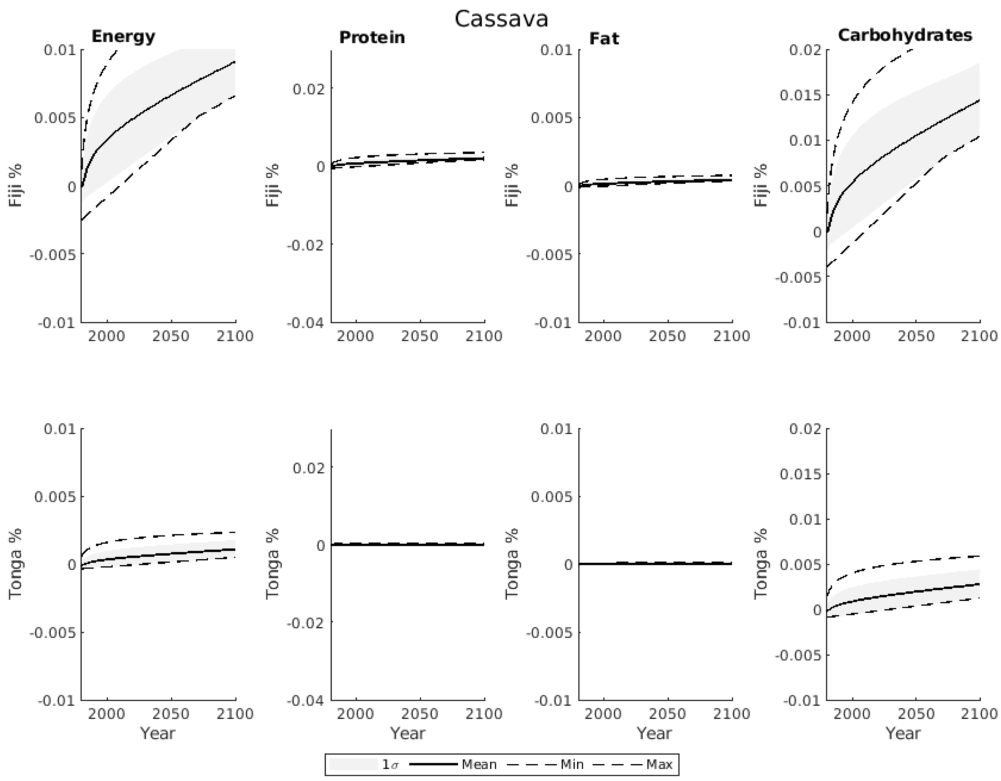


Figure 10: Estimated macronutrient losses due to production declines in the cassava sector over time in Tonga and Fiji resulting from cyclones and heat under a severity scenario of 3.

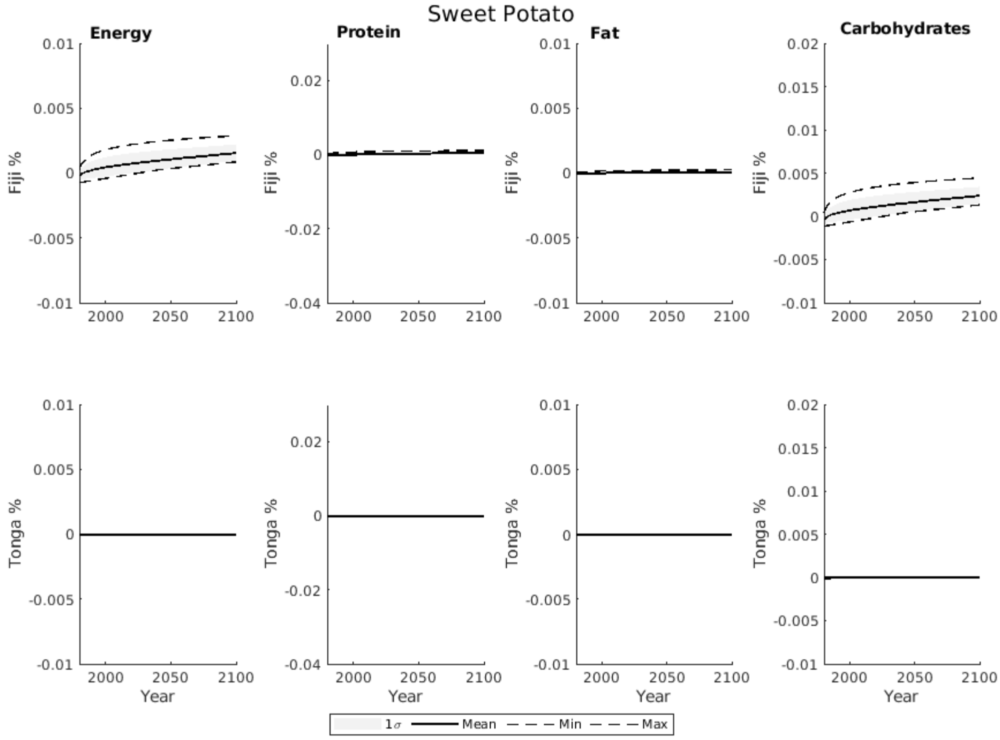


Figure 11: Estimated macronutrient losses due to production declines in the sweet potato sector in Tonga and Fiji over time resulting from cyclones and heat under a severity scenario of 3.

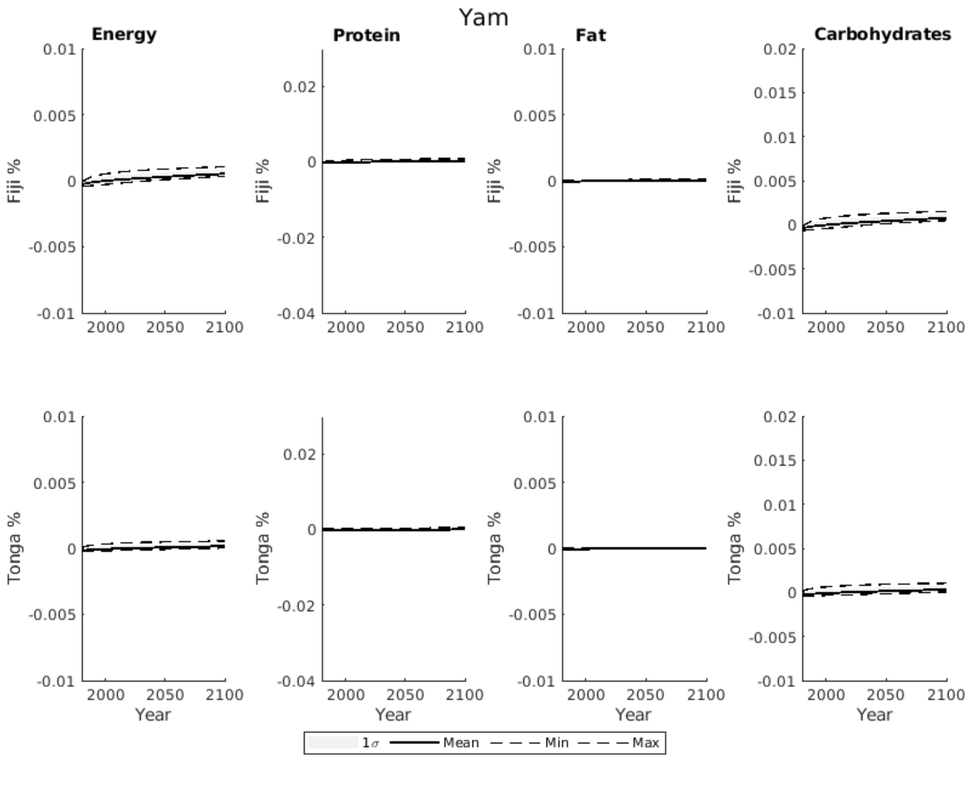


Figure 12: Estimated macronutrient losses due to production declines in the yam sector over time in Tonga and Fiji resulting from cyclones and heat under a severity scenario of 3.

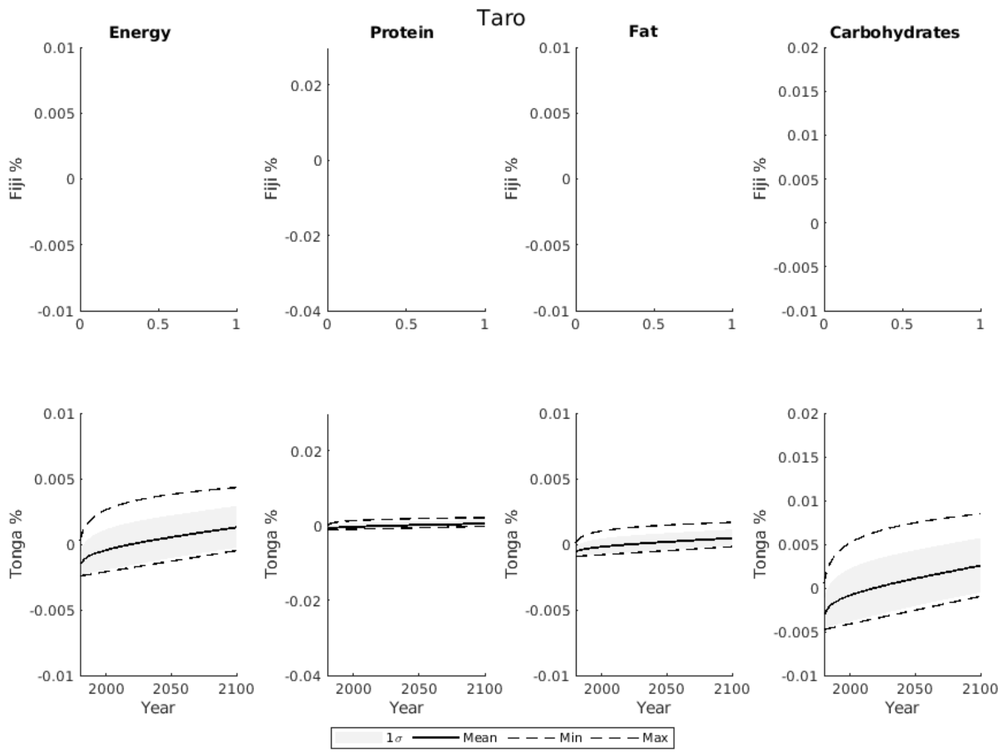


Figure 13: Estimated macronutrient losses due to production declines in the taro sector in Tonga and Fiji over time resulting from cyclones and heat under a severity scenario of 3.

4. Discussions

4.1 Discussion of economic spillover results

The fishing sector likely experiences greater economic spillovers than root crops due to its higher export volume. These losses occur as supply chains from other countries additionally become involved in various processes, such as value-adding products, resulting in more sectors experiencing economic losses. The importing countries often receive fish as raw material and must value-add the product domestically through practices such as packaging and conversion into fish products. These activities provide economic value through job creation and contribute to the GDP of the importing countries. Therefore, when there is a supply shock, these other sectors are also impacted. Products mainly consumed domestically, such as root crops, ensure that sectoral losses along supply chains are mainly incurred domestically, reducing the areas where losses may occur.

4.2 Discussion of regression analysis results

Out of all impact types, cyclones cause the most significant production losses, as they cause more physical damage, which other impact types (such as heat) cannot do. This is supported by a study that found that cyclones and floods result in 64% of disasters in the Pacific Islands annually (UN; Economic and Social Commission for Asia and the Pacific, 2020). We found that droughts, as an impact type, result in substantial production losses as root crops require water to survive, and droughts cause increased evaporation levels of waterways and oceans, which would increase salinity levels, reducing fish survival. Rain increases cause above-average production losses, which may result from waterlogging root crops, causing plant rot and subsequent plant death. For example, root rot can reduce cassava crop output by 80% (Palanivel and Shah, 2021). Heat may have a lower production impact on the fishing industry than other impact types as heat acts on terrestrial livestock more than aquatic animals. It takes longer for water to warm, thus making temperature rises in fishing less impactful. In the long term, however, it is important to note that oceans take longer to cool than land, retaining temperatures that are harmful to aquatic life e.g., temperature increases reduce oxygen solubility required by fish (Gui et al., 2023). Carbon dioxide additionally has a lower production loss. This is supported by studies indicating that some plant production levels increase with greater carbon dioxide levels due to higher levels of photosynthesis (Ziska, 2022). The by-product of photosynthesis, however, is sugar, which is stored at the expense of other nutrients, making the plants less nutritious (Ziska, 2022).

In many studies, fish production has been found to be increasing with rising climate disasters in the Pacific Islands (Bell et al., 2012, Dey et al., 2016, Rosegrant, 2015, Vaihola and Kininmonth, 2023). This is apparent as anticipated changes to the Pacific Ocean are believed to benefit some of the region's prominent fish catches, such as skipjack tuna, in the short term (Lehodey, 2011). Areas experiencing increases in production are anticipated to shift slowly towards the east with climate change, with fish catches remaining high in the east Pacific but low in the west Pacific. This effect is expected to decline by 2100 with current climate trends, resulting in a 10% decline in tuna numbers across the Pacific region compared to 1980-2000 (Lehodey, 2011). These declining fish populations will result from many reasons, such as increased atmospheric carbon dioxide, decreasing ocean pH by 0.3 by 2100, rising water temperatures and increased runoff from increased rain (Bell et al., 2012). The FAO (2018a) argue that studies that show climate-induced increases in fish production have significant bias levels as coastal areas experience significant upwelling of nutrients, resulting in higher fishery populations. Thus, these studies have a low confidence factor as models do not always consider changes in nutrient upwelling and current impacts from climate change/mesoscale dynamics (FAO, 2018). Many studies indicate that fish production levels will increase due to increased ecosystem productivity (FAO, 2018b). Gillett (2009) supports this in their analysis, indicating no apparent trend for fish production in the Pacific Islands at regional or national levels. Therefore, it is important to consider these opinions when interpreting the results.

Our analysis shows that all root crops resulted in a decline in production subsequent to a climate disaster when compared to sweet potatoes (the root crop set as a benchmark of the population average). This is supported by Oluwatimilehin and Ayanlade (2023), who conducted a study in Sub-Saharan Africa, which highlighted that all root crops experience production declines from climate change. Cassava production indicated an above-average decline. This is challenged by studies that suggest that cassava is more capable of withstanding the effects of climate change than other crops (Jarvis et al., 2012), resulting from accumulating and synthesising abscisic acid when water deficit commences, allowing leaf shedding, limiting new growth and only forming small leaves, allowing a better chance of survival (Gweyi-Onyango et al., 2020). Cassava plants can also close their stomata before water stress signs develop and form symbiotic relations with mycorrhiza, which is believed to assist in drought survival (Horton, 1988). A meta-analysis by Gweyi-Onyango et al. (2020), however, suggested that despite this, cassava did not seem to withstand climate impacts such as drought any better than other root crops (Gweyi-Onyango et al., 2020). Yam and taro have a below-average production decline. This is supported by Daryanto et al. (2016a), who conducted a meta-analysis and found that yam is better suited for drought-prone areas and that sweet potatoes are more sensitive to drought than other root crops. Whilst the study by Daryanto et al. (2016a) only explores droughts, it can help explain a production difference in root crop response to climate disasters.

The year of impact had a strong effect on production loss. This supports the literature as seen by the UN’s Disaster Risk Reduction 2022 report, which argued that due to factors such as climate disasters, global disaster rates have increased rapidly, with 350-500 large and medium-sized disasters occurring globally between 2001-2020 (UNDRR, 2022). This number is expected to rise to 560 times yearly by 2030 (UNDRR, 2021). The rise in disasters also indicates a trend that climate impacts in the future will be more frequent and severe than thought, further supporting our results that there is a relationship between disaster severity and production loss. The UNFCCC (2021) further supports our results by stating that disasters have risen by a factor of five over the past 50 years, driven by extreme weather, climate change and improved reporting. The enhanced reporting methods have reinforced our findings, indicating a clear correlation between production loss and the year of study. A more comprehensive dataset facilitates an in-depth exploration for scientists to make future predictions. Furthermore, a rise in climate-related disasters would prompt a heightened interest in conducting additional studies to anticipate future trends.

Work by Armati et al. (2024), which conducted a meta-analysis on climate disasters in Australia, supports these regression results where the variables of the year of impact, year of study, disaster severity, cyclone, rain and drought also had above-average production losses. The Armati et al. (2024) paper also found that carbon dioxide emissions negatively correlated with production losses. Our paper, however, found that heat waves had an above-average production loss. As the Pacific Islands have a maritime climate and are always warm, the sectors assessed in this study have already adapted to this environment.

4.3 Discussion of nutritional dietary change results

When these traditional food sources experience supply shocks from climate disasters, these commodities are typically replaced with imported processed goods. When this substitution occurs, the required energy will come from high-calorie, low-nutrient foods, which may cause fat consumption to rise and lead to health issues such as obesity and heart disease (Davila et al., 2024). This is evident as there is a growing reliance on meat imports from Australia, USA and New Zealand, wheat from Australia, and rice and highly processed goods from South-East Asia (Brewer et al., 2023). Fish currently supplies 50-90% of the essential animal protein for 50% of the Pacific Island population (‘Ofa and Gani, 2017, SPC, 2015, Thow et al., 2022). The average Pacific Islander consumes 18-64kg of fish a year (Charlton et al., 2016, Thow et al., 2022). Fish production loss is likely to be more significant than our results indicate due to other factors not assessed, such as ocean acidification, urban tourist development, algal bloom eutrophication, and warming waters (Johnson et al., 2016). As fish are highly nutritious, it is difficult to ascertain how protein will be obtained in the future to ensure the Pacific Islands population achieves food security (Bell et al., 2009). Based on the protein leverage hypothesis, humans still attempt to consume similar protein quantities when protein is diluted (e.g., reduced protein from fish due to a climate disaster), consequently consuming more carbohydrates and fat, typically from low-protein, highly-processed foods, to achieve this (Raubenheimer and Simpson, 2019). This rise in carbohydrate and fat consumption may result in an increased energy intake and subsequent health issues.

In some areas of the Pacific Islands, up to 80% of communities are subsistence farmers (Georgeou, 2022). As many communities in the Pacific Islands are mainly subsistence farmers, climate disasters are detrimental to achieving essential production outputs and food security. Root crops are one of the most common crops used for subsistence farming which is alarming as a study conducted by AusAid found that drought reduces cassava’s nutritional value by 10% (Gleadow, 2017). This issue is further exacerbated by rising population levels, resulting in a decrease in land availability for subsistence farming. The rise in urbanisation has been evident in towns such as Suva (Davila et al., 2024). The communities within these urban and peri-urban areas often have reduced hectares for agricultural production and live below the poverty line. Their livelihoods are determined based on what they can purchase (Davila et al., 2024). A final issue with declining root crop production, as mentioned, is that rising carbon emissions result in the dilution of nutrients in plants, whilst increasing the quantity of carbohydrates in the plant, making it less nutritious (Ziska, 2022). Therefore, climate impacts on root crop production are problematic to achieving food security in the Pacific Islands.

4.4 Limitations

Throughout the nutritional balance data collection, data gaps were present as the FAO data contains only some of the required information to complete this study. For example, there is no information on the nutritional consumption of Taro in Fiji. It is important to note that the spillovers derived during the IO analysis were calculated using international trade data and only approximate the impact on regions and sectors. The IO tables additionally do not account for subsistence farming, which is how many individuals in Tonga and Fiji farm their root crops and collect fish. The spillovers recorded are quite small; therefore, it is essential to consider that these losses may be clouded by more prominent macroeconomic activity. The IO analysis method additionally does not consider the substitution of commodities or model price impacts of different commodities post-disaster (Okuyama and Santos, 2014). When collecting production loss data for the regression models, it was noted that production losses from climate disasters are often not reported, and not all affected areas were assessed in Tonga and Fiji. This is apparent as many disaster events were reported; however, no assessment of production losses was conducted. Furthermore, there is a lack of reporting periods, quality and granularity of data (Brewer et al., 2023, Hughes and Kamea, 2015). Fewer data were available for root crops than in other sectors, which is supported by Daryanto et al. (2016a) and Daryanto et al. (2016b) who suggest there has been 2-4 times more research conducted on the impacts of droughts on cereal production and legumes than on root crops. Many studies that explore climate disaster-induced production losses were very disaggregated into specific regions and sectors, such as a particular species of fish or a sub-national region. This made it challenging as calculations had to be conducted to allocate these values to Fiji or Tonga, root crops, or fishing. Finally, some studies only examined the impact of simultaneously occurring climate disasters, which made it problematic to ascertain which climate-induced production impact resulted from which disaster.

5. Conclusions

5.1 Extensions

In this study, we focused on the impact of climate disasters on fish and root crops, as these were larger staple food sectors in the Pacific Islands' economy. Should improvements in data collection occur, future work could explore the impact of climate disasters on other food sectors within the Pacific Islands' economy. Due to the limited data availability to complete this study, it would also be interesting to conduct a Monte Carlo analysis to provide parameter uncertainties to the output values in this study (Bullard and Sebald, 1988). Additionally, it could be interesting to extend this study by using import data to model how diets would change when root crop and fish declines are substituted with ultra-processed imported products to assist in predicting long-term health issues such as obesity and diabetes. Greater data availability in the Pacific Islands would also allow us to extend our methods to other countries to provide a more reliable and individualised climate impact assessment for each country. As IO analysis cannot determine price changes of commodities post-disaster, Computable General Equilibrium modelling could also be employed to see how prices of goods change when there are supply disruptions, as this would also impact an individual's ability to be food secure (Okuyama and Santos, 2014). Further analysis could be conducted to determine supply chain networks with a more disaster-resilient network to ensure the most negligible loss of economic spillovers (Lenzen et al., 2019). Finally, it would be fascinating to conduct the analysis again, separating data collected from internal sources (from Tonga and Fiji) and external sources to see if there are any differences in the results from primary sources.

5.2 Recommendations

Climate disasters result in supply chain spillovers and nutritional losses that reduce the ability of communities to reach food security. The impacts are felt differently through different regions and sectors; however, all will feel the impacts (Davila et al., 2024). Given the high rates of subsistence farming, it is recommended that greater data collection by governments be conducted within the Pacific Islands on subsistence farming output, especially on post-disaster output. Increased data availability will improve climate disaster research reliability and will ensure better recommendations are implemented to ensure food security. In the short term, communities should consider implementing a diverse cropping mix and ensure that drought-resistant root crops are included to ensure food security during periods of drought and heat (Daryanto et al., 2016a, FAO, 2010). Communities should focus on drought-resistant types of cassava as current cassava crops are expected to suffer the most significant climate impacts compared to other root crops. Communities could also concentrate on substituting root crops with taro or yam as these crops are expected to be less impacted by climate disasters. These drought-resistant varieties will help reduce price fluctuations during some climate disaster scenarios. Farmers could also use rhizobium bacteria to promote plant growth and improve yields (Gweyi-Onyango et al., 2020). As the meat and dairy product sector and cropping sector are anticipated to experience the greatest economic declines post-disaster, these sectors should be considered first when disaster management strategies are implemented such as exploring livestock feed substitutes. Research should also be prioritised on root crop production instead of fishing, as fish output will not be as adversely impacted until closer to 2080.

The food system within the Pacific Islands remains dependent on international trade agreements that ensure cheap, ultra-processed food is imported from wealthier countries (‘Ofa and Gani, 2017). It is vital that equitable trade systems are established to improve the availability of nutritious food and mitigate health issues in the future (‘Ofa and Gani, 2017). As economic data is currently limited in the Pacific Islands, increased regional trade data are required to quantify the impact of food trade on rising nutritional issues and to ensure a unified response to non-communicable diseases and food insecurity (Hughes and Lawrence, 2005). Under current scenarios, ultra-processed convenient food will become more easily accessible, and the health crisis will subsequently continue. Trade policies within the Pacific Islands, therefore, need to place greater emphasis on ensuring improved diets and decrease non-communicable diseases. Pacific Island communities can reduce the impact of climate disasters by relying on trade agreements that involve a more nutritious, diverse range of imported products. This ensures a more stable and resilient economy post-disaster. As Fiji is expected to suffer the greatest nutritional losses from root crop decline, Fiji should prioritise new trade policies that ensure less processed carbohydrate food substitutes. In contrast, as Tonga is expected to experience more significant macronutrient losses from fish, the government of Tonga should prioritise trade policies that ensure healthier protein substitutes are made available.

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7. Appendix

7.1 Base Table Production

To explore the economic ripple effect of climate disasters along supply chains in Fiji and Tonga, we extended a previously generated Base Table called GLORIA, established by the University of Sydney for the United Nations International Resource Panel in the Global IELab, to develop a MRIO table for this study (IELab, 2023, Lenzen et al., 2017, Lenzen et al., 2022). GLORIA comprises 164 regions, 120 sectors, and five value-added transactions (trade margins, basic prices, taxes on products, transport margins and subsidies on products) (IELab, 2023). The following data feeds were selected in the generation of GLORIA: World Bank HES database (World Bank, 2017), Main Aggregates database (UNSD, 2020), UNSNAMA (USDA, 2011), MINSTAT database (UNIDO, 2020b), Inter-Country Input-Output Tables (OECD, 2018), Fisheries and Aquaculture Statistics (FAO, 2018b), food and agriculture statistics from FAO STAT (FAO, 2019), ADB MRIO, industrial statistics from the INDSTAT database (UNIDO, 2020a), global trade statistics from the UN Comtrade database (UN and COMTRADE, 1990), mining and utilities statistics acquired from the MINSTAT database (UNIDO, 2020b). Statistical organisations can take a few years to publish their data, so for this study, we selected the 2018 GLORIA base table, as this year holds the most recent and the most significant data availability. GLORIA contains 164 regions globally, with Fiji and Tonga aggregated into a larger region called the Rest of Asia Pacific. We augmented this MRIO table by adding Tonga and Fiji as individual regions, creating 166 regions and allowing for region disaggregation. We then manually added the inter-regional transactions and built up the MRIO table for each sector.

7.2 Sectoral and regional classification

Appendix Tables 1 & 2: Aggregated sectors (left) and regions (right) used from the augmented GLORIA MRIO.

Wheat
Maize
Cereals n.e.c
Legumes
Rice
Vegetables
Sugar beet/cane
Root crops
Fruits and nuts
Beverage crops
Cattle
Sheep
Pigs
Poultry
Other Agriculture
Forestry
Fishing
Fuel ores
Mining
Beef meat
Sheep meat
Pork
Poultry meat
Other meat products
Fish products
Cereal products
Vegetable products
Fruit products
Food products and feeds n.e.c
Sugar refining, confectionary
Animal oils and fats
Vegetable oils and fats
Dairy products
Alcoholic and other beverages
Tobacco and fibre products
Wood and paper
Fuel refining
Fertiliser
Chemical and plastic products
Mineral products
Metal products
Machinery and equipment
Utilities
Construction
Trade and transport
Businesses services
Public services
Commercial services

Fiji
Tonga
Rest of Asia-Pacific
Australia
New Zealand
USA
China and Hong Kong
Japan
South Korea
Malaysia and Singapore
Rest of South-East Asia
India
MENA
Rest of Asia
EU+
Rest of Europe
Rest of North America
Latin America
Rest of Africa

7.3 Augmenting T, y and v matrix

*Appendix Table 3: UN Main Aggregate data for 2018 to form the Tonga and Fijian **T, y** and **v** matrix values (UN, 2024).*

	Final consumption expenditure	Household consumption expenditure (including non-profit institutions serving households)	General govt final consumption expenditure	Gross capital formation	Gross fixed capital formation (including acquisitions less disposals of valuables)	Changes in inventories	Exports of goods and services	Imports of goods and services	GDP
Fiji (US$D)	4,838,465,578	3,700,307,684	1,138,157,894	1,174,814,835	1,049,095,928	125,718,907	2,665,063,650	3,096,944,808	5,581,399,255
Tonga (US$D)	558,835,892	466,660,948	92,174,944	114,929,100	104,891,949	10,037,150	102,682,161	317,381,799	479,553,601
	P3 Hn & G	P3 H & P3 N	P 3 G	P 51, P 52 and P53	P 51	P52 and P53			

To determine production losses, the **T** matrix production values for fish and root crops were cross-checked with values published by the FAO as the FAO published data on the percentage of GDP that the fishing industry accounted for in Tonga and Fiji (FAO, 2018a, FAO, 2018c). This allowed us to determine the economic output of fisheries by using the World Bank statistics on the 2018 GDP of Tonga and Fiji (Appendix Tables 4 & 5). As root crops (sweet potato, cassava, taro and yams) were aggregated with other sectors under an umbrella sector called 'Tobacco, Fibre and Other Products', this sector was relabelled 'Root crops'. The FAO additionally had information on root crop production for Fiji and Tonga in their Value of Agricultural Production database (FAO, 2024). Using these tables from the FAO, we determined the economic output of yams, sweet potato, cassava and taro, which were totalled to produce a value for Fiji's and Tonga's aggregated sector of root crops. The values for Tonga were recorded as an international dollar value, so these were converted to U$SD by multiplying by the implied purchasing power parity (PPP) conversion rate of 1.81 (International Monetary Fund, 2021). We then summed the values of cassava, taro, sweet potato and yam to provide the root crop value. This then provided the root crop sectoral value in the **T** matrix. We then adjusted the **T** matrix values for fishing and root crops with statistics provided by the FAO in literature: Fiji fish production 35.16 US$m, Tonga fish production 9.24 US$m, Fijian root crops 82.64 US$m and Tongan root crops 2.17 US$m.

*Appendix Table 4: Root crop production values used in the **T** matrix.*

Country	***Sector***	***US$m***
Tonga	*Root crops*	*2.17*
Fiji	*Root crops*	*82.64*

*Appendix Table 5: Fishing production values used in the **T** matrix.*

Country	***US$ GDP***	***Fishing section % GDP***	***Fishing US$m***
Tonga	*488.9 m*	*1.89*	*9.240210*
Fiji	*5.581 bn*	*0.63*	*35.1603*

Appendix Table 6: Spillovers felt by each region and sector due to production losses in the Fijian root crop sector.

	Fiji	Tonga	Rest of Asia Pacific	Australia and NZ	North America	Asia	Middle East and Africa	Europe	Latin America
					(US$m)				
Root Crops	0.00	0.00	0.16	0.33	0.00	0.41	0.43	0.30	0.34
Fishing	0.11	0.08	0.36	0.00	0.06	0.41	0.14	0.34	0.29
Livestock	0.19	0.35	0.57	0.66	0.06	1.03	1.75	0.04	0.03
Crops	0.21	0.50	0.76	1.38	0.34	1.94	2.25	1.88	1.31
Forestry and Other Agriculture	0.00	0.14	0.51	0.38	0.37	0.75	0.75	0.64	0.43
Mining	0.05	0.12	0.60	0.13	0.46	0.64	0.50	0.44	0.38
Meat and Dairy Products	0.42	0.29	1.27	2.24	1.90	3.49	2.62	2.63	2.56
Cereal Products	0.25	0.32	1.20	0.77	0.09	2.16	1.20	2.30	1.95
Other Food and Beverages	0.39	0.17	0.84	0.75	0.66	1.40	0.49	1.01	0.82
Manufacturing	0.33	0.10	0.62	0.88	0.70	0.81	0.08	0.99	0.86
Utilities and Construction	0.39	0.00	0.68	0.01	0.26	0.75	0.50	0.71	0.70
Trade and Transport	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Services	0.59	0.08	0.86	0.29	0.09	0.53	0.54	0.67	0.75

Appendix Table 7: Spillovers felt by each region and sector due to production losses in the Fijian fishing sector.

	Fiji	Tonga	Rest of Asia Pacific	Australia and NZ	North America	Asia	Middle East and Africa	Europe	Latin America
					(US$m)				
Root Crops	0.00	0.00	0.17	0.70	0.08	0.97	0.98	0.81	0.72
Fishing	0.10	0.08	0.87	0.31	0.26	0.82	0.32	0.75	0.70
Livestock	0.21	0.37	0.67	1.17	0.04	2.21	3.67	0.00	0.00
Crops	0.21	0.51	0.96	2.74	0.43	4.23	5.19	3.78	2.40
Forestry and Other Agriculture	0.00	0.15	1.06	0.67	0.63	1.23	1.56	1.15	0.62
Mining	0.05	0.12	0.75	0.29	0.66	1.37	1.17	0.44	0.37
Meat and Dairy Products	0.43	0.31	2.11	5.38	4.36	7.56	5.88	5.90	5.89
Cereal Products	0.26	0.31	1.69	2.02	0.10	5.30	2.75	5.19	4.22
Other Food and Beverages	0.43	0.18	1.77	1.90	1.49	3.06	1.09	2.25	1.85
Manufacturing	0.66	0.11	1.20	2.59	1.78	1.75	0.31	2.28	2.06
Utilities and Construction	0.45	0.00	1.71	0.09	0.65	1.69	1.06	1.60	1.55
Trade and Transport	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Services	1.20	0.08	1.94	0.76	0.63	1.19	1.18	1.51	1.67

Appendix Table 8: Spillovers felt by each region and sector due to production losses in the Tongan root crop sector.

	Fiji	Tonga	Rest of Asia Pacific	Australia and NZ	North America	Asia	Middle East and Africa	Europe	Latin America
					(US$m)				
Root Crops	0.00	0.00	0.17	0.70	0.08	0.97	0.98	0.81	0.72
Fishing	0.12	0.08	0.87	0.31	0.26	0.83	0.32	0.75	0.70
Livestock	0.21	0.37	0.67	1.17	0.04	2.21	3.67	0.00	0.00
Crops	0.21	0.51	0.96	2.74	0.43	4.23	5.19	3.78	2.40
Forestry and Other Agriculture	0.00	0.15	1.06	0.67	0.63	1.23	1.56	1.15	0.62
Mining	0.05	0.12	0.75	0.29	0.66	1.37	1.17	0.44	0.37
Meat and Dairy Products	0.43	0.31	2.11	5.38	4.36	7.56	5.88	5.91	5.89
Cereal Products	0.26	0.31	1.69	2.02	0.10	5.30	2.75	5.19	4.22
Other Food and Beverages	0.43	0.18	1.77	1.90	1.49	3.06	1.09	2.25	1.85
Manufacturing	0.66	0.11	1.20	2.59	1.78	1.75	0.31	2.28	2.06
Utilities and Construction	0.45	0.00	1.71	0.09	0.65	1.69	1.06	1.60	1.55
Trade and Transport	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Services	1.20	0.08	1.94	0.76	0.63	1.19	1.18	1.51	1.67

Appendix Table 9: Spillovers felt by each region and sector due to production losses in the fishing sector.

	Fiji	Tonga	Rest of Asia Pacific	Australia and NZ	North America	Asia	Middle East and Africa	Europe	Latin America
					(US$m)				
Root Crops	0.00	0.00	0.17	0.70	0.08	0.97	0.98	0.81	0.72
Fishing	0.12	0.09	0.87	0.32	0.27	0.83	0.32	0.75	0.71
Livestock	0.21	0.37	0.67	1.17	0.04	2.22	3.69	0.00	0.00
Crops	0.21	0.51	0.96	2.75	0.44	4.25	5.21	3.79	2.41
Forestry and Other Agriculture	0.00	0.15	1.06	0.67	0.63	1.23	1.57	1.15	0.62
Mining	0.05	0.12	0.75	0.29	0.66	1.38	1.17	0.44	0.37
Meat and Dairy Products	0.43	0.31	2.12	5.41	4.38	7.59	5.90	5.93	5.91
Cereal Products	0.26	0.31	1.69	2.03	0.10	5.32	2.76	5.21	4.24
Other Food and Beverages	0.43	0.18	1.78	1.91	1.50	3.07	1.10	2.26	1.85
Manufacturing	0.67	0.11	1.21	2.61	1.80	1.76	0.31	2.29	2.07
Utilities and Construction	0.45	0.00	1.71	0.09	0.65	1.70	1.06	1.60	1.56
Trade and Transport	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Services	1.21	0.08	1.95	0.76	0.64	1.19	1.19	1.52	1.68

7.4 Aggregation of variables for IO spillover results

Appendix Tables 10 & 11: Aggregation of regions and sectors for the results section.

Disaggregated sector	*Aggregated sector*
Root crops	*Root crops*
Fishing	*Fishing*
Wheat	*Rest of Agriculture*
Maize	*Crops*
Cereals n.e.c	
Legumes	
Rice	
Vegetables	
Sugar beet/cane	
Fruits and nuts	
Beverage crops	
Cattle	*Livestock*
Sheep	
Pigs	
Poultry	
Other Agriculture	*Forestry and Other Agriculture*
Forestry	
Fuel ores	*Mining*
Mining	
Beef meat	*Meat Products*
Sheep meat	
Pork	
Poultry meat	
Other meat products	
Fish products	
Cereal products	
Vegetable products	
Fruit products	
Food products and feeds n.e.c	
Sugar refining, confectionary	
Animal oils and fats	
Dairy products	*Dairy Products*
Vegetable oils and fats	*Other Food and Beverages*
Alcoholic and other beverages	
Tobacco and fibre products	
Wood and paper	*Manufacturing*
Fuel refining	
Fertiliser	
Chemical and plastic products	
Mineral products	
Metal products	
Machinery and equipment	
Utilities	*Utilities and Construction*
Construction	
Trade and transport	*Trade and Transport*
Businesses services	*Services*
Public services	
Commercial services	

Disaggregated region	*Aggregated region*
Fiji	*Fiji*
Tonga	*Tonga*
Rest of Asia-Pacific	*Rest of Asia-Pacific*
Australia	*Australia and New Zealand*
New Zealand	
USA	*North America*
Rest of North America	
Rest of Asia	*Asia*
China and Hong Kong	
Japan	
South Korea	
Malaysia and Singapore	
Rest of South-East Asia	
India	
MENA	*Middle East and Africa*
Rest of Africa	
EU+	*Europe*
Rest of Europe	
Latin America	*Latin America*

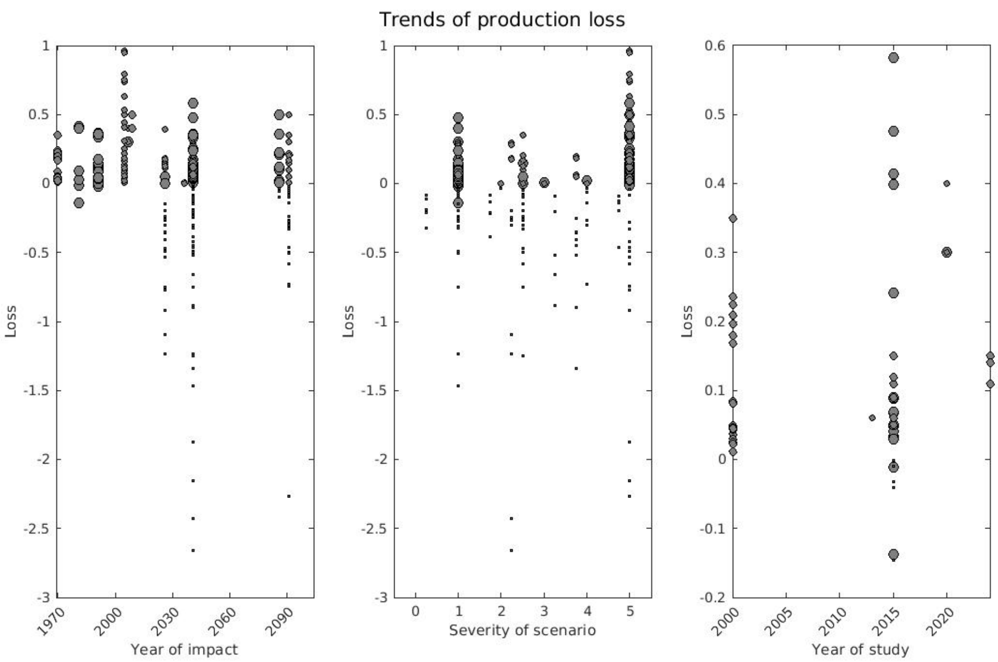
7.5 WLS with manually assigned weights

In the WLS regression with manually assigned weights, each category allows a maximum of +0.2 (Appendix Table 12). The weights of studies that explored just carbon dioxide increase were reduced by an additional 0.1 as this typically results in a production rise when the carbon dioxide increase is usually experienced simultaneously as an additional climate disaster; therefore, these studies do not consider the simultaneity of climate impacts. We additionally downweighed studies that had a positive effect by 0.1.

Appendix Table 12: Criteria used to determine manually assigned weights for each study.

	+0.2	*+0.1*	*+0*
Proxy	*Production impacts as a percentage.*	*Production impact proxy required conversion into a production loss percentage e.g., t/ha.*	*Production impact proxy required conversion into a production loss percentage and required further sub-region disaggregation e.g., t/ha in Viti Levu Fiji.*
Reliability	*Based on the methodology producing stable and consistent results.*	*The methodology produced consistent but potentially unstable results.*	*Unstable and inconsistent results.*
Assumptions to justify conclusions and to produce the methodology (subjective)	*Logical and justified.*	*Some illogical justifications.*	*No justifications of assumptions used to produce results, methods and conclusions.*
Sample size	*Sample size greater than 50.*	*Sample size between 10-49.*	*Sample size less than 10.*
Clarity	*Subjectively clear explanation of information and of how results are obtained. The method is easily repeatable.*	*Some unclarity of how results are obtained. Greater depth is required so the methods are repeatable.*	*Uncertainty regarding how results are obtained and information is unclear e.g., limited to no description of methods, unclear description of how different production losses from climate severity scenarios were calculated.*

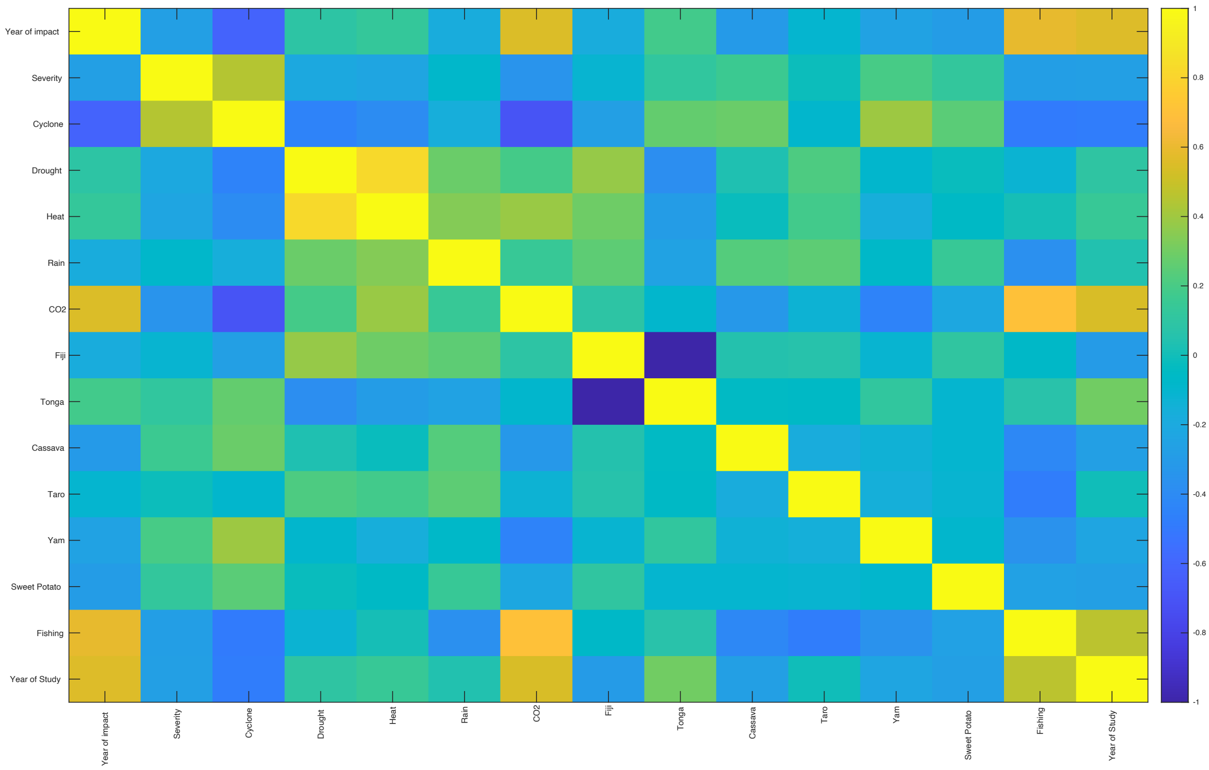
7.6 Regression analysis production loss trends



Appendix Figure 1: Fractional Production loss trends for the variables of year of impact, disaster severity and year of study.

7.7 Multicollinearity of explanatory variables in the regression analysis

We tested the correlation between all regression variables using a Pearson's correlation matrix heatmap (Appendix Figure 2). Values closer to 1 have a positive correlation, indicating that the variables increase or decrease together. Values closer to -1 have a negative correlation, indicating that as one variable increases, the other decreases. The colours green and light blue suggest weaker correlations. The colours yellow and dark blue suggest strong correlations between variables. Variables are aggregated in the regression analysis as they should not be isolated individually.



Appendix Figure 2: Pearson's correlation between the explanatory variables.

7.8 Multiple regression robustness tests

Tables SI13-20: Result comparison between the eight regression methods. A Student's t-test was used to compare the average of the examined data sets to their standard deviation, determining the likelihood of differences between the sets (Ibinson and Vogt, 2017). The probability values (p) explain this: when p < 0.33, p < 0.1, p < 0.05, and p < 0.01, the results were respectively documented as '.', '', '**', '***'. If there was no significance between variables present, no '.' or '*' was reported.*

Appendix Table 13: OLS regression results.

Variable	Coef.	Stand. error	t-stat.	Sign.
Year of impact	0.0022	0.0017	1.31	*
Severity	0.0068	0.023	0.30	
Cyclone	0.29	0.19	1.52	*
Drought	0.15	0.15	0.94	.
Heat	-0.050	0.15	0.32	
Rain	0.12	0.16	0.76	.
CO2	-0.12	0.16	0.77	.
Fiji	-0.048	0.096	0.50	.
Cassava	0.014	0.17	0.082	
Taro	-0.083	0.18	0.47	.
Yam	-0.056	0.18	0.31	
Sweet Potato	0	0	NaN	
Fishing	-0.28	0.22	1.30	*
Year of Study	0.0050	0.0055	0.92	.
Constant	-0.18	0.29	0.61	.

Appendix Table 14: Log OLS regression results.

Variable	Coef.	Stand. error	t-stat.	Sign.
Year of impact	0.17	0.23	0.76	.
Severity	0.0078	0.023	0.35	
Cyclone	0.31	0.21	1.46	*
Drought	0.15	0.16	0.98	.
Heat	-0.061	0.15	0.40	
Rain	0.14	0.17	0.81	.
CO2	-0.1	0.16	0.64	.
Fiji	-0.068	0.094	0.72	.
Cassava	0.081	0.14	0.57	.
Taro	0.0037	0.15	0.02	
Yam	0	0	NaN	
Sweet Potato	0.086	0.18	0.47	.
Fishing	-0.16	0.19	0.84	.
Year of Study	-0.013	0.25	0.05	
Constant	-0.27	0.32	0.83	.

Appendix Table 15: WLS optimised regression results.

Variable	Coef.	Stand. error	t-stat.	Sign.
Year of impact	0.0014	0.00060	2.17	**
Severity	0.018	0.0084	2.17	**
Cyclone	0.2	0.072	2.79	***
Drought	0.058	0.058	1.00	.
Heat	-0.05	0.056	0.90	.
Rain	0.062	0.060	1.038	.
CO2	-0.073	0.061	1.20	.
Fiji	0.06	0.036	1.68	**
Cassava	0.042	0.062	0.67	.
Taro	-0.072	0.066	1.080	.
Yam	-0.025	0.067	0.37	
Sweet Potato	0	0	NaN	
Fishing	-0.16	0.081	2.029	**
Year of Study	0.0072	0.0020	3.54	***
Constant	-0.28	0.11	2.60	***

Appendix Table 16: WLS Log optimised results.

Variable	Coef.	Stand. error	t-stat.	Sign.
Year of impact	0.096	0.086	1.12	.
Severity	0.019	0.0085	2.21	**
Cyclone	0.25	0.079	3.18	***
Drought	0.063	0.058	1.08	.
Heat	-0.066	0.056	1.18	.
Rain	0.072	0.063	1.14	.
CO2	-0.056	0.061	0.93	.
Fiji	0.058	0.035	1.63	*
Cassava	0.083	0.054	1.54	*
Taro	-0.0044	0.057	0.08	
Yam	0	0	NaN	
Sweet Potato	0.069	0.069	1.00	.
Fishing	-0.07	0.071	0.99	.
Year of Study	0.12	0.095	1.27	.
Constant	-0.4	0.12	3.30	***

Appendix Table 17: WLS manual weights regression results.

Variable	Coef.	Stand. error	t-stat.	Sign.
Year of impact	0.0019	0.0013	1.42	*
Severity	0.016	0.017	0.94	.
Cyclone	0.24	0.14	1.70	**
Drought	0.12	0.12	1.08	.
Heat	-0.056	0.11	0.50	.
Rain	0.12	0.11	1.04	.
CO2	-0.14	0.12	1.17	.
Fiji	0.0011	0.082	0.013	
Cassava	-0.21	0.20	1.03	.
Taro	-0.3	0.20	1.51	*
Yam	-0.26	0.21	1.25	.
Sweet Potato	-0.24	0.22	1.09	.
Fishing	-0.35	0.22	1.57	*
Year of Study	0.006	0.0042	1.44	*
Constant	0	0	NaN	*

Appendix Table 18: Log WLS manual weights regression results.

Variable	Coef.	Stand. error	t-stat.	Sign.
Year of impact	0.14	0.14	0.90	.
Severity	0.017	0.02	1.00	.
Cyclone	0.28	0.28	1.84	**
Drought	0.12	0.12	1.06	.
Heat	-0.061	-0.06	0.54	.
Rain	0.13	0.13	1.11	.
CO2	-0.12	-0.12	0.99	.
Fiji	-0.0057	-0.01	0.07	
Cassava	-0.28	-0.27	1.20	.
Taro	-0.35	-0.35	1.58	*
Yam	-0.34	-0.34	1.42	*
Sweet Potato	-0.29	-0.29	1.22	.
Fishing	-0.36	-0.36	1.56	*
Year of Study	0.046	0.05	0.25	
Constant	0	0.00	NaN	

Appendix Table 19: WLS manual and optimised weights regression results.

Variable	Coef.	Stand. error	t-stat.	Sign.
Year of impact	0.0012	0.0005	2.32	**
Severity	0.018	0.0069	2.60	***
Cyclone	0.19	0.057	3.36	***
Drought	0.059	0.047	1.26	.
Heat	-0.054	0.045	1.19	.
Rain	0.049	0.047	1.04	.
CO2	-0.067	0.049	1.38	*
Fiji	0.067	0.033	2.01	**
Cassava	-0.24	0.081	2.96	***
Taro	-0.36	0.081	4.42	***
Yam	-0.31	0.084	3.67	***
Sweet Potato	-0.29	0.088	3.29	***
Fishing	-0.38	0.091	4.21	***
Year of Study	0.0077	0.0017	4.55	***
Constant	0	0	NaN	**

Appendix Table 20: Log WLS manual and optimised regression results.

Variable	Coef.	Stand. error	t-stat.	Sign.
Year of impact	0.083	0.065	1.28	.
Severity	0.018	0.0069	2.62	***
Cyclone	0.25	0.062	3.99	***
Drought	0.061	0.047	1.3	*
Heat	-0.067	0.046	1.47	*
Rain	0.062	0.049	1.28	.
CO2	-0.049	0.048	1.01	.
Fiji	0.066	0.033	2.01	**
Cassava	-0.32	0.093	3.42	***
Taro	-0.4	0.089	4.54	***
Yam	-0.4	0.098	4.11	***
Sweet Potato	-0.34	0.095	3.59	***
Fishing	-0.4	0.095	4.25	***
Year of Study	0.14	0.075	1.83	**
Constant	0	0	NaN	

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Conclusions

5.1 Overall findings

Disasters both directly and indirectly impact the world and are increasing in frequency and intensity. The uniqueness of each disaster, the complexity of supply chain networks and mismatched disaster variables used in studies make the trends and effects of these disasters challenging to examine (Okuyama, 2007). This manuscript outlines the benefits of IO analysis, data restructuring and multiple regression analysis to assist in quantifying disaster impacts and to determine trends between disaster variables.

This dissertation provides insights on how data can be restructured and made congruous from mismatched studies that explore disaster impacts in different regions and sectors, with varying impact and study years, using unique ways to measure disaster severities and different production loss units. By aligning these data, this dissertation shows how multiple regression analysis can be employed to draw trends between the explained variables (production losses) and explanatory variables (study years, impact types, severity, year of disaster impacts, disaster severities, regions and sectors). The dissertation also presents how different multiple regression analysis methods may be conducted. For example, by developing criteria to manually provide weights to each data point based on their dependability to ensure that more reliable data points offer a stronger anchorage to the regression line. These results highlight which regions and sectors will experience the greatest production declines and which impact types are the most responsible for these losses.

Chapter 2 shows that climate-induced disasters adversely impact the Australian livestock production sector more than the cropping sector. These production losses are greater from the impact types of rain, cyclones and heatwaves when compared to droughts, floods and bushfires. Interestingly, the regression analysis on root crops and fishing sectors in Fiji and Tonga also found cyclones and rain resulted in the most significant production losses (Chapter 4). The Pacific Islands study, however, did not find heat to be one of the main concerning impact types. This difference may result from the maritime climate of the Pacific Islands, as water is a slow conductor of heat (USGS, 2018), suggesting that root crops may be better adapted to a warm environment and result in a smaller effect on fish production. It is important to note, however, that once the ocean temperature has risen, the ocean takes longer to cool than the land, maintaining temperatures that are harmful to aquatic life. Rises in water temperature decrease the solubility of oxygen used by fish that support fisheries which are important to lives of Pacific Islanders (Kenneth et al., 2019, Kim et al., 2023).

The use of MRIO analysis successfully quantified the economic impacts that are felt both directly and indirectly along supply chains. Our research indicates that all regions and sectors within an economy will experience post-disaster economic impacts directly or indirectly. Both Chapters 3 and 4, which employ MRIO analysis, found that the indirect losses are greater than the direct losses. Chapter 4, examining economic spillovers from climate disasters in Tonga and Fiji, found the main trading partners to experience the most significant losses post-climate disaster. Chapter 3, however, found that economic spillovers were greatest in countries that did not appear to be closely related to the Fusarium wilt TR4 outbreak in the Philippines. Therefore, spillovers do not necessarily occur where expected, thus depicting the importance of disaster analysis. Sectoral losses are typically smaller where the direct impacts occur and are felt greatest by sectors that require outputs or supply goods to the directly hit sector. These findings indicate to governments which sectors and regions should receive greater support with disaster management planning.

Extending the multiple regression analysis with a daily macronutrient database, allowed the assessment of macronutrient losses caused by the climate scenarios of cyclones and carbon dioxide increase (with a moderate severity) over time. This study found that all macronutrient availability in the Pacific Islands will decline from production losses, with protein suffering the most significant loss in the food group of fish and carbohydrates in the food group of root crops. The results show that Fiji will suffer from more significant macronutrient impacts than Tonga. Fish declines will also result in more substantial macronutrient losses than root crops. This research helps governments determine how Fijian and Tongan diets may change when climate impacts alter the staple foods of fish and root crop production. The fishing sector can, therefore, be seen as a priority area for climate management investment. Fiji will likely require more assistance in assisting communities in reaching food security than Tonga. Both regions need to consider their trade agreements to ensure healthy options are available to substitute these macronutrient declines when climate disasters occur.

The findings from these chapters can assist governments in strengthening policies to aid in developing disaster management strategies. Policies should assist the development of innovative research into climate change-resistant breeds e.g., new root crop varieties. Governments could also provide incentives to farmers to encourage them to produce commodities that are both nutritious and better adapted to the changing environment. To further encourage sectors to implement climate adaptation measures to decrease climate impacts, they could be provided tax breaks or grants. Finally, to ensure disaster management decisions are formed using the most up-to-date data, vulnerability assessments should be conducted regularly so evolving climate scenarios are considered.

5.2 Extensions

The Fijian and Tongan climate disaster study (Chapter 4), could be further extended by incorporating food import data from the OEC to determine how these macronutrient losses from staple whole foods are supplemented with imported high-energy, low-nutrient food and how this impacts daily energy consumption to predict health issues in different regions (OEC, 2018a, OEC, 2018b). Exploring how international trade and food policies impact macronutrient availability from available foods in trade offerings would be interesting. Implementing food taxation policies has proven to be a beneficial technique to alter consumption preferences (Walby et al., 2023). Finally, a potential expansion of the manuscript could explore how other climate impact types alter the daily macronutrient composition of all food groups in the Pacific Islands. Including every Pacific Island nation, investigation other impact types, and considering all food sectors will provide a more holistic assessment of how diets will change over time.

In Chapters 3 and 4, which adopted IO analysis, Computable General Equilibrium (CGE) modelling could supplement the IO data to determine price changes of commodities post-disaster (Okuyama and Santos, 2014). Household expenditure survey data could also be employed in these chapters to ascertain production loss impacts on household spending and, therefore, assist in examining poverty impacts during a climate crisis (Menaouer, 2023, Fiji Bureau of Statistics Office, 2020, Australian Bureau of Statistics, 2017). As there is a significant contrast between rural and city living, when greater data availability is present, exploring sub-regional differences in diet and production losses would be beneficial to determine economic and nutritional regional divides. The impact of disasters on governments, both at the direct site and overseas, should also be assessed to explore debt through aid provisions.

As disaster data are continually published, these new data could be routinely added to the regression analyses (Chapters 2 and 4) to strengthen and update the results. As some production loss units are hard to convert to a production loss fraction, such as growing degree days, further calculation methods that were out of this dissertation's scope of study can be determined to deal with these proxies. A systemic review by Kc et al. (2024) developed indicators to measure food system resilience. These indicators include household (e.g., soil, food prices), community (e.g., income, gender equality), subnational (e.g., food production, population, freshwater access), and national (e.g., water availability, percentage of agricultural land). Of 1,547 reviewed studies, 113 studies were included. If our studies fit their inclusion criteria, these indicators could also be applied to our collected restructured disaster data to determine the resilience of different regions and sectors over time.

Finally, subsistence farming is not accounted for in datasets that the IELab uses. Subsistence farming and village-level analysis are rarely explored as there is a lack of socioeconomic statistics, and conducting individual surveys on each village is time-consuming and expensive (Hongsakhone et al., 2021). Few studies have examined the impact of subsistence farming within an economy, however, one such study extended IO analysis to produce a village Input-Output table (VIOT) (Hongsakhone et al., 2021). Household survey data from a rural village in Laos between 2015 and 2016 were collected to isolate the interdependency between individual transactions and their households, allowing economic transactions between villagers to be isolated. Their findings highlight that middle and lower-income households are dependent on supplies from wealthier counterparts. Another study combined household survey information from a rural Mexican village in 1982, a small five-sector IO table, CGE modelling and social accounting matrices to focus on village retail activities, construction, resource extraction and farming (Taylor and Adelman, 1996). Therefore, an extension of this dissertation for Chapters 3 and 4 could involve conducting regular village-level surveys during normal climate conditions as well as post-disasters to extend IO analysis or combine IO tables with household expenditure surveys as the above examples have done. The results would produce a village-level analysis that would be beneficial to generate village-specific disaster management strategies.

5.3 Summary

This dissertation employs methods to reorganise data for analysis and quantify the impacts of disasters, including changes to macronutrient availability and economic spillovers. With the rising rate of global disasters, it is imperative to explore the direct and indirect impacts of disasters, allowing vulnerable regions and sectors to be isolated. The dissertation results show governments the potential impacts of similar disasters and identify vulnerable regions and sectors that require disaster management strategies to mitigate their effects.

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