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Climate change impacts and associated economic costs in Ireland

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Abstract

This paper presents updated and newly derived estimates using various impact models, including biophysical and econometric models, to evaluate the direct economic costs of climate change in Ireland. The estimates are completed for five climate impacts: sea level rise, heat effects on labour productivity, human health, agricultural production, and river flooding. The key findings include (1) Under a moderate warming scenario of SSP2-RCP4.5, with a global mean sea level rise of 0.56 meters, the projected annual cost for the year 2050 would be around €2 billion (2) Rising temperatures and humidity within workplaces can decrease labour productivity (3) The projected changes in climatic conditions are expected to benefit major crops such as barley and wheat moderately, primarily due to the beneficial effects of CO_2 fertilisation (4) The projected annual economic damage resulting from river flooding is expected to increase in the future in the absence of additional adaptation measures, and (5) Higher temperatures can contribute to an increase in emergency hospital admissions. It is essential to note that the analyses exclude numerous other impact categories, such as ecosystem services and biodiversity due to the lack of appropriate data. Therefore, these results should be interpreted as a first step to monetise impacts for Ireland, where additional research is needed.

1 Introduction

In 2023, the Earth experienced its hottest year ever recorded since the 1880s. The year was marked by several extreme weather events, including scorching heatwaves that swept across Europe and North America and devastating wildfires that ravaged regions like Canada and Greece. July 2023 was particularly noteworthy as the hottest July globally ever recorded, with a monthly average temperature of 16.95°C. This significantly surpassed the previous record set in July 2019 (Copernicus Climate Change Service, 2023). While attributing single weather events to climate change remains a complex task, it is extremely likely that human activities, particularly the burning of fossil fuels and deforestation, have played a dominant role in driving the surge in global temperatures and the disruptive patterns in weather and climate being experienced (IPCC, 2013; Desmond et al., 2017). This highlights the pressing need to step up action on mitigation and adaptation at global and national levels.

Policy tools to combat climate change can be broadly divided into *mitigation* and *adaptation*. Mitigation focuses on reducing greenhouse gas emissions and increasing carbon sinks, hence limiting the level of climate change. In contrast, adaptation focuses on addressing the negative effects of a given level of climate change and taking advantage of any opportunities that may arise from these changes (IPCC, 2022). In terms of mitigation, Ireland has taken proactive steps by implementing ambitious climate legislation to contribute to global efforts to reduce anthropogenic greenhouse gas (GHG) emissions. The Climate Action and Low Carbon Development (Amendment) Act 2021 lays out a pathway to transition the country to a low-carbon society and economy by 2050. In line with this commitment, the government introduced carbon budgets and sector-specific emissions limits in 2022, with the primary goal of achieving a 51% reduction in GHG emissions by 2030 in comparison to 2018 levels. Also, the National Adaptation Framework (NAF) sets out a roadmap to build a climate-resilient economy and society by prioritising and mainstreaming climate adaptation actions into all national plans and policies. Whilst these policies are consistent with international agreements, such as the Paris Agreement, realising their ambitious objectives requires significant economic and societal investments. Therefore, it is important to assess and understand how climate-induced physical damages translate into economic costs to inform the optimal design of policies.

The economic impacts of climate change exhibit a dual nature with respect to their timing. They encompass immediate, short-term damages caused by extreme weather events and long-term effects on the economy's overall productive capacity resulting from gradual shifts in climatic conditions (Dell et al., 2012; Kalkuhl & Wenz, 2020). The gradual changes in temperature and precipitation patterns are important factors that influence the productivity of sectors predominantly reliant on outdoor conditions, such as agriculture and construction (Kjellstrom et al., 2009). Additionally, extreme weather events can lead to the loss of capital assets due to river floods and rising sea levels, necessitating the need for insurance coverage (Botzen & Van Den Bergh, 2008; Botzen et al., 2009). Furthermore, both types of damage, whether immediate or gradual, can have adverse effects on human health and ecosystems. For instance, they can result in workers facing increased exposure to heat-related stress, and cause water quality issues stemming from heavy rainfall and flooding events. When all these effects are combined, they result in reduced wealth and well-being when compared to a scenario where climate change impacts are absent.

To estimate the damages caused by climate change, economists use what are known as "damage functions". These mathematical relationships link specific climate-induced changes (like rising temperatures or sea-level increases) to real-world consequences, such as reduced crop yields, increased flooding, or health problems (Roson & Sartori, 2016; Auffhammer, 2018). In essence, economists calculate the damages from climate change by comparing the economic costs and benefits in a reference period without climate change, to a counterfactual future impacted by climate change.

The available evidence indicates that climate change is likely to have an impact on economic growth (Dell et al., 2014; Burke et al., 2015; Carleton & Hsiang, 2016), human well-being (Hsiang et al., 2013; Deschenes, 2014) and will also have substantial effects on technology, both in terms of efforts to reduce emissions and adapt to changing conditions. In Ireland, prior studies have examined the impact of climate change on various aspects, including agriculture (Holden et al., 2003; Flood, 2013), coastal flooding and erosion (Devoy, 2008; Flood & Sweeney, 2012; Flood et al., 2020; Paranunzio et al., 2022), marine ecosystems (Cheung et al., 2012), and wind energy (Doddy Clarke et al., 2022). However, there are gaps in assessments specific to Ireland, particularly in examining multiple impacts simultaneously. In addition, some of the existing estimates have become outdated due to advances in knowledge, data, and research methods. Furthermore, certain studies provide estimates for broader European regions (see, for example, Gosling et al., 2018; Ščasný et al., 2019; Szewczyk et al., 2021), which do not accurately capture Ireland's unique characteristics. Therefore, this paper aims to update and provide Irish-specific estimates for various impact categories, including the impact of heat stress on labour productivity and human health.

A range of impact models were employed in the analysis. A process-based approach was used to assess agricultural impacts, combining agronomic and economic mechanisms to determine the direct effects of climate change on crop productivity and farmers' responses regarding land use and crop choices. The latest coastal assessment model, DSCIM-Coastal (Data-driven Spatial Climate Impact Model – Coastal Impacts) was employed for coastal impacts. DSCIM-Coastal enhances previous global coastal assessment models with current knowledge and up-to-date local data on socioeconomic and physical conditions along coastlines worldwide. In the case of river flooding, the GLOFRIS model, a grid-based global framework that covers all major river basins globally, was used. Finally, econometric analyses were conducted to evaluate the impact of occupational heat stress on labour productivity and variations in temperature on in-patient hospital admissions. It is important to note that numerous other impact categories, due to the lack of suitable data and/or methods, are not included in this analysis, such as ecosystem services, mental health impacts, biodiversity, and tourism. Hence, these results should be interpreted as the lower bound of impacts. The analysis is structured into five distinct categories, each addressing a specific aspect of climate change impacts in Ireland.

2 Impacts of Coastal Flooding

2.1. Introduction

The consequences of climate change, such as rising sea levels, heightened occurrences of high tides, and increased storm-surge flooding, have significant impacts on social, economic, and ecological systems (Hinkel et al., 2013). As ocean temperatures rise, water expands, and the melting of ice sheets, polar ice caps, and glaciers adds further volume to ocean basins (Fox-Kemper et al., 2021). The global mean sea level has risen about 210–240 mm since 1880. In 2022, it was 101.2 mm above 1993 levels, making it the highest recorded average in the satellite record (i.e., 1993-present) (Lindsey, 2022).

Furthermore, it is projected that by the end of the century, the global mean sea level is likely to rise at least one foot (0.3 meters) above 2000 levels, even if greenhouse gas emissions follow a relatively low pathway in the coming decades (Lindsey, 2022). This represents a 29% increase compared to the contribution between 2001 and 2011 and an approximately 700% increase compared to the period between 1992 and 2001 (Meredith et al., 2019). A recent National Oceanic and Atmospheric Administration (NOAA) report confirms that the rate of sea level rise is accelerating and projects a 305 mm increase by 2050. The report also notes that, on average, sea levels have risen approximately 203 mm since 1880, with approximately 60 mm occurring in the last 25 years (Devoy, 2015; Sweet et al., 2022).

Ireland is particularly vulnerable to sea level rise, with major cities like Dublin, Cork, and Galway facing potential damage. Coastal flooding, depletion of wetlands, erosion, and sediment accumulation are all consequences of sea level rise (SLR). For example, a 1-meter SLR in Ireland could put approximately 30% of coastal wetlands at risk of disappearing (Devoy, 2008). Flood & Sweeney (2012) estimated that around 350 km^2 of coastal land is at risk in a 1-meter SLR scenario, with an estimated economic cost related to property insurance claims reaching approximately €1.1 billion. They also projected that if sea levels were to rise by 3 meters, approximately 600 km^2 of coastal land would be vulnerable, and the potential economic cost would increase to €2.1 billion. The SLR scenarios in this study were generated using the Irish digital terrain model (DTM) and were combined with a geocoded list of Irish property addresses and historical data on flood insurance claims to estimate the potential economic impacts. However, it is worth noting that these estimates were based on a relatively straightforward method and did not account for diverse growth trajectories of factors such as human population and capital assets or potential adaptation strategies.

To address these limitations, global coastal models are developed to incorporate assumptions or forecasts regarding the trajectories of physical risks (including SLR and extreme sea levels), adaptive decision-making (such as the construction of protective barriers), and socioeconomic variables (such as human population and capital assets) over time. Furthermore, these models incorporate comprehensive geographical information about coastlines, including measurements of coastline length, elevation, land areas, and coastal ecosystems (Depsky et al., 2023). In this context, the latest coastal assessment model, known as DSCIM-Coastal (Data-driven Spatial Climate Impact Model – Coastal Impacts), was used to provide updated assessments of potential losses resulting from SLR under various climate change scenarios in Ireland.

2.2. Methods

Over the last three decades, significant efforts have been made to develop guidelines and methodologies to assess coastal vulnerability on a global scale (Hoozemans et al., 1993; Hinkel & Klein, 2009; Depsky et al., 2023). Early global vulnerability assessments had several drawbacks including (i) neglecting biophysical, geophysical, and socioeconomic dynamics and feedback, (ii) relying on arbitrary or simplistic adaptation assumptions, and (iii) overlooking socio-economic aspects (Gornitz et al., 1994; Hinkel & Klein, 2009). To address these shortcomings and to establish a standardized approach and dataset for assessing coastal vulnerability at subnational, national, regional, and global scales, the EU-funded project DINAS-COAST (Dynamic and Interactive Assessment of National, Regional, and Global Vulnerability of Coastal Zones to Sea-Level Rise) developed DIVA (i.e., Dynamic and Interactive Vulnerability Assessment). Therefore, to provide context for the choice of the DSCIM-Coastal model, brief descriptions are provided of the models that influenced its development, specifically DIVA and the Coastal Impacts and Adaptation Model (CIAM).

2.3. DIVA

DIVA serves a dual role, acting both as a modelling approach and a tool for evaluating vulnerability (Hinkel & Klein, 2009). In its capacity as a modelling approach, DIVA provides a systematic means to integrate knowledge from various disciplines, including the natural, social, and engineering sciences. As a vulnerability assessment tool, it operates as dynamic, interactive, and adaptable software. This tool enables users to generate quantitative information related to a wide range of coastal vulnerability indicators. Users have the flexibility to select from a variety of climatic and socioeconomic scenarios and adaptation strategies. Moreover, DIVA functions on a global scale, covering all coastal nations at the national, regional, and global levels.

The DIVA model relies on the DIVA coastal database, which was established in conjunction with the DINAS-COAST project. This database employs a linear data structure to provide consistent base data for the model. It subdivides the coastlines of the world (excluding Antarctica) into over 12,000 linear segments of varying lengths. These segments are associated with physical, ecological, and socioeconomic parameters, allowing for a comprehensive analysis of their impacts.

In one of its early applications, Hinkel et al. (2014) applied the DIVA model and database to compute the global costs associated with coastal flooding damage and adaptation to sea level rise in the 21st century. The analyses revealed that the choice of protection or adaptation strategy had a significantly greater influence on flood-related damages by the end of the century than variations in climate and socioeconomic scenarios. However, due to data constraints, their study only considered a single adaptation measure, specifically, the construction of dikes.

2.4. CIAM

Building upon the work of Hinkel et al. (2014), Diaz (2016) introduced the Coastal Impact and Adaptation Model (CIAM), a global modelling tool aimed at estimating costs and adaptation strategies for each segment defined in the DIVA database. A significant innovation in CIAM was its capacity to enable each segment to choose between the construction of protective dikes, as previously done by Hinkel et al. (2014), and the adoption of managed or reactive retreat strategies.

The architecture of CIAM was designed to capture fundamental aspects of local adaptive decision-making likely to be used by coastal communities worldwide. Its goal was to establish an optimization framework that could be applied locally, whilst maintaining global applicability. To manage the complexity of solving dynamic programmes for numerous independent coastline segments, Diaz (2016) simplified adaptation choices into discrete decisions customized to local conditions. CIAM addressed six categories of costs related to relative sea-level rise (RSLR) and extreme sea levels (ESLs): (a) expenses associated with immobile capital or land inundation, (b) capital damages related to ESLs, (c) costs linked to mortality, (d) outlays for protection (e.g., infrastructure), (e) costs of relocation, and (f) wetland loss. Protective measures in CIAM included the construction of dikes at various ESL heights, whilst retreat strategies involved vacating land areas affected by local sea levels or within floodplains of varying ESL frequencies. CIAM operates in discrete time intervals, referred to as "adaptation planning periods," during which segments adjust their protection or retreat strategies based on the maximum projected RSLR. Additionally, there is an option for a "no planned adaptation" choice, which permits a reactive rather than proactive retreat strategy. However, CIAM has not seen widespread adoption, primarily due to its development within the closed-source General Algebraic Modelling System (GAMS) platform.

2.5. DSCIM-Coastal

Depsky et al. (2023) recently expanded upon Diaz's (2016) approach by modifying and enhancing the decision framework of CIAM, using an entirely new set of global data inputs in place of the previous DIVA dataset, which is no longer publicly accessible. Additionally, they employed an open-source programming language, specifically Python, for the implementation of their model. The modelling platform they created, known as DSCIM-Coastal (Data-driven Spatial Climate Impact Model – Coastal Impacts), is a component of the larger Data-driven Spatial Climate Impact Model (DSCIM) architecture. DSCIM-Coastal consists of two primary parts: SLIIDERS (Sea Level Impacts Input Dataset by Elevation, Region, and Scenario) and pyCIAM (Python-based CIAM). SLIIDERS manages the collection, harmonization, and aggregation of updated physical and socioeconomic input datasets for each coastal segment, while pyCIAM is the modelling platform itself, utilizing the data gathered and processed by SLIIDERS.

The SLIIDERS dataset shares similarities with DIVA in that it covers a diverse range of variables relevant to modelling coastal impacts across various coastal segments. However, a key distinction is that unlike DIVA, which lacks public availability, SLIIDERS and its components are accessible through open-access licenses with the advantage that other researchers can replicate coastal damage analyses. Moreover, SLIIDERS incorporates updated topographic, geographic, and socioeconomic input datasets such as improved coastal digital elevation models (DEMs) and more refined socioeconomic growth projections.

pyCIAM is an open-source and computationally efficient modelling platform designed for making adaptation decisions at the segment level. It builds upon the original CIAM framework by Diaz (2016) and includes several improvements: (i) updated data, (ii) improved model representation, (iii) open-source accessibility, and (iv) enhanced computational efficiency. The model is designed to work with the SLIIDERS dataset and sea-level rise (SLR) projections. In this context, the DSCIM-Coastal model was used to generate revised estimates of potential damages resulting from SLR within diverse climate change scenarios in Ireland.

2.6. Results and discussion

To assess the potential impacts of climate change-induced sea-level rise in Ireland, various scenarios and timeframes were analysed. We use the Kopp et al. (2014) sea level rise scenarios as input into our analysis. These scenarios account for different combinations of future emissions and underlying physical processes that influence sea levels. Table 2.1 shows the estimated global mean sea levels (g.m.s.l.) by warming scenario by 2050 and 2100. Table 2.1 is based on future climate scenarios, and uncertainties persist in these climate projections, driven by variations in greenhouse gas emissions, climate sensitivity, and regional climate patterns. Therefore, the table includes the 5th, 50th and 95th percentile estimates.

Table 2.1. Values for median g.m.s.l. rise between 2005 and 2050/2100, Kopp et al. (2014)

	Scenario	**g.m.s.l. in 2050 (m)**	**g.m.s.l. in 2100 (m)**
5th percentile	**RCP2.6**	0.18	0.30
	RCP4.5	0.18	0.35
	RCP8.5	0.21	0.51
50th percentile	**RCP2.6**	0.25	0.50
	RCP4.5	0.26	0.60
	RCP8.5	0.29	0.77
95th percentile	**RCP2.6**	0.33	0.82
	RCP4.5	0.35	0.94
	RCP8.5	0.38	1.19

Notes: The g.m.s.l. values are expressed as changes compared to g.m.s.l. in 2005

Before discussing the findings, it is worth mentioning that they are based on all the coastlines of Ireland, corresponding to 22 administrative regions in the DSCIM-Coastal model. In addition, the four categories of costs are discussed: inundation, wetland, capital stock, and population mortality. Inundation cost refers to the assessed value of land and immobile capital lost due to inundation, whilst wetland cost refers to the valuation of lost wetlands resulting from either SLR or protective measures. Capital stock cost refers to the valuation of capital loss incurred during extreme sea level events, and population mortality refers to the estimated annual costs of mortality arising from such events, with death equivalents valued using a Value of Statistical Life (VSL) framework[1]. Table 2.2 provides an overview of these annual costs under the no additional adaptation scenario for the four types of costs in the years 2050 and 2100, considering the five AR6 SLR scenarios.

Table 2.2. Annual costs of climate-driven SLR in Ireland

	2050			2100		
SLR scenario	**RCP2.6**	**RCP4.5**	**RCP8.5**	**RCP2.6**	**RCP4.5**	**RCP8.5**
Wetlands	0.01	0.02	0.04	0.01	0.03	0.06
Inundation	0.43	0.53	0.69	0.83	1.06	1.16
Relocation	0.55	0.72	0.98	0.93	1.19	1.04
Storm Capital	0.56	0.58	0.64	1.57	2.68	2.74
Storm Population	0.44	0.45	0.50	1.24	2.07	2.10
Total	2.00	2.31	2.85	4.58	7.03	7.11

Source: DSCIM-Coastal model. Notes: Costs are expressed in billions of constant 2019 PPP Euros[2], including the cost of existing coastal protection measures, and are based on the IIASA socioeconomic trajectory.

Table 2.2 indicates that costs increase and continue over time as sea levels rise. Costs related to capital stock and population mortality are higher than those associated with inundation and wetlands, which suggests that the Irish shorelines have high population density and capital investment. In the year 2050, the projected annual cost considering all five types of costs, under a moderate warming scenario of RCP4.5, is approximately €2.3 billion without additional adaptation measures. By the end of this century, under the same scenario, it is expected to reach €7 billion. These findings are consistent with previous studies, such as Devoy (2008) and Flood & Sweeney (2012) and confirm that Ireland is vulnerable to the impacts of climate-induced sea level rise.

2.7. Conclusion

This section investigated the potential damages from SLR within diverse climate change scenarios in Ireland using a state-of-the-art coastal assessment model, DSCIM-Coastal (Data-driven Spatial Climate Impact Model – Coastal Impacts). This model enhances previous global coastal assessment models with current knowledge and up-to-date local data on socioeconomic and physical conditions along coastlines worldwide. The estimations indicate that, under a moderate warming scenario of SSP2-RCP4.5, with a global mean sea level rise of 0.56 meters, the projected annual cost for the year 2050 would be around €2 billion. By the close of this century, under the same scenario, this cost is expected to rise to approximately €7 billion.

It is essential to note that DSCIM-Coastal, like any modelling tool, relies on certain assumptions and may contain uncertainties that can affect the accuracy of its predictions. For example, it incorporates assumptions about future population growth, urbanisation, and land use change to estimate exposure and vulnerability to coastal flooding. Variations in socio-economic

[1] The annual cost of population mortality was calculated by multiplying the exposed area by the population density, scaled by a flood mortality factor of 0.01 times the national value of statistical life (Diaz, 2016).
[2] We have converted the currency from USD2019 to Euro2019 using the exchange rate of $1 for €1.

development pathways and policy decisions can affect the accuracy of these assumptions and introduce uncertainties into the model outputs. In addition, the model assumes a certain level of adaptation, such as the presence of coastal defences or land use planning measures, to reduce vulnerability to coastal flooding. Uncertainties in the effectiveness, timing, and implementation of these adaptation measures can affect the model's projections of future flood risk. Lastly, DSCIM-Coastal has inherent limitations in its ability to represent complex coastal processes and interactions, such as localised storm surge effects, wave overtopping, or interactions between coastal ecosystems and geomorphology. These limitations can affect the accuracy and reliability of the model's predictions, particularly in areas with unique coastal characteristics or complex topography.

3 Impacts on Labour Productivity

3.1. Introduction

There are two major pathways by which climate change impacts labour productivity. The first of these pathways involves the number of hours worked by individuals, often referred to as labour supply (Graff Zivin & Neidell, 2014; Dasgupta et al., 2021; Somanathan et al., 2021). Sectors with high exposure to extreme temperatures, such as agriculture, are particularly vulnerable to this effect. When temperatures rise beyond specific thresholds, workers may reduce their working hours to safeguard their long-term health, steering clear of the risks associated with heat exhaustion or heat stroke. This not only affects individual income and economic productivity but can also lead to labour shortages, disrupting various industries reliant on manual labour.

In addition to affecting the number of working hours, climate change has a significant influence on the quality and efficiency of work during the hours employees are on the job (Kjellstrom et al., 2009; Sahu et al., 2013; Dasgupta et al., 2021). Heat stress is one of the most prominent factors contributing to this decline in productivity. As temperatures increase, workers exposed to extreme heat conditions tend to slow their work pace and take more frequent breaks to rehydrate and cool down. This hinders the overall output and efficiency of labour, particularly in sectors like construction, where physical exertion is substantial.

Crucially, the dissipation of heat generated during work plays a pivotal role in maintaining workers' productivity and well-being (Kjellstrom et al., 2009; Li et al., 2016). The human body must effectively release heat to regulate body temperature and prevent heat stress. This process is contingent on various factors, primarily the ambient temperature, but also influenced by humidity and wind speed. With climate change leading to hotter and more unpredictable weather patterns, the challenges in managing heat stress are amplified, further heightening the reduction in labour productivity across numerous industries.

Empirical evidence drawn from occupational health and environmental economics underscores the considerable impact of heightened temperatures on the average productivity of the labour force. The body of occupational health research has predominantly focused on the adverse consequences of temperature elevation on labour efficiency, primarily within distinct occupational settings such as factory facilities and outdoor labour scenarios. Most of these research studies primarily rely on the Wet Bulb Globe Temperature (WBGT), a heat exposure metric that combines temperature, humidity, wind speed, and solar exposure. Higher WBGT values signify an increased thermal stress level (Lemke & Kjellstrom, 2012; Szewczyk et al., 2021). For instance, Sahu et al. (2013) shed light on the adverse effects of elevated heat exposure during rice harvesting in India, focusing on the relationship with WBGT. Their findings underscore that even a one-degree increase in heat exposure leads to an approximate 5% reduction in work productivity. Similarly, Li et al. (2016) uncovered a noticeable decline in the actual working hours of rebar workers in China, with an average decline of 0.57% for every 1ºC rise in WBGT. Zhang et al. (2023) also focused on the Chinese construction sector, but their findings unveiled a non-linear relationship between temperature and labour productivity, with peak productivity occurring at an average temperature of 25°C. Furthermore, Somanathan et al. (2021) identified that individual workers and worker teams experience diminished output during hot days and weeks. Their study combined several microdata sets and a nationally representative panel of manufacturing facilities in India to quantify the impact of elevated temperatures on labour. However, generalizing the findings of these studies across multiple working environments requires caution, given their roots in specific and distinct work environments.

Economics studies predominantly utilise panel data techniques to identify the relationship between temperature, heat stress, and labour productivity. The central objective is to furnish robust findings applicable across multiple working environments and geographical regions (Zivin & Neidell, 2010; Dell et al., 2012; Burke et al., 2015; Kalkuhl & Wenz, 2020). For instance, Zivin and Neidell (2010) leveraged exogenous temperature variations within U.S. counties over time to assess the impact of climate change on the allocation of time. Their study revealed that in highly exposed sectors, labour supply diminishes as temperatures increase, and outdoor leisure activities decline as well. Kalkuhl and Wenz (2020) also showed that temperature exerts discernible effects on productivity levels, with greater damage incurred in tropical and economically disadvantaged regions. Moreover, Hsiang (2010) identified that even short-term temperature increases are linked to significant declines in economic output across industries previously deemed less vulnerable to climate change. Additionally, Schleypen et al. (2019) observed that both gradual temperature changes and extreme heat events adversely affect industrial and construction labour productivity within the European context.

The current research on Ireland (in multiregional studies) suggests that climate-induced heat stress is unlikely to significantly impact worker productivity (Roson & Sartori, 2016; Gosling et al., 2018; Schleypen et al., 2019; Szewczyk et al., 2021). These findings are mainly based on exposure-response functions (ERFs) underpinned by occupational health standards that specify productivity loss thresholds. However, most ERFs were developed in environments and geographic regions with climatic conditions that differ markedly from those in Ireland (see, for example, Sahu et al., 2013; Li et al., 2016). Hence, there is a growing argument that, given Ireland's temperate climate and the population's limited acclimatization to higher temperatures, labour productivity may decline as temperatures rise, even below the established thresholds.

In this study, we investigated the impact of Wet Bulb Globe Temperature (WBGT) on labour productivity in Ireland, incorporating seasonal variations and interaction effects. Our model is consistent with previous studies such as Hsiang (2010), Zivin and Neidell (2010), Dell et al. (2012), Burke et al. (2015), and Coronese et al. (2019). However, unlike these studies, we employed a time series regression approach where the dependent variable is labour productivity per capita growth rate. This approach helps address potential non-stationarity issues and allows for examining short-term fluctuations in labour productivity. As such, excluding certain relevant variables, like technological advancements and investments in physical capital due to data limitations, is unlikely to significantly affect the observed relationships between variables in our model. The results suggest that in Ireland, rising temperatures and humidity levels in work environments can lead to reduced productivity even when below the recognised international heat stress threshold. Specifically, the findings indicate that a one-degree increase in outdoor WBGT corresponds to a 0.87% decline in labour productivity. When WBGT is held constant, there are slight seasonal variations in productivity, with the highest levels observed in autumn and the lowest in winter. However, when examining the interaction between WBGT and seasons, it was found that increased temperatures during the winter months could significantly enhance worker productivity in Ireland. In contrast, higher temperatures and heat stress during the summer could harm productivity.

3.2. Data

3.2.1. Economic data

The economic data used in this study was obtained from the Central Statistics Office (CSO) and covers Gross Value-added (GVA) and employment across production sectors in Ireland. The data, spanning from 1998 to 2022, is reported at a quarterly frequency. GVA is the output value at basic prices minus the cost of intermediate consumption, assessed at purchasers' prices. Employment is measured by the number of individuals engaged in the workforce. To calculate labour productivity, expressed as GVA per capita, the GVA was divided by the working population.

3.2.2. Climate data

To compile historical climate data, we used Met Éireann station-level data measured at a daily frequency, covering 1km cells. We aggregated the data, taking into account the population within each 1km cell. This allowed us to derive national-level averages for each climate variable needed to compute WBGT, considering population-weighted values. Subsequently, we transitioned the daily frequency of this population-weighted national data to a quarterly frequency to align it with the labour productivity data.

3.3. Methods

3.3.1. Computation of WBGT

WBGT is a heat stress indicator grounded in physiology, used to evaluate the combined impact of temperature, humidity, wind speed, and solar radiation on human well-being and health, especially in hot and humid conditions (Lemke & Kjellstrom, 2012; Dunne et al., 2013). It offers a more precise assessment of the potential risks of heat-related illnesses in settings where individuals are exposed to high temperatures and must take precautions to prevent heat-related health issues. This index takes into consideration three primary components: the natural wet bulb temperature (T_{nwb}, which accounts for air humidity and is measured using a wetted thermometer exposed to wind and heat radiation on-site), the black globe temperature (T_g, accounting for the influence of direct sunlight and measured within a 150 mm diameter black globe), and the dry bulb temperature (T_a, indicating air temperature and measured with a standard thermometer shielded from direct heat radiation). The index can be calculated using the following formulae for outdoor and indoor work environments (Kjellstrom et al., 2009). For outdoor conditions, WBGT is determined as follows:

$$0.7T_{nwb} + 0.2T_g + 0.1T_a$$

In indoor settings, the WBGT formula is as follows:

$$0.7T_{nwb} + 0.3T_g$$

The coefficients 0.7, 0.2, 0.1, and 0.3 reflect the relative significance of each parameter. It is important to note that some of the variables included in the WBGT formula can be estimated by combining climate data with other information.

Since specialized WBGT measurements are not typically available from standard weather stations, several formulae have been developed to estimate WBGT using routinely collected meteorological data. In their review, Lemke and Kjellstrom (2012) evaluated various methods for estimating WBGT from meteorological data. They recommended using Bernard's (1999) approach for calculating indoor WBGT and the method described by Liljegren et al. (2008) for determining outdoor WBGT when assessing the impact of climate change on occupational heat stress at a population level. Following their guidance, daily WBGT values were estimated, both for indoor and outdoor conditions, using nationally aggregated and population-weighted climate data from Met Eireann.[3]

3.3.2. Baseline impact

A time-series regression model was used to calculate the baseline impact. The dependent variable, denoted as $\Delta \ln Y_t$, represents the quarterly per capita growth rate in labour productivity. This dependent variable allows us to address possible non-stationarity concerns and to examine short-term changes in labour productivity. Therefore, excluding certain relevant variables, such as technical progress and investment in physical capital due to data constraints, may not drastically alter the observed relationships between the variables in the model. This is because these omitted variables generally increase steadily over time, particularly within the timeframe of our study. The independent variables consist of the heat stress index WBGT, a seasonal indicator, and the interaction between WBGT and season. The model is formally described as follows:

[3] Appendix C includes detailed steps for estimating natural wet bulb temperature and black globe temperature from climate data.

$$\Delta\, lnY_t = \beta_0 + \beta_1 WBGT_t + \beta_2 Season_t + \beta_3 (WBGT_t * Season_t) + \varepsilon_t \qquad (1)$$

Here, β_0 serves as the intercept, β_1 represents the coefficient for the impact of the WBGT index on the per capita growth rate in labour productivity, β_2 denotes the coefficient for the influence of seasonality on the per capita growth rate in labour productivity, β_3 indicates the coefficient for the interaction term between WBGT and season, showing how the effect of WBGT varies across different seasons and ε_t represents the error term. It is essential to emphasize that the time series characteristics of the data, including stationarity and structural break, were assessed and that appropriate measures were taken accordingly. Furthermore, our model specification and identification strategy are similar to those used in studies by Hsiang (2010), Zivin and Neidell (2010), Dell et al. (2012), Burke et al. (2015), and Coronese et al. (2019). We examine the impact of WBGT on short-term changes in labour productivity using the per capita growth rate while controlling for any omitted variables that typically increase with labour productivity.

Table 3.1. Descriptive statistics of key variables (1998 – 2022)

Variable	Mean	Maximum	Minimum
Per capita growth rate in labour productivity	0.0150	0.2717	-0.0748
Outdoor WBGT (^oC)	11.3	16.5	6.3
Indoor WBGT (^oC)	7.1	10.46	2.3

3.4. Results and discussion

3.4.1. Descriptive statistics

Table 3.1 summarizes the key variables. It shows that the average output per worker increased by 1.5% per quarter from 1998 to 2022. The mean outdoor working temperature (i.e., outdoor WBGT) during the same period was estimated to be 11.3^{o}C, with the highest estimated temperature at 16.5^{o}C and the lowest at 6.3^{o}C. As expected, the estimated indoor working temperatures (i.e., indoor WBGT) are generally lower than outdoor temperatures, with an average of 7.1^{o}C. It is important to note that the WBGT values were estimated based on the combined influence of various climatic factors affecting human beings, including air temperature, solar radiation, wind speed, and relative humidity.

3.4.2. Baseline regression results

Equation (1) was applied to assess the impact of heat stress levels on the workforce in Ireland, considering both outdoor and indoor work environments. The results show that an increase in occupational heat stress, whether experienced in outdoor or indoor working environments, significantly reduces labour productivity (see Table 3.2). For example, a 1^{o}C increase in outdoor WBGT is associated with a statistically significant decrease of 0.87%[4] in labour productivity. This result highlights the tangible consequences of rising WBGT values, even when they remain below the established thresholds for productivity loss. It is posited that this finding may, in part, be attributed to the notably high relative humidity conditions prevalent

[4]Note that our impact model is structured in a log-level format, which means that a one-unit increase in the independent variable is approximately associated with a change of about 100*β% in the dependent variable.

in Ireland, with an annual average of about 83%. High relative humidity hinders the process of evaporative cooling, a fundamental mechanism by which the body releases heat. Consequently, the combination of high relative humidity and a marginal increase in temperature can intensify the perception of heat and discomfort among individuals, thereby contributing to heightened stress and fatigue among the working population. Ultimately, in conditions where the air is already saturated with moisture, the effectiveness of sweat evaporation from the skin's surface is compromised, impeding the body's natural cooling mechanisms.

Furthermore, the analysis highlights the impact of seasonal variation on labour productivity, notably revealing a significant decline during the winter season compared to autumn. Interestingly, the productivity levels in summer and spring did not show statistically significant reductions when contrasted with the autumn baseline.

The interaction between season and WBGT reveals that an increase in outdoor WBGT during winter can significantly improve labour productivity. This finding might seem surprising, but it is believed that this could be because the rising temperatures at the lower end of the temperature distribution could reduce wind chill effects, especially given Ireland's strong winds. However, this result calls for further investigation into the specific factors that cause these season-specific effects.

Table 3.2. Impact of WBGT on labour productivity with seasonal interaction effects

Variable	**Outdoor**	**Indoor**
WBGT	-0.0087* (0.0052)	-0.0059* (0.0033)
Winter	-0.0800** (0.0380)	-0.0692* (0.0391)
Summer	0.0974 (0.0711)	0.0706 (0.0518)
Spring	0.1628 (0.1310)	0.1260 (0.1051)
Winter*WBGT	0.0348* (0.0211)	0.0227 (0.0569)
Summer*WBGT	-0.0386 (0.0317)	-0.0291 (0.0250)
Spring*WBGT	-0.0664 (0.0528)	-0.0544 (0.0447)
Constant	0.0335** (0.0169)	0.0180* (0.0102)
Observations	99	99
R^2	0.1245	0.0891
Adjusted R^2	0.0910	0.0743

Notes: * indicates significance at the p<0.1 level, ** at the p<0.05 level, and *** at the p<0.01 level. Standard errors are provided within parentheses.

3.4.4. Robustness check

A bin regression analysis was conducted as a supplementary step to check the robustness of the primary findings. In this analysis, the dependent variable was the natural logarithm of labour productivity, and the independent variable consisted of WBGT bins, each representing a 2°C range. A time trend was included for possible trends and other omitted variables. The results are detailed in Table 3.4, and the corresponding boxplots can be found in Appendix A for further reference. In this bin regression, each coefficient represented a change in the log of labour productivity associated with a specific WBGT bin relative to a chosen reference category. The supplementary analysis generally indicates that labour productivity decreases with each two-degree increase in WBGT, although some coefficients are insignificant. This supplementary finding further supports the proposition that even when WBGT remains below established thresholds, rising temperatures can harm labour productivity. Furthermore, it is worth mentioning that three previously published ERFs from studies by Sahu et al. (2013), Dunne et al. (2013), and Li et al. (2016) were also used, and the results align with the existing literature in Ireland (see, for example, Roson & Sartori, 2016; Grosling, 2018).

Table 3.3. Regression with WBGT bins

Outdoor		**Indoor**	
Reference bin = [6°C, 8°C)		Reference bin = [2°C, 4°C)	
[8°C, 10°C)	-0.0077* (0.0045)	[4°C, 6°C)	-0.0049 (0.0467)
[10°C, 12°C)	-0.0143** (0.0069)	[6°C, 8°C)	-0.0023* (0.0014)
[12°C, 14°C)	-0.0247 (0.0348)	[8°C, 10°C)	-0.0035** (0.0017)
[14°C, 16°C)	0.0048 (0.0324)		
Time trend	0.0128*** (0.0004)	Time trend	0.0125*** (0.00039)
Constant	2.4356*** (0.0387)	Constant	2.4857*** (0.0482)

Notes: [i, j) = 1 if WBGT is greater than or equal to *i* but less than *j* and zero otherwise. For instance, [6°C, 8°C) = 1 if the outdoor WBGT value falls within this bin and zero otherwise. * Indicates significance at the p<0.1 level, ** at the p<0.05 level, and *** at the p<0.01 level. Standard errors are provided within parentheses.

3.5. Conclusion

This section highlights the implications of climate-induced heat stress on Irish labour productivity. The findings underscore the pressing need for proactive measures to mitigate the adverse effects of rising temperatures and humidity levels on the workforce. Our analysis reveals that even in Ireland's moderate climate, increasing levels of occupational heat stress, as measured by the Wet Bulb Globe Temperature (WBGT), can detrimentally impact productivity.

Our observation that the negative impact on productivity persists even when heat stress thresholds are not exceeded is particularly important. This highlights the complex interplay between temperature, humidity, and productivity. We attribute this phenomenon to the elevated relative humidity conditions in Ireland, which impede the body's natural cooling mechanisms and exacerbate stress and fatigue among workers.

To address these pressing concerns, policymakers, employers, and stakeholders must prioritise implementing comprehensive strategies to mitigate heat stress in the workplace. This may involve improving ventilation systems, implementing heat stress management protocols, providing adequate rest breaks, and promoting awareness and education regarding heat-related risks.

4 Impacts on Agriculture

4.1. Introduction

Agriculture is critical in Ireland's economy, social fabric, and cultural heritage. From an economic perspective, the sector significantly contributes to employment, exports, and Gross National Income (GNI). In 2022 alone, it accounted for 6.5% of employment and 6.7% of GNI (Department of Agriculture, Food, and the Marine, 2020). On the societal level, it is intricately woven into the identity of many rural communities, extending its significance beyond mere food production (Emmet-Booth et al., 2019). Therefore, understanding how climate change impacts the entire sector, and its subsectors is immensely significant from economic and policy perspectives.

Climate change has a significant impact on agricultural production and productivity, primarily through changes in temperature and rainfall patterns. These changes can lead to shifts in growing seasons, increased occurrence of extreme weather events, and variations in water availability. As a result, crop yields are directly affected along with livestock productivity (IPCC, 2022). To illustrate, rising temperatures can lead to heat stress in crops and livestock, affecting their growth and reproduction. Moreover, changes in precipitation patterns like intensified or unpredictable rainfall alongside prolonged droughts, further compound challenges for farmers. In addition, warmer conditions contribute to an increased prevalence of pests and diseases which pose a threat to the health of crops and livestock. Collectively, these climate-induced changes pose substantial risks to global and local food production systems.

Extensive research has been conducted to examine the impacts of climate change on agricultural production, particularly focusing on crop production. These studies use various approaches including crop simulation and statistical models (see, for example, Mendelsohn et al., 1994; Chen et al., 2004; Deschênes & Greenstone, 2007; Rosenzweig et al., 2014; Challinor et al., 2014; IPCC, 2022). Crop simulation models are used to analyse the impact of environmental conditions (e.g., sunlight, water availability, air and soil temperature, carbon dioxide concentrations, air humidity, etc.) on crop growth and yield. These models can simulate crop growth at both the field scale and regional scale, providing insights into how climate change influences crops (Antle & Stöckle, 2017). In addition, they allow researchers to assess the role of farm-level adaptation (such as crop diversification, irrigation, and changes in land use practices) in mitigating the negative impacts of climate change. To represent the economic implications of these changes in yield on agricultural markets, researchers commonly use Partial Equilibrium (PE) and Computable General Equilibrium (CGE) models, along with various econometric approaches or simulation models (Nelson et al., 2014).

An earlier use of crop simulation models in Ireland revealed that certain crops, including potatoes, would face challenges in drier parts of eastern Ireland. Moreover, there would be a notable decrease in grass growth during dry summers in the southeast (Holden et al., 2003). However, this research did not provide specific recommendations for Irish farmers on adapting their farming practices to better address changing agroclimatic conditions. Subsequent research showed that implementing adaptive practices can help mitigate the impacts of climate change (Sweeney et al., 2008). For instance, reducing fertilizer inputs in specific locations can enhance soil drainage and mitigate production losses. Furthermore, climate change is projected to reduce Irish agricultural output by between €1 billion and €2 billion per annum by the middle of the century through its impacts on crop yield losses, flooding, and the emergence and spread of pests and diseases (Flood, 2013).

It is worth mentioning the potential fertilizing effect of higher CO_2 concentrations in the atmosphere due to climate change. Whilst it is difficult to accurately model and project these benefits, it is expected that crops such as wheat, barley, and grass in Ireland would benefit from this effect, which in turn would indirectly benefit the livestock subsector (Sweeney et al., 2008; IPCC, 2022). In addition, Perez Dominguez et al. (2016) have shown that without considering the beneficial effects of CO_2 fertilization, the impacts of climate change would lead to an expansion of agricultural land in the EU. This expansion is necessary to make up for productivity losses on existing land, and it benefits crops in Eastern Europe whilst causing more stress on agriculture in Southern Europe. However, when the positive effects of CO_2 fertilization are taken into consideration, the harmful impacts of climate shocks are balanced out in most EU regions. This leads to a significant decrease (-5%) in the overall agricultural land because increased yields offset the need for expanding agricultural land.

To update the literature on the impact of climate change on agriculture in Ireland and its economic implications, the approach and data from the CO-designing Assessment of Climate CHange costs (COACCH) project will be used. The approach and findings of the COACCH project will be presented and compared with previous assessments in the literature.

4.2. Methods

To assess the impacts of climate change on the agricultural sector, a two-step process based on the COACCH project (Boere et al., 2019) was followed. First, a crop simulation model was used to determine the direct impact of climate change on crop yields. Second, an agroeconomic model was employed to consider how farmers adjust their input management in response to climate-induced changes in crop yields.

The EPIC (i.e., Environmental Policy Integrated Climate) and GEPIC (i.e., Geographic Information System (GIS)-based EPIC) crop simulation models were used to examine the direct impacts of climate change on crop yields. These dynamic system models consider various factors such as genetic characteristics, soil properties, water availability, temperature, humidity, and tillage practices to predict different stages of crop growth and outcomes like emergence, flowering, and grain yield. In addition to simulating plant growth under changing climatic conditions at a global scale including Ireland, these models also incorporate carbon and water cycles. They also account for the positive impact of elevated CO_2 levels on crops' productivity, thus mitigating yield losses caused by climate change stressors.

The EPIC and GEPIC models used climate projection data from the EURO-CORDEX project, which provides regional climate projections for Europe based on downscaled global climate projections. This data includes minimum and maximum temperature, precipitation, relative humidity, and wind speed. Multiple global climate models were used to account for uncertainties in projecting the impacts of climate change. The COACCH project specifically considered four RCPs, namely the 2.6, 4.5, 6.0, and 8.5 trajectories that represent different greenhouse gas scenarios for the future.

In the second step, the impacts of climate change on crop yields are incorporated into an agro-economic model to determine changes in farmers' inputs, allocation of land, productivity changes, and price changes. This agro-economic model takes a Ricardian perspective by examining how climate change alters the relative productivity of crops in different regions. As a result, farmers will adapt autonomously by shifting towards more favourable crops while also considering market conditions such as commodity prices. The COACCH project used the GLOBIOM model to assess changes in production areas (Havlík et al., 2014). The GLOBIOM model is a partial equilibrium model that focuses on the agricultural and forestry sectors, as well as bioenergy. It divides the agricultural sector into various small regions where agricultural commodities are produced and traded. Consequently, data regarding crop yields from EPIC is inputted into the model to determine alterations in land allocation for different crops, adjustments in inputs used, and changes in overall areas dedicated to agriculture versus those dedicated to forestry and natural land.

It should be noted that this crop model, like others, has some important limitations. Firstly, they examine the impacts of climate change on crop yield but do not include the impacts of extreme weather and weather variability. Extreme hot days, extreme cold days, extreme winds and storms are expected to increase as global temperatures increase. These models focus on average changes in climate stimuli, which would underestimate the actual impacts of climate change. Secondly, these models focus on specific "subsistence" crops, not considering other agricultural outputs such as fruit and vegetable tillage. These subsistence crops represent only approximately 57% of Irish Crop Gross Value Added (GVA) and less than 5% of total agricultural GVA. Thirdly, when Flood (2013) categorises potential threats and opportunities, he classified crop yield changes as either a threat or an opportunity depending on the climate change effects on a particular crop. The classification shown in Flood (2013) is shown in Table 4.1 below:

Table 4.1. Classification of threats and opportunities in agriculture by Flood (2013)

Rank	Climate change Impact	Threat or opportunity
1	**Pests and diseases** – air borne pathogens influenced by changes in air temp and humidity – soil borne pathogens by soil temp, soil moisture and winter kill effects	T
2	**Crop yield** – could increase or decrease dependent upon the crop/variety response to the projected change (e.g. yield response to heat/drought/water logging stress)	O/T
3	**Stress factors** – changing temperatures could increase the risks associated with frost damage, drought and field water logging (wide range of effects dependent upon crop but tendency will be for deleterious consequences)	T
4	**Drought effects** (soil moisture availability) – increased risk due to higher ET rates combined with reduced summer rainfall	T
5	**Weeds** – changes in weed spectrums driven by winter survival, soil conditions, crop competition changes (range of consequences dependent upon species and environment but tendency will be for greater weed activity)	T
6	**Flooding** – increased risk due to more frequent extreme rainfall events, both in winter and summer	T
7	**Salinity** – increased risk of inundation of low lying land on coastal regions due to sea level rise	T
8	**Water logging effects** (seasonal, anaerobic conditions) due to more frequent high intensity rainfall events	T
9	**Changes in crop development** (sowing dates, day length effects, growth rates, earlier springs, flowering dates, yield building and harvest dates). Wide range of consequences dependent upon crop/variety.	O/T
10	**Crop quality** – could increase or decrease dependent upon crop/variety response to the projected change	O/T

Notes: This table is from Flood (2013:p.5) and was originally adapted from Defra (2012).

Furthermore, this approach does not directly address the impacts of climate change on livestock and ecosystem services. The hybrid approach developed in the COACCH project focuses solely on evaluating the effects of climate change on crops, which indirectly contribute to livestock meat and dairy production. However, in reality, research shows that changes in climate directly impact livestock (Baumgard et al., 2012; Das et al., 2016; Godde et al., 2021; Mauger et al., 2015; Thornton et al., 2021).

Flood (2013) uses both a crop simulation model and a dairy response function to provide estimates of climate change impacts in the agricultural sector in Ireland. By including the dairy response function, he aims to capture the direct impacts of a changing temperature and humidity on dairy cattle. This is important given that 16% of total agricultural output in 2012 was dairy output (Department of Agriculture, Food and the Marine, 2013; Teagasc, 2013) . With this method, Flood (2013) found that climate change damages from agriculture will be an annual cost of €1-2 billion by 2050. When estimating costs for the livestock sector and the arable sector, Flood (2013) found the total costs per year to be €530 million in the arable sector and €745 million in the livestock sector. As such, analysis that does not focus on the direct impacts of climate change on livestock may produce results that are underestimated.

Finally, the results are distinguished for the two 2013 Irish NUTS-2 regions: the "Border, Midland and Western" and the "Southern and Eastern" regions. Figure 4.1 depicts these two regions which differ both in terms of agriculture and climate. The "Southern and Eastern" region is the main agricultural area with 2 million hectares of cropland and grassland compared to 0.9 million hectares in the "Border, Midland and Western" region. The former region accounts for 66% of Ireland's agricultural output value. Temperature changes are also expected to vary along a North/South gradient, with an anticipated increase of 1.2°C at the most northern point compared to a 0.8°C increase at the most southern points during winter months. During the summer months, it is projected that there will be an average temperature increase of 0.8°C in northern parts of Ireland, compared to a 1.3°C increase in southern areas. Heatwave scenarios indicate that the "Southern and Eastern" regions will experience hotter climates overall, while the "Border, Midland, and Western" region will see milder changes.

Figure 4.1. Ireland disaggregated into its two 2013 NUTS-2 regions.
Source: Eurostat Statistical Atlas, NUTS and territorial typologies

4.3. Results and discussion

The impacts of climate change on agricultural production in Ireland were examined across different climate change scenarios and timeframes. These impacts were measured by comparing a reference scenario without climate change to various scenarios represented by the RCPs for the short- (2030), medium- (2050), and long-term (2070) timeframes.

Based on the crop simulation models, it is projected that under most RCPs, major Irish crops such as barley, wheat, and potato will experience an increase in yields in the future. The expected yield increase ranges between 15% to 20%, depending on the specific crop and scenario considered. This boost in productivity can be attributed to the positive impact of CO_2 fertilization. It is important to note that C3 crops, predominantly grown in Ireland, tend to benefit more from increased levels of atmospheric CO_2 concentration than C4 crops[5]. In addition, it should be noted that the impacts are greater under the RCP4.5 scenario due to higher CO_2 concentration when compared with other scenarios (see Figure 4.2).

The GLOBIOM model provides insights into the reallocation of land between different crops, consumption patterns, trade dynamics, and prices in domestic and international markets. The results indicate that farmers tend to shift their land resources towards more profitable crops. Specifically, it is expected that the two Irish regions will witness an expansion in the land allocated to oats, a stabilization in the land allocated to wheat, and a reduction in the land allocated to barley. It should be noted that these reallocation patterns are influenced by changes in crop profitability based on yields as well as additional costs associated with cultivating certain crops elsewhere. Consequently, the reduction in the land allocated to barley indicates improved productivity and a relatively lower level of profitability. In addition, there is an expected expansion in the land allocated to other green fodders, such as grass and alfalfa (lucerne), which serve as feed sources for livestock.

These findings are consistent with prior studies conducted in Ireland. For instance, according to Holden et al. (2003), climate change is expected to have a limited impact on barley production and may play a more significant role in supplementing livestock feed supply. However, the effect on potato crops will significantly depend on the availability of irrigation water. In addition, the research by Hennessy and Shrestha (2010) suggests that climate change may positively influence grass growth because of higher atmospheric CO_2 concentrations.

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[5] Plants are classified as C3 or C4 based on the biochemical process of converting carbon dioxide into sugar during photosynthesis. Common C3 agricultural crops include wheat, barley, potatoes, and sugar beets. Common C4 plants important to agricultural production include maize, sugar cane, millet, and sorghum (Hertel & Rosch, 2010).

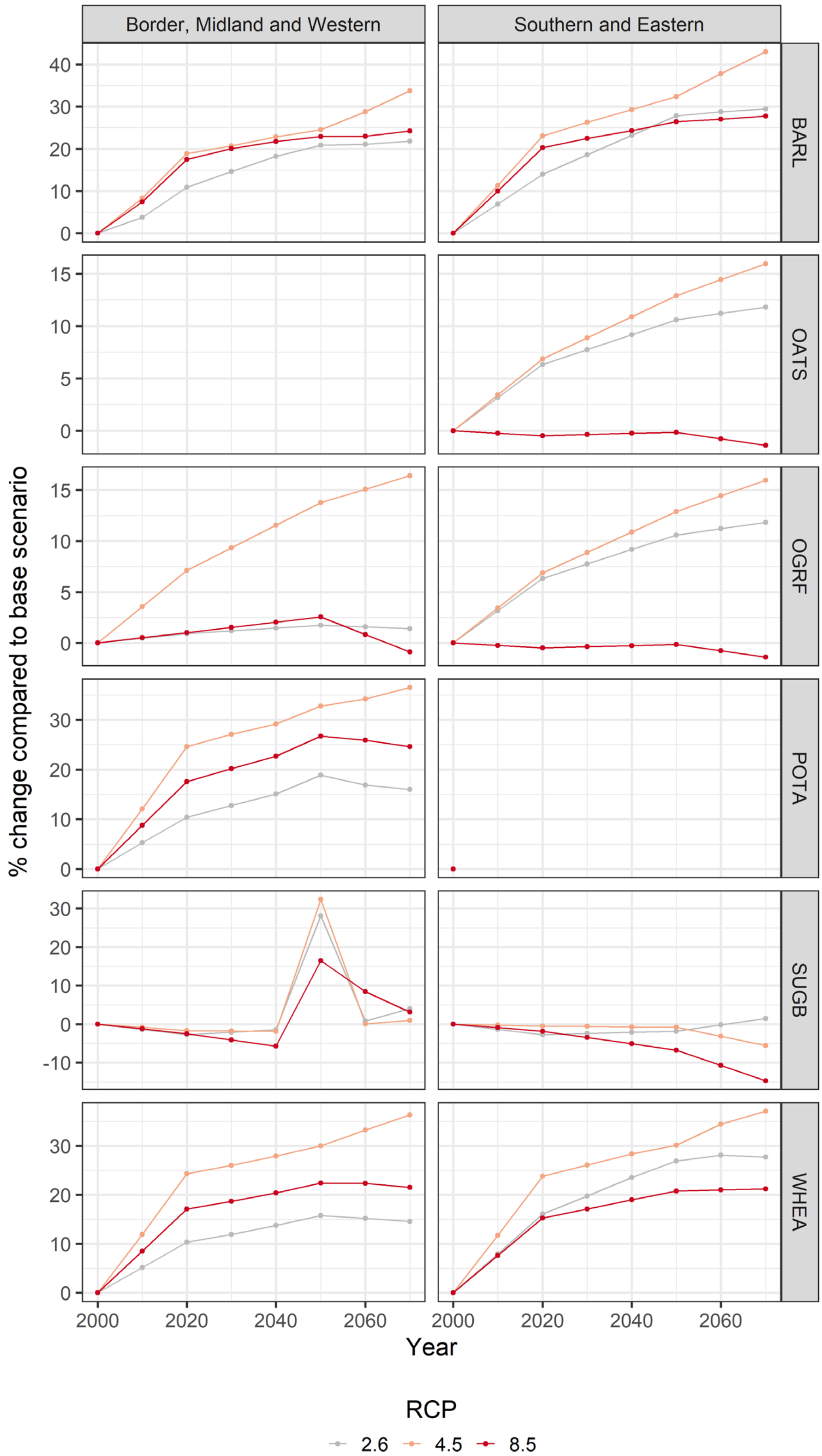

Figure 4.2. The projected impact of climate change on major Irish crops under different climate change scenarios.

Source: COACCH project, based on the EPIC-GLOBIOM models for the Irish case

Notes: From top to bottom panel: barley, oats, other green fodder, potato, sugar beetroot, and wheat. Evolutions are represented for the two Irish NUTS-2 regions: the "Border, Midland and Western'' region and the "Southern and Eastern'' region.

It is noted that Flood (2013) uses estimates that expect wheat, potato, and maize crops to experience reductions in yield whilst increases in yield for wheat and potatoes are found in this paper. This difference partially explains why a positive and small impact from climate change on the agriculture sector is found in this paper, whereas Flood (2013) finds a negative impact from climate change. Flood (2013) estimates a much larger negative impact which may be because he also considers the direct impact of temperature and humidity on dairy, whilst only the indirect impacts of climate change on livestock are considered in this paper.

4.4. Conclusion

Climate change poses both positive and negative impacts on the agricultural sector. Adverse effects include lower rainfall, increasing variability in weather patterns, and extreme heat, which directly affect production. Also, positive impacts like increased carbon dioxide levels can contribute to crop fertilization and extended growing seasons. These effects will have consequences on production, consumption, prices, trade decisions, and land use.

These impacts were examined using a process-based approach that incorporates agronomic and economic mechanisms to determine their direct consequence on crop productivity. Farmers' responses regarding land use and crop choices were also considered. The results indicate that the projected changes in climatic conditions are expected to moderately benefit major crops such as barley and wheat grown in Ireland. Furthermore, there may be indirect benefits for the livestock subsector due to improvements in grass production caused by climate change. These positive projections primarily stem from the beneficial effects of CO_2 fertilization. Overall, there is a greater prevalence of C3 crops in Ireland that stand to gain from increased levels of atmospheric CO_2 concentrations, compared to the number of C4 crops cultivated.

The findings presented in this section have many limitations. Firstly, the analysis does not consider the effects of ecosystem service losses, pests and diseases, water availability, and extreme weather events. Secondly, this method does not consider various crops, such as mushrooms and fruit. Secondly, GLOBIOM operates in a recursive-dynamic manner, which may underestimate producers' ability to plan for future decisions. In addition, being a partial equilibrium model, it does not consider the interconnections between the agricultural sector and other sectors. Hence, the projected positive impacts are likely to be a partial estimate of the impacts of climate change on Ireland's agricultural sector.

5 Impacts on River Flooding

5.1. Introduction

One of the major concerns related to climate change is its impact on river flooding (Winsemius et al., 2013; IPCC, 2022). As the climate continues to warm, there is a higher moisture capacity in the air, leading to an increased risk of more frequent and intense precipitation events, resulting in overflowing rivers and a greater likelihood of flooding. This intensification of the hydrological cycle poses significant risks, with projected estimates indicating a potential doubling of flood risk and a 1.2- to 1.8-fold increase in GDP loss due to flooding between temperature increases of 1.5°C and 3°C. If global warming exceeds three degrees Celsius in Europe, the economic costs and number of people impacted by precipitation and river flooding could double (IPCC, 2022).

The impacts of climate change on river flooding are complex and influenced by factors such as hydrology and geography. However, the frequency and severity of flooding events are projected to increase in a warmer climate. These changes will significantly affect human lives, livelihoods, property, ecosystems, and critical infrastructure.

Previous studies in Ireland have investigated the effects of climate change on the hydrological cycle, including flood risk and its impact on property sales and rentals (see, for example, Charlton et al., 2006; Steele-Dunne et al., 2008; Pilla et al., 2019; Sarkar Basu et al., 2022). For instance, Charlton et al. (2006) discovered that increases in winter precipitation will lead to higher runoff levels, particularly in the western regions of Ireland. This is expected to result in more frequent and severe flooding events as well as more extended periods of seasonal flooding. The findings of Steele-Dunne et al. (2008) further support this notion by illustrating how hydrology in Ireland will be affected by climate change, highlighting changes expected for winter and summer flows whilst providing more reliable information regarding flood risk. In addition, Pilla et al. (2019) suggest that properties situated within areas previously impacted by floods tend to have lower sale prices and rental values compared to equivalent properties outside these flood-prone zones. This implies that households generally consider past flood events when making housing decisions.

The approach and data from the COACCH project were used to examine the impact and costs of river flooding in Ireland.

5.2. Methods

The GLOFRIS (i.e., GLObal Flood Risks with IMAGE Scenarios) model is commonly used to assess the direct economic impacts of river flooding on infrastructure. This global grid-based framework covers all major river basins worldwide[6] and encompasses the three key factors that influence flood risk: hazard (which involves expected climate shifts or climate projections), exposure (representing socioeconomic variables like GDP and population), and vulnerability (such as flood protection standards or measures of flood adaptation) (IPCC, 2013; Winsemius et al., 2013).

The process of assessing flood risk using GLOFRIS consists of several steps. Firstly, the framework generates a baseline hazard, drawing on data from PCR-GLOBWB, a global hydrological model responsible for calculating the occurrence, extent, and depth of flooding events. Next, GLOFRIS utilizes bias-corrected meteorological data from established global circulation models like EC-EARTH, HadGEM2-ES, and MIROC5 to project future flood hazards. In the final step, the flood hazard data derived from GLOFRIS is combined with exposure data

[6] The model does not include all river basins in Ireland. However, it includes the Shannon River basin, the largest in the country and is particularly significant for flood risk assessments.

sourced from the HYDE database, which provides information on the urban area fraction within each grid cell, and vulnerability data based on the FLOPROS database, offering insights into local flood protection standards. This combination yields an indicator for flood risk, represented in terms of expected annual damage (EAD) (Winsemius et al., 2013). EAD, in essence, quantifies the damage caused by flooding in each grid cell, considering the probability of a flooding event occurring in that specific grid cell (Ignjacevic et al., 2020).

5.3. Results and discussion

In the context of this paper, estimations derived from the GLOFRIS model, which were generated as part of the COACCH project, were employed to evaluate the economic consequences of river flooding in Ireland across various climate scenarios (corresponding to the Representative Concentration Pathways, RCP), socioeconomic conditions (related to the Shared Socioeconomic Pathways, SSP), and adaptation strategies (as outlined in Lincke et al., 2019). The findings and projections from this analysis are presented in Tables 5.1 and 5.2.

Table 5.1. Expected Annual Damage (EAD in millions of euros) for River Flooding in Ireland under a no-adaptation scenario.

Scenario	2030	2040	2050	2060	2070
SSP1-RCP2.6	24.19	44.65	67.98	92.36	119.14
SSP2-RCP4.5	24.24	41.27	59.41	77.53	95.22
SSP2-RCP6.0	24.45	40.97	58.25	76.11	96.25
SSP5-RCP8.5	30.08	62.52	108.07	167.03	243.5

Data Source: COACCH Project. Notes: EAD values represent changes with respect to the base year (i.e., 2010). Units are in €millions (2015) PPP.

Table 5.2. Expected Annual Damage (EAD in millions of euros) for River Flooding in Ireland under an optimal adaptation scenario.

Scenario	2030	2040	2050	2060	2070
SSP1-RCP2.6	9.13	17.08	25.55	34	42.99
SSP2-RCP4.5	8.91	15.02	21.39	27.58	33.47
SSP2-RCP6.0	9.09	15.15	21.26	27.31	33.7
SSP5-RCP8.5	10.71	22.21	37.4	56.47	80.93

Data Source: COACCH Project. Notes: EAD values represent changes with respect to the base year (i.e., 2010). Units are in €millions (2015) PPP.

Table 5.1 indicates that if no additional measures are taken to adapt to river flooding, the expected annual economic damage will increase in the coming years. The values in the rows show this, and damages are likely to be even greater if current socioeconomic practices continue or worsen, as indicated by the values in the columns. Table 5.2 also reflects this trend but emphasizes the importance of implementing additional adaptation strategies. The expected annual damages reported in Table 5.2 are generally about 50% lower than those in Table 5.1, highlighting the significance of adopting additional adaptation measures.

5.4. Conclusion

This section examined the potential impact and costs associated with river flooding in Ireland using the GLOFRIS model. This model includes all major river basins worldwide and considers three key factors that contribute to flood risk: hazard (i.e., expected changes in climate or climate projections), exposure (i.e., socioeconomic variables such as GDP and population size), and vulnerability (i.e., flood protection measures or level of adaptation). The analysis was conducted under various climate change scenarios, socioeconomic conditions, and adaptation strategies. The findings indicate that without implementing additional adaptation measures, annual economic damages from river flooding are projected to increase in the future. For instance, if no additional adaptation measures are undertaken, the projected annual cost for the year 2070 under a moderate warming scenario of SSP2-RCP4.5 is about €95 million.

It is important to note that the GLOFRIS model, like all modelling tools, relies on certain assumptions and may contain uncertainties that can affect the accuracy of its predictions. The accuracy of GLOFRIS predictions depends on the quality and resolution of input data such as digital elevation models (DEMs), hydrological data, and climate projections. Uncertainties in these data sources, such as errors in measurement, interpolation, or outdated information, can propagate through the model and affect the reliability of its outputs. Also, GLOFRIS simulates flood events based on hydrological processes, including rainfall-runoff relationships, river routing, and floodplain inundation. Uncertainties in these processes, such as variations in rainfall patterns, soil properties, and land use changes, can affect the accuracy of the model's predictions, particularly in regions with complex topography or hydrology. Lastly, GLOFRIS relies on parameters and equations to simulate flood events and estimate flood risk. Uncertainties in these model parameters, such as Manning's roughness coefficient for floodplain inundation or the parameters governing rainfall-runoff relationships, can affect the accuracy of the model's predictions.

6 Impacts on Health

6.1. Introduction

Climate change has various detrimental impacts on human health, which can significantly increase rates of morbidity and mortality (Watkiss & Ebi, 2022; Woodland et al., 2023). As temperatures rise, heat waves are projected to become more frequent and severe, which could lead to a rise in cases of heat-related illnesses such as heat stroke and heat exhaustion. These conditions often place a significant strain on the cardiovascular system, particularly among individuals with pre-existing heart conditions (Liu et al., 2022). Urban areas face additional vulnerability due to the urban heat island effect, where the replacement of natural land covers with materials like asphalt and concrete absorbs and retains heat, leading to a modification in local climate conditions, higher temperatures, and a heightened incidence of heat-related illnesses and mortality (Ščasný et al., 2019). Furthermore, changes in temperature and weather patterns increase the risk of vector-borne, waterborne, and respiratory diseases by influencing the geographic distribution of disease vectors, as well as the quality of air and water (Rocklöv & Dubrow, 2020).

These impacts on human health can have significant economic costs globally. A recent assessment revealed that climate-driven events resulted in a loss of US$253 billion in the global economy in 2021 (Romanello et al., 2022). European countries are also expected to incur substantial economic losses from climate-induced mortality and morbidity. For instance, a single hot day in Germany with temperatures over 30°C could lead to health losses ranging between €750,000 to €5 million per 10 million population (Karlsson & Ziebarth, 2018). In France, the health effects of heat waves from 2015-2019 resulted in an estimated economic impact of about €25.5 billion, including mortality and morbidity (Adélaïde et al., 2022). In addition, it is predicted that by the end of this century, temperature-induced mortality effects could cause annual losses of up to €100 billion for Europe (Watkiss & Hunt, 2012).

Temperature changes have been highlighted as a significant concern for human well-being in the face of climate change (Kaźmierczak et al., 2022). Numerous studies have investigated the relationship between temperature and health, with a particular focus on mortality and morbidity outcomes (see, for example, Breitner et al., 2014; White, 2017; Gasparrini et al., 2022; Deschenes, 2022; Liao et al., 2023; Gibney et al., 2023). Mortality is typically assessed by analysing death rates (both overall and cause-specific), whilst morbidity is proxied by calculating hospital admission rates or the rate of visits to emergency departments (EDs). For instance, Breitner et al. (2014) investigated the short-term effects of air temperature on mortality in three cities of Bavaria, Germany. Their findings revealed that even a slight increase in temperature could lead to a significant rise in non-accidental mortality, with an 11.4% increase observed when the 2-day mean temperature increased from the 90th to the 99th percentile. Similarly, Gasparrini et al. (2022) found that higher temperatures are associated with increased mortality risk. Their study assessed the relationship between temperature and all-cause mortality in England and Wales from 2000 to 2019. Regarding morbidity, Gibney et al. (2023) found an immediate effect of high temperature on heat-related morbidity, as measured by ED visits. In contrast, cold-related morbidity has a lagged response of up to three weeks after the temperature shock, with a significant cumulative effect.

Existing Irish studies have examined the mortality effects of temperature changes, specifically cold-weather impacts (see, for example, Healy, 2003; Goodman et al., 2004; Baccini et al., 2008; Zeka et al., 2014). However, there are gaps in assessments specific to Ireland that need to be addressed. Most of these studies were conducted before 2010, and there is a lack of focus on morbidity. Therefore, the aim is to update and expand the existing literature by analysing the relationship between temperature and morbidity using emergency in-patient hospital admissions data from 2015 to 2019.

6.2. Data

The potential impact of temperature changes on morbidity was investigated by combining data on emergency in-patient hospital admissions from the Hospital In-patient Enquiry (HIPE) system with meteorological data from Met Éireann. This combination was based on the patient's county of residence as well as the week and year of admission. Although it would be better to use data on emergency department (ED) presentations, as it is less affected by hospital supply-side constraints like bed capacity or workforce, such data in Ireland lacks diagnostic information on patients and has very limited demographic information. Hence, hospital admissions data was used in the analysis as it has detailed diagnostic and socio-demographic information.

6.2.1. Health data

Data was accessed from the Healthcare Pricing Office (HPO) called Hospital In-Patient Enquiry (HIPE), which covers the period from 2015 to 2019. It is important to note that this dataset does not include information from the COVID-19 pandemic period, during which hospital activities were affected by public health restrictions that were put in place from early 2020.

The HIPE is a system that collects clinical and administrative data of patients who are discharged from or died in, acute public hospitals in Ireland. This data is collected for both in-patient and day discharges, including elective, emergency, and maternity cases across 53 acute public hospitals.[7] Each HIPE discharge record contains administrative, demographic, and clinical details of a distinct episode of care. An episode of care begins at the patient's admission to the hospital and ends at the time of discharge or death. However, since there is no unique patient identifier in the Irish healthcare system, it is not possible to associate multiple discharges with the same patient across different hospitals (Keegan et al., 2020).

Importantly, the dataset includes information on the home residence of each patient, which is aggregated to the county council level. To merge this information with the meteorological data, city councils (e.g., Waterford) were combined with their corresponding counties (e.g., Waterford County). Similarly, Tipperary North and South were aggregated into one category, while North Dublin and South Dublin were kept separate. All observations with "no fixed abode" or "unknown" values were excluded as they could not be matched to the meteorological data. This resulted in 27 counties for analysis. It was decided to use the county of residence as the geographic unit of this analysis instead of the hospital or health region, which was used in previous literature (see Gibney et al., 2023). This allowed for an individual's exposure to temperature to be captured more accurately. Under the Irish healthcare system, it would be difficult to accurately determine people's exposure to temperature based on the hospital they were admitted to because they may be outside their county of residence.

To specifically examine the impact of temperature change on hospitalisations, the sample was limited to emergency in-patient hospitalizations only. This means that patients who were admitted for elective care as a day patient or for maternity care have been excluded. In addition, not all patient groups are equally susceptible to temperature changes. Therefore, only diagnosis groups that have been identified in previous research as being most impacted by temperature changes were considered. This includes hospital admissions data related to circulatory diseases, respiratory diseases, metabolic diseases[8], infectious diseases, and injuries, based on studies by Lin et al. (2009), White (2017), Rizmie et al. (2022), and Romanello et al. (2022). Finally, we exclude HIPE discharges with a length of stay exceeding

[7] Private hospital activity is not captured in HIPE. The Irish healthcare system is a mixture of public and private delivery and financing.

[8] Metabolic diseases include hereditary and acquired diseases such as diabetes and obesity. Rizmie et al. (2022) include these diseases in their study because they are underlying health conditions that are particularly vulnerable to temperature shocks.

180 days and any discharges with missing key variables such as county of residence.[9] It is important to mention that hospital discharges are calculated as a ratio per 100,000 individuals in each county. This calculation is based on population data obtained from the 2016 Census of Population (CSO Dataset E2011).

6.2.2. Meteorological data

The meteorological data used in this analysis is obtained from the historical 1km x 1km grid data provided by Met Éireann. The data is aggregated to the county level, except for Dublin, for each day between 2014 and 2019.[10] In addition, daily maximum rainfall measurements (in millimetres) are included to account for humidity, as suggested by Barreca and Shimshack (2012). The temperature data is adjusted to account for the spatial distribution of the population in each county, providing a more accurate reflection of the weather experienced by the people living in each county. For example, the unpopulated mountainous area around the Wicklow Mountains in Wicklow might produce inaccurate results, potentially biasing the temperature downwards. This adjustment provides a better picture of the exposure variable (temperature) and how it affects population health.

The daily county-level data are aggregated to the weekly level based on the mean for each week. Weeks based on the HIPE definition of weeks numbered from 0 to 52 were constructed, with each week starting on a Sunday. A week-start variable is built based on this information and used to calculate the weekly mean temperature. Also, lagged values are computed for one, two, and three weeks for each county. This accounts for the delayed effect that a temperature in a previous week may have on emergency hospital admissions. For instance, the temperature in week one might have residual effects on emergency hospital admissions in week 3.

6.2.3. Methods

In line with previous research by White (2017) and Gibney et al. (2023), panel fixed-effects models were used with county-week-year as the unit of analysis. As a result, each county-week-year observation in the HIPE dataset was matched with the corresponding meteorological data for that county, week, and year. The merged dataset contains 7,020 observations and covers a period of 5 years, 52 weeks, and 27 counties. The general specification of the model used is as follows:

$$Y_{c,w,y} = \alpha + \sum_{j=1}^{9} \beta_j temp_{c,w,y} + \sum_{j=1}^{9}\sum_{k=1}^{3} \phi_{j,k} temp_{c,w-k,y} + \boldsymbol{X}_{c,w,y} + CI_{c,w,y} + \eta_{c,w,y} + \tau + \varphi + m + \varepsilon_{c,w,y} \qquad (6.1)$$

The indices *c*, *w*, and *y* represent the county of residence, week, and year, respectively. The dependent variable $Y_{c,w,y}$ is, therefore, the emergency hospital admission rate per 100,000 population in county *c* during week *w* of year *y*. To calculate this variable, the weekly

[9] While HIPE data relates to hospital discharges, the term "admission" is used to coincide with the occurrence of the weather event.

[10] To account for the lag effects of temperature in the model, additional temperature data for 2014 is needed.

emergency hospital admissions for each county and year combination were divided by the county population and then multiplied by 100,000. The independent variables include temperature bins of width 3ºC and their lags, rainfall along with its lags, a set of socio-demographic variables, the Charlson co-morbidity index, and a set of fixed effects. Rainfall is used to account for the effects of humidity, as has been done in previous studies (White, 2017). However, for simplicity, it has been omitted from equation (6.1) but was controlled for during the estimation process.

Specifically, $temp_{c,w,y}$ represents the indicator variable for temperatures in bin *j* for the current week. Similarly, $temp_{c,w-k,y}$ represents the indicator variable for temperatures in bin *j* for the *k*-th lagged week, where k = 1, 2, 3. For instance, $temp_{c,w-1,y}$ represents the indicator variable for temperatures in bin *j* for the first lagged week. The coefficients associated with these variables are represented by β_j and $\phi_{j,k}$ respectively. The intercept and error terms are represented by α and $\varepsilon_{c,w,y}$. In addition, the diagnosis categories are represented by $\eta_{c,w,y}$, year trend by τ, county fixed effect by φ, and month-fixed effect by m. The year trend and month fixed effects are included to control for annual and seasonal factors.

The vector of socio-demographic variables, represented by $\boldsymbol{X}_{c,w,y}$ includes variables such as age, sex, marital status, the public/private status of the patient, and whether the patient has a medical card. On the other hand, $CI_{c,w,y}$ represents the average Charlson co-morbidity index per county, week, and year. The Charlson co-morbidity index is a measure that assesses the severity of a patient's multiple health conditions, using specific diagnostic codes, to predict the likelihood of death within one year following hospitalizations (Charlson et al., 1987).

The identification strategy used in this analysis takes advantage of temperature being an exogenous shock. This means that the coefficients can be interpreted as causal estimates, as there is no mechanism where hospital admission changes affect temperature. However, it is important to note that the analysis uses emergency hospital admissions, not ED presentations. As a result, the estimates may be biased downwards due to supply-side constraints in hospitals. For instance, such constraints can reduce the number of people admitted to hospitals from the ED, potentially underestimating the effect.

6.2.4. Results and discussion

Before presenting the main findings, the distributions of temperature and the rate of emergency hospital admissions are shown in Tables 6.1 and 6.2, respectively. Table 6.1 reveals that about 0.41% of weekly maximum temperatures fall within the two highest temperature ranges, [25ºC, 28ºC) and [28ºC,), while the lowest bins, [1ºC, 4ºC) and [4ºC, 7ºC) account for 4%. The most common range is [10ºC, 13ºC), accounting for 22.88% of weekly maximum temperatures. The distribution of the temperature variable shows the infrequency of extremely high temperatures (i.e., 25 and above) in Ireland. Similarly, extreme low or sub-zero temperatures are uncommon.

Table 6.1. Temperature bins used in the analysis

Temperature bin	% of weekly maximum temperature
[1°C, 4°C)	0.35
[4°C, 7°C)	3.65
[7°C, 10°C)	19.69
[10°C, 13°C)	22.88
[13°C, 16°C)	17.48
[16°C, 19°C)	20.49
[19°C, 22°C)	12.84
[22°C, 25°C)	2.21
[25°C, 28°C)	0.28
[28°C,)	0.13

Source: Duffy et al. (2024) calculations based on Met Éireann's data. Notes: [i, j) = 1 if the weekly maximum temperature is greater than or equal to *i* but less than *j* and zero otherwise. For instance, [1°C, 4°C) = 1 if the weekly maximum temperature falls within this bin and zero otherwise.

Table 6.2 shows the average weekly emergency hospital admission rate across counties for each year-quarter. Notably, admissions are heightened in the first and fourth quarters of the year, where public holidays and cold weather likely contribute to the observed pattern.

Table 6.2. Emergency in-patient hospital admissions (per 100,000 population) 2015-2019

	2015	2016	2017	2018	2019
Quarter 1	57.8	58.6	58.5	64.9	64.9
Quarter 2	53.3	56.3	58.3	59.2	59.8
Quarter 3	48.3	52.3	53.6	55.0	55.4
Quarter 4	53.3	61.0	61.4	62.1	59.9

Source: Duffy et al. (2024) calculations based on HPO's data.

The main findings are displayed in Table 6.3, with the reference category being the temperature bin [10°C, 13°C). The coefficients for all other bins are interpreted relative to this reference category. These coefficients are also plotted in Figure 6.1. In addition, the reported coefficients are in levels, indicating changes in hospital admissions per 100,000 population. However, these coefficients can be converted into percentage changes by dividing each respective coefficient by the mean weekly admission rate. For instance, when temperatures range from 22°C to 25°C, there was a rise in emergency hospital admissions of 4.7 per 100,000 population compared to the reference category [10°C, 13°C). In terms of percentage changes, this translates to an 8.36%[11] increase in emergency admissions when the temperature is between 22°C and 25°C, relative to [10°C, 13°C).

[11] That is, ((4.7/56.21) *100)

Table 6.3. Baseline results

Reference bin = [10°C, 13°C)	**Coefficient**
[1°C, 4°C)	-5.16* (2.29)
[4°C, 7°C)	1.72* (0.83)
[7°C, 10°C)	-1.70*** (0.48)
[13°C, 16°C)	0.83 (0.59)
[16°C, 19°C)	2.08** (0.78)
[19°C, 22°C)	3.42*** (0.92)
[22°C, 25°C)	4.70*** (1.30)
[25°C, 28°C)	3.98 (2.83)
[28°C,)	2.34 (3.91)
Mean dependent variable	56.21
County fixed effects	Yes
Year trends	Yes
Month fixed effects	Yes
Lagged temperature bins	Yes
Socio-demographic controls	Yes
Rainfall controls	Yes
N	6760[12]
R^2	0.56

Source: Estimations from Duffy et al. (2024). Notes: * indicates significance at the p<0.5 level, ** at the p<0.01 level, and *** at the p<0.001 level. Standard errors are provided within parentheses.

Overall, the main analysis reveals that higher temperatures exceeding 16°C are associated with increased rates of emergency hospital admissions. A statistically significant relationship is observed between temperatures in the range [16°C, 19°C) and emergency hospital admissions. Figure 6.1 shows the increasing magnitude of the coefficient at higher temperatures. However, the two highest temperature bins indicate no statistically significant relationship, possibly due to the infrequent incidence of temperatures within these ranges in Ireland. This result is in line with Gibney et al. (2023), who found significant effects of hotter temperatures on morbidity in the context of a relatively mild climate. It is also interesting to note that the coefficients for temperature bins [1°C, 4°C) and [7°C, 10°C) are statistically significant and negative. This suggests that relatively cold temperatures may have some health

[12] To calculate the admissions rate, Dublin observations had to be aggregated. Therefore, the final sample size is 6760 (5 years x 52 weeks x 26 counties).

benefits for the Irish population, as they reduce emergency hospital admissions. One possible explanation could be people's behavioural response during cold weather, as activities during colder temperatures are less likely to cause health problems (White, 2017). It is worth mentioning that the coefficients for the lag terms are, in general, not statistically significant. The full model results, including the coefficients of the lag terms and other control variables, are presented in Appendix B.

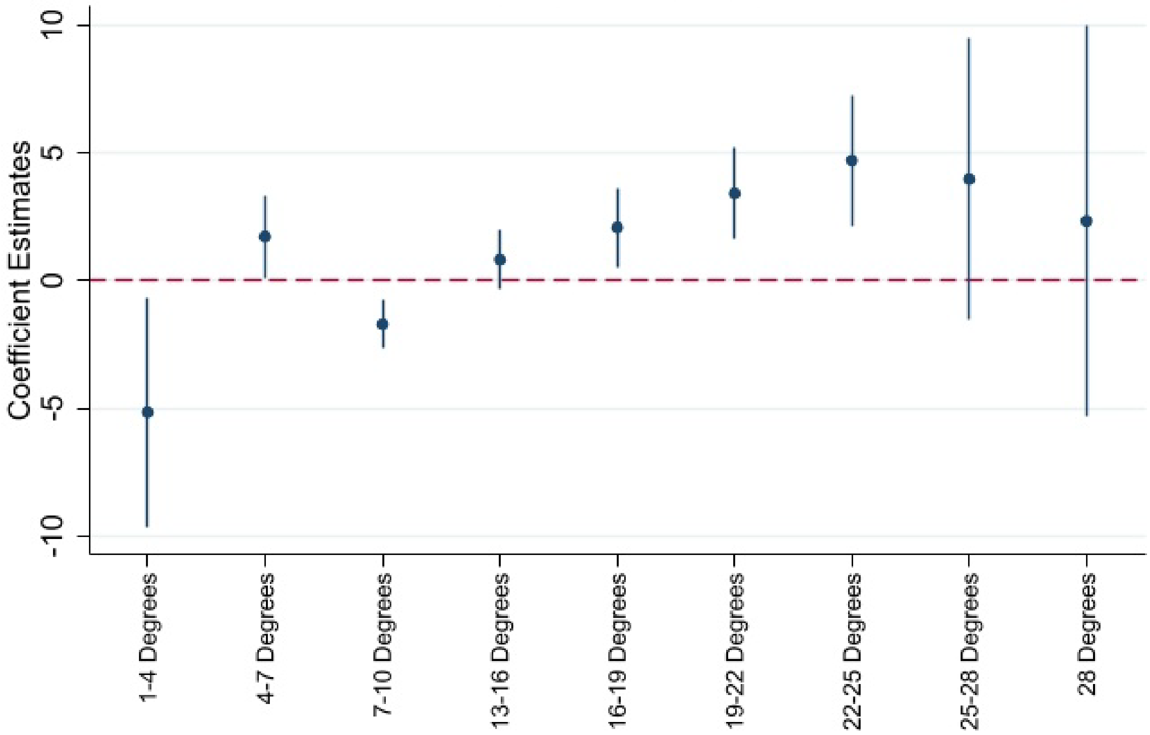

Figure 6.1. Coefficient plot for baseline results

To examine the impact of temperature on morbidity across different age groups, emergency admissions were divided into three categories: 0-14 years old, 15-64 years old, and over 64 years old. The findings are presented in Table 6.4, and the coefficient plot is represented in Figure 6.2. The plot effectively demonstrates how the relationship between temperature and emergency hospital admissions varies among different age groups. Looking at the coefficient plot, it is evident that for children aged (0-14), temperatures above 16°C have a statistically significant effect on hospital admissions, consistent with the main analysis. In contrast, for the working-age group (15-64), the effects are smaller in magnitude and remain significant only within a temperature range of 16 to 25 °C. The pattern of hospital admissions for the older age group is similar to that shown in Figure 6.1, although none of the effects are statistically significant except for the temperature bin [4^{o}C, 7^{o}C). The lack of statistical significance in the effect of temperature change on emergency in-patient hospitalizations for the older population during the sample period is somewhat puzzling and warrants further investigation.

Table 6.4. Age group results

Reference bin = [10^{o}C, 13^{o}C)	**Child (0-14) Age**	**Working Age (15-64)**	**Older Age (65+)**
[1^{o}C, 4^{o}C)	-8.02 (4.51)	-2.45 (1.76)	-16.59 (11.57)
[4^{o}C, 7^{o}C)	-0.89 (1.64)	-0.09 (0.64)	15.11*** (4.20)
[7^{o}C, 10^{o}C)	-2.03 (0.94)	-1.21** (0.37)	0.47 (2.40)
[13^{o}C, 16^{o}C)	2.02 (1.17)	0.45 (0.45)	1.23 (2.96)
[16^{o}C, 19^{o}C)	3.99* (1.55)	1.49* (0.60)	1.28 (3.95)
[19^{o}C, 22^{o}C)	6.91*** (1.82)	1.77* (0.71)	3.07 (4.65)
[22^{o}C, 25^{o}C)	7.77** (2.57)	2.49* (1.00)	9.91 (6.56)
[25^{o}C, 28^{o}C)	1.87 (5.56)	0.98 (2.17)	18.37 (14.21)
[28^{o}C,)	-3.70 (7.68)	2.87 (3.01)	0.80 (19.64)
Mean dependent variable	62.59	31.06	212.18
County fixed effects	Yes	Yes	Yes
Year trends	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes
Lagged temperature bins	Yes	Yes	Yes
Socio-demographic controls	No	No	No
N	6,723	6,756	6,754
R^2	0.65	0.82	0.88

Source: Estimations from Duffy et al. (2024). Notes: * indicates significance at the p<0.5 level, ** at the p<0.01 level, and *** at the p<0.001 level. Standard errors are provided within parentheses. The sample sizes differ across specifications because some county-week-year units will have no HIPE observations for that age group.

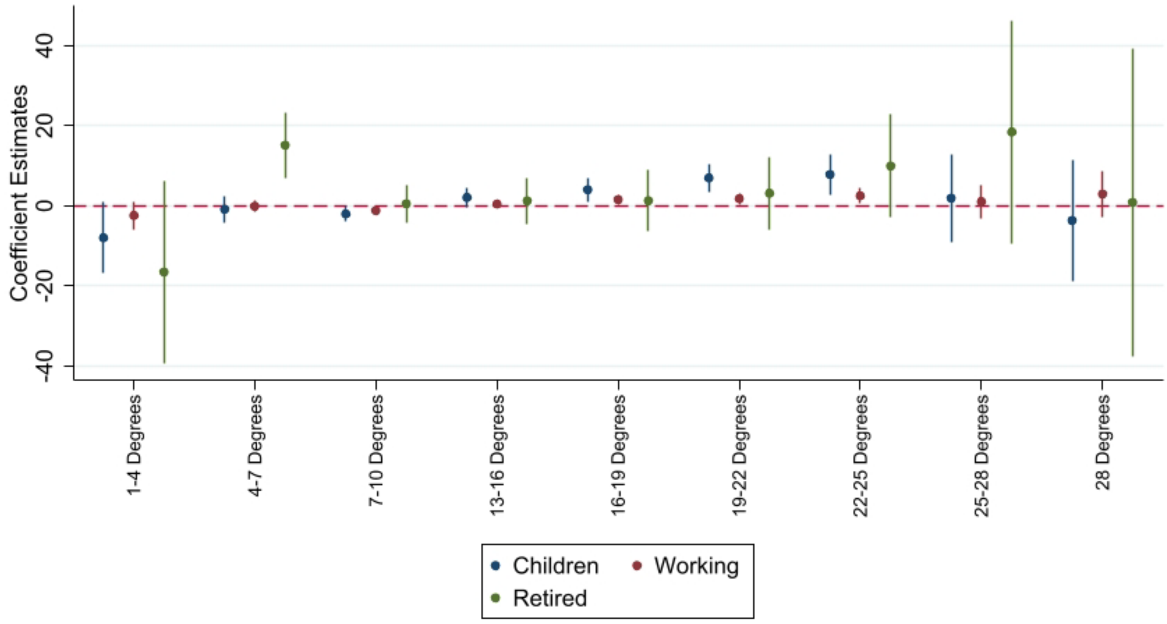

Figure 6.2. Coefficient plot for age group analysis

The analysis is further segmented based on diagnosis categories. The findings in Table 6.5 exhibit similar patterns to the main results. Notably, the statistically significant coefficients at lower temperatures for all categories of diseases, barring metabolic diseases. It is evident that there is a decrease in the rate of emergency hospital admissions across all diagnostic groups when temperatures range from 1-4°C and 7-10°C. As previous studies have highlighted, this could be attributed to a behavioural effect where individuals refrain from seeking medical care during extremely cold weather conditions (White, 2017; Gibney et al., 2023).

Certain health conditions, including circulatory, respiratory, and infectious diseases as well as injuries, tend to worsen with higher temperatures. The analysis reveals that emergency admissions for metabolic diseases are not significantly affected by cold temperatures but show a significant increase in response to warmer temperatures. International literature also suggests that rising temperatures can contribute to the prevalence of infectious diseases such as E. coli VTEC due to contaminated water sources. Warmer weather allows bacteria to survive longer and enter drinking water streams (Romanello et al., 2022).

Table 6.5. Diagnosis group results

	(1) Circulatory Disease	(2) Respiratory Disease	(3) Metabolic Diseases	(4) Infectious Diseases	(5) Injuries
Reference bin = [10°C, 13°C)					
[1°C, 4°C)	-4.84* (2.26)	-5.02* (2.30)	-4.27 (2.22)	-5.18* (2.25)	-5.15* (2.28)
[4°C, 7°C)	1.78* (0.82)	1.68* (0.83)	1.07 (0.84)	1.88* (0.81)	1.55 (0.83)
[7°C, 10°C)	-1.58** (0.47)	-1.74*** (0.48)	-0.85 (0.46)	-1.19* (0.46)	-1.56** (0.48)
[13°C, 16°C)	0.69 (0.58)	0.68 (0.59)	0.84 (-.57)	0.66 (0.58)	0.74 (0.59)
[16°C, 19°C)	1.70* (0.78)	1.58* (0.79)	1.95* (0.76)	1.73* 0.76)	1.74* (0.78)
[19°C, 22°C)	3.04** (0.92)	2.90** (0.92)	2.94** (0.89)	3.05** 0.90)	3.25** (0.92)
[22°C, 25°C)	4.32** (1.29)	4.28** (1.30)	4.54*** (1.27)	4.40*** (1.26)	4.44** (1.29)
[25°C, 28°C)	3.30 (2.79)	3.38 (2.83)	6.26* (2.79)	4.28 (2.78)	3.50 (2.80)
[28°C,)	0.65 (3.86)	0.86 (3.91)	2.69 (3.75)	0.85 (3.76)	0.96 (3.86)
Mean dependent variable	56.30	56.22	57.63	56.54	56.28
County fixed effects	Yes	Yes	Yes	Yes	Yes
Year trends	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes
Lagged temperature bins	Yes	Yes	Yes	Yes	Yes
N	6,739	6,757	5,839	6,613	6,744
R^2	0.57	0.56	0.61	0.58	0.57

Source: Authors' estimations. Notes: * indicates significance at the p<0.5 level, ** at the p<0.01 level, and *** at the p<0.001 level. Standard errors are provided within parentheses. The sample size differs by diagnosis group because, for some county-week-year units, there were no HIPE observations for certain diagnosis groups.

Finally, the economic burden of temperature-induced emergency hospital admissions was estimated. To do this, the estimated effect of temperature on emergency hospital admissions was multiplied by an estimate of the average cost of emergency hospital treatment. It is important to note that the estimates in this paper only consider the cost of providing hospital services and do not consider willingness to pay to avoid negative health outcomes. Therefore, the calculation represents a conservative estimate of the healthcare cost associated with temperature-induced morbidity. The calculation suggests that the economic burden, in terms of delivering hospital services,[13] related to a weekly maximum temperature increase from the range [10°C, 13°C) to [22°C, 25°C) varies from €3,000 to €7,000 for every 100,000 population per week, contingent on the disease category.

6.3. Conclusion

This section investigated the relationship between temperature and morbidity by analysing data on emergency hospital admissions between 2015 and 2019 using panel fixed-effects methods. The empirical results indicate that even in a country with moderate climate conditions, higher temperatures can increase emergency hospital admissions. For example, in a week where the maximum temperature either reached or exceeded 22°C but remained below 25°C, there were an additional 4.7 cases of emergency hospital admissions for every 100,000-population compared to a week with a maximum temperature falling within the reference range of [10°C,13°C). Regarding providing hospital services, the annual economic burden associated with this temperature-related morbidity varies from €156,000 to €364,000 for every 100,000 population, contingent on the length of stay.

It is recognised that the data and analysis in this paper have certain limitations. Firstly, there was difficulty in determining the specific individuals who were most susceptible to higher temperatures based on the available data. To mitigate this limitation, it was decided to focus on identifying diagnoses more vulnerable to healthcare needs resulting from high temperatures. The absence of a unique patient identifier in Ireland prevented us from tracking patients across multiple hospital episodes. As a result, the impact of varying temperatures at an individual level could not be investigated. Secondly, it is important to acknowledge that the data is based on hospital admissions at the discharge level. Therefore, healthcare capacity and supply-side constraints that could limit the response in hospital admissions to temperature variation cannot be accounted for. Finally, whilst year trends and county and seasonal patterns that may affect emergency in-patient hospitalisations over time have been controlled for, it is still possible that there are omitted variables that may be correlated with temperature.

7 Conclusions and Recommendations

This paper examines the economic impacts of climate change in Ireland across five categories: coastal flooding, labour productivity, agriculture, river flooding, and health. Different methods and models based on available data were used to quantify these impacts.

The financial impacts differ depending on the category. Without any additional mitigation measures, the total cost of sea level rising by 0.56 meters under SSP2-RCP4.5 is approximately

[13] Cost estimates provided by the HPO, which are based upon Activity-Based Funding (ABF), were used. These costs reflect all resources used to care for a patient and as well consider the complexity of the care provided and the patient case mix. For example, patients with longer length of stay are provided with greater weight when determining the resources they consume.

€2 billion in 2050 and may grow to €3 billion by 2100. An increase in WBGT reduces labour productivity in Ireland even when this is still below the established heat stress thresholds. There are positive impacts on barley and wheat growth and improved grass production, which benefits livestock, due to the climatic changes. Without implementing additional adaptation measures, the projected annual economic damage from river flooding for 2070 under a moderate warming scenario of SSP2-RCP4.5 is about €95 million. When the temperature increases from [10°C,13°C) to [22°C, 25°C), the economic burden in terms of delivering hospital services ranges from €156,000 to €364,000 for every 100,000 population per annum.

While the analysis provides valuable insights into the economic costs associated with climate change impacts, it is important to recognise the limitations and uncertainties inherent in such assessments. The estimates are based on current knowledge and available data, but future developments in climate science, socio-economic trends, and adaptation efforts may influence these projections. Also, although this work has quantified certain impacts for Ireland, many others remain. Biodiversity, energy demand changes, or extreme events, to name a few, were not considered. This was due to the lack of appropriate data and the limitations of this project. Hence, the main conclusion is that Ireland will face significant impacts, some of which have been quantified, and others are still not fully understood.

This work has led to some surprising findings. In some cases, impacts were larger than expected (e.g., health care costs) or lower than expected (agriculture). This highlights the importance of continued research on the impacts of climate change in Ireland. Effective and efficient policy setting relies on reliable evidence of potential climate impacts, which this work hopes to provide. However, further research is needed. Future research within this project will consider (i) how different adaptation strategies reduce these costs and (ii) how these initial impacts affect the rest of the Irish economy.

Ultimately, addressing the impacts of climate change requires a concerted and collaborative effort at all levels of society. By taking proactive steps to adapt to a changing climate, Ireland can minimise economic costs, protect vulnerable communities and ecosystems, and build a more resilient and sustainable future for future generations.

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Appendix A: Boxplots for Labour Productivity and WBGT

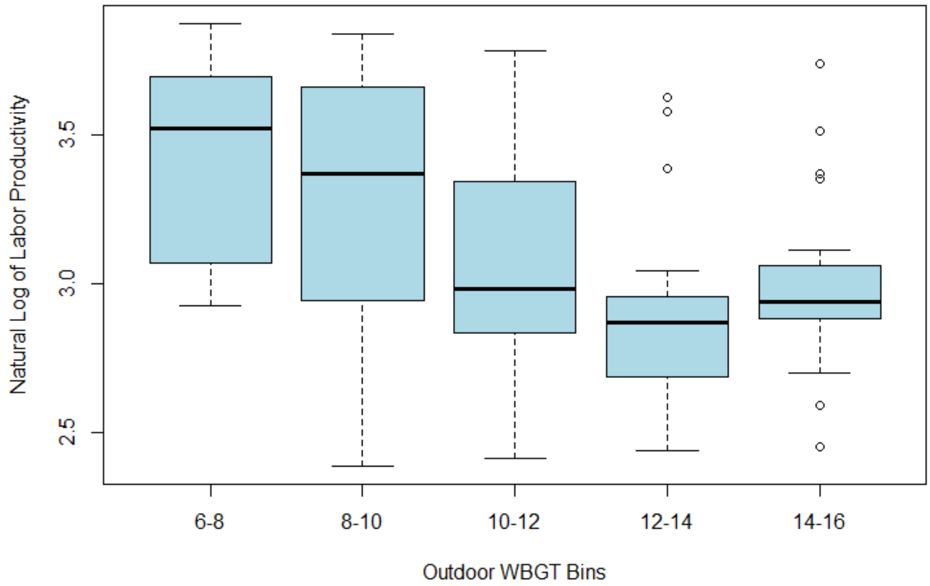

Figure A.1: Labor Productivity by Outdoor WBGT Bins

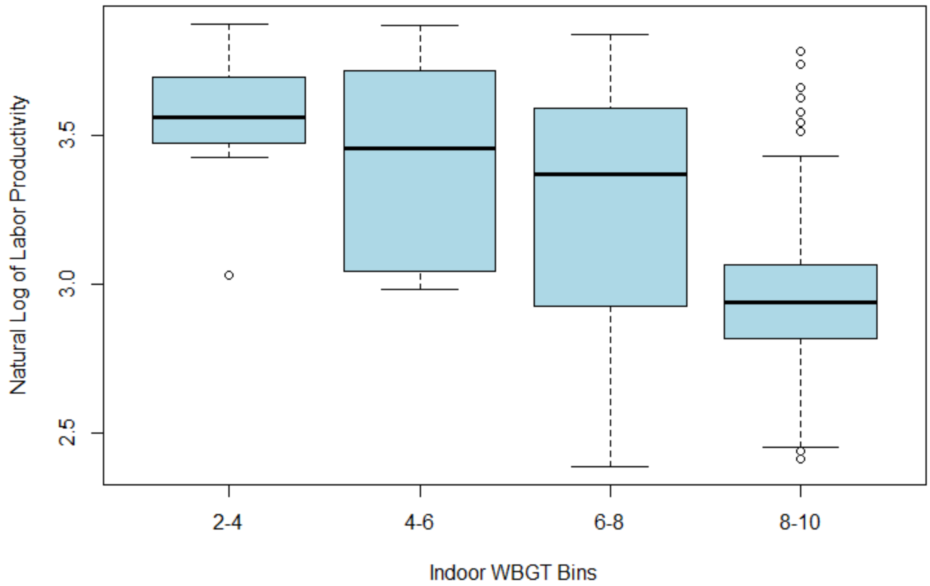

Figure A.2: Labor Productivity by Indoor WBGT Bins

Appendix B: Additional Results for Health Impacts

Table B.1: Lagged temperature effects

	1-Week Lag Coefficients	2-Week Lag Coefficients	3-Week Lag Coefficients
Reference bin = [10°C, 13°C)			
[1°C, 4°C)	7.71** (2.34)	1.25 (2.33)	-2.75 (2.34)
[4°C, 7°C)	2.60** (0.84)	3.92*** (0.83)	-4.28*** (0.84)
[7°C, 10°C)	0.94* (0.47)	1.16* (0.48)	-1.92*** (0.47)
[13°C, 16°C)	-0.89 (0.59)	-2.01*** (0.60)	-0.57 (0.59)
[16°C, 19°C)	-2.01** (0.77)	-2.01* (0.81)	0.22 (0.79)
[19°C, 22°C)	-2.02* (0.94)	-2.45* (0.96)	-0.15 (0.93)
[22°C, 25°C)	-1.54 (1.31)	-2.37 (1.32)	0.36 (1.29)
[25°C, 28°C)	0.73 (2.92)	-3.76 (2.90)	-0.38 (2.79)
[28°C,)	2.09 (4.03)	-2.88 (4.00)	-2.83 (4.01)

Notes: * indicates significance at the p<0.5 level, ** at the p<0.01 level, and *** at the p<0.001 level. Standard errors are provided within parentheses.

Table B.2: Coefficients for other control variables

	coefficient
Mean of Charlson Co-Morbidity Index	0.32 (0.69)
Mean Number of Medical Card	7.08*** (1.91)
Mean Public/Private Status	5.92* 2.41
Mean Marital Status	-1.55 (1.06)
Male – Age 0-9	-7.77 (6.28)
Male – Age 10-19	-5.88 (7.30)
Male – Age 20-29	-2.13* (0.83)
Male – Age 30-49	-12.93

	(6.69)
Male – Age 50-69	-1.83 (6.51)
Male – Age 70-79	-7.02 (6.57)
Male – Age 80-89	-.56 (6.67)
Male – Age 90+	10.41 (9.41)
Female – Age 0-9	5.26 (6.14)
Female – Age 10-19	5.54 (7.87)
Female – Age 20-29	-12.25 (8.91)
Female – Age 30-49	-7.83 (7.32)
Female – Age 50-69	-1.83 (6.51)
Female – Age 70-79	-1.81 (6.72)
Female – Age 80-89	2.44 (6.73)
Female – Age 90+	-3.19 (7.95)

Appendix C: Estimating natural wet bulb temperature and black globe temperature from climate data

Using air temperature in degrees Celsius and relative humidity as a percentage, we estimated the natural wet bulb temperature (T_{nwb}) using the empirical relationship provided by Stull (2011).

$$\begin{aligned} T_{nwb} = \ & T_a \times \arctan\left(0.151977 \times \sqrt{RH + 8.313659}\right) + \arctan(T_a + RH) \\ & - \arctan(RH - 1.676331) \\ & + \ 0.00391838 \times \sqrt[3]{RH} \ \times \arctan(0.023101 \ \times RH) - \ 4.686035 \end{aligned}$$

where T_a is the air temperature and RH is relative humidity.

We used air temperature in degrees Celsius, wind speed in meters per second, and surface net downward shortwave radiation in watts per square meter to estimate the black globe temperature using the following approximations based on Liljegren et al. (2008).

Step 1: The Mean Radiant Temperature (MRT) was estimated using the following formula:

$$MRT = \left(\frac{S}{\epsilon\sigma}\right)^{0.25}$$

where ϵ is the emissivity of the black globe (typically 0.95 for a black globe), σ is the Stefan-Boltzmann constant (i.e., $5.67 \times 10^{-8} \ W/m^2K^4$), and S surface net downward shortwave radiation.

Step 2: The convective heat transfer coefficient (h_c) was estimated as follows:

$$h_c = 1.4 + 0.135 \times T_a + 0.055 \times v^2$$

where T_a is the air temperature and v is wind speed.

Step 3: The black globe temperature (T_g) was estimated as follows:

$$T_g = \left(\frac{S \times \alpha_g + \epsilon \times \sigma \times (MRT)^4}{h_c}\right)^{0.25}$$

where α_g is the absorptivity of the globe (with a value of 0.05) and the other terms remain the same as in the previous descriptions. For indoor conditions, the black globe temperature was assumed to be approximately equal to the air temperature (i.e., $T_g \approx T_a$) (Lemke & Kjellstrom, 2012).