The relation between extreme heat and ENSO and characterization of health risks in relation to varying levels of UTCI

An investigation of the thermal environment in Taiwan

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Master thesis (MAMM10)

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2022

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Title: The relation between extreme heat and ENSO and characterization of health risks in relation to varying levels of UTCI
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Language: English
Year: 2022
Keywords: El Niño, ENSO, relative risk, heat waves, cold spells, UTCI, cardiovascular diseases, exposure, Taiwan.

Abstract

As a result of climate change, temperatures have been steadily increasing in the last half century and extreme weather events such as storms, extreme heat, extreme precipitation and cold spells have been observed to occur more frequently. This comes with potential consequences for lives and health. There are several factors affecting the climate in a region. A phenomenon that has a large impact in the pacific region is the El niño southern oscillation (ENSO) which dictates variables such as temperature, humidity and precipitation. In this study an ENSO index called ONI was used to represent ENSO and the relationship between high temperature and ONI was investigated. Additionally, five different health outcomes were analyzed to see how they were affected by different levels of the Universal Thermal Climate Index (UTCI) which is a climate index that is based on several atmospheric variables. This thesis is part of the Belmont collaborative AWARD-APR project and the health data was collected through contacts within the project. The data used is daily mortality count for the ICD10 codes X30, X32, I50.0, I50.1 and I50.9 for the period 2008 to 2019. The UTCI data was acquired through an open source database from Copernicus, European Union's Earth Observation Programme. The data was processed into daily average and maximum UTCI for the period 2008 to 2019. To see if there was a relation between extreme heat and ONI in Taiwan, linear regression models were applied. To investigate the relation between the health outcomes and UTCI, a Poisson regression model was used to describe the incidence. The results indicate that there is a positive relation between 95th percentile average daily temperature during June, July and August in the southern and mid-western parts of Taiwan. Further there is a rather weak indication of a positive relation between average monthly temperature and ONI in the winter and spring months. The results of the health analysis indicate that there is an increased risk of mortality due to these health outcomes during cold conditions. The main reason for the health outcomes being sensitive to low UTCI intervals(<5 °C) is that the cardiovascular health outcomes that were included exhibit this trend. The two health outcomes strictly related to heat seem to exhibit the opposite relation although their incidence is rather low to begin with, making the model uncertain. The results show that there is a possibility to use ONI to predict when there will be extreme heat in some regions. Thereby, ONI could indirectly be used to predict when the incidence for certain health outcomes is more prone to increase. For two regions there seemed to be an increase for all health outcomes with increasing UTCI. Thereby the relation between extreme heat and ONI might be useful for predicting and preventing mortality in these regions. For the majority of the regions, cold conditions implicate an increase of the cardiovascular health outcomes. As there is an indication of a positive relation between average monthly temperature and ONI in the winter, this could potentially be investigated further and then be used to predict when the incidence of cardiovascular health outcomes will increase. If the predictions are accurate, preventative measures can be applied. Future studies might want to investigate more closely how cold temperatures are correlated with ONI. Also it could be of interest to investigate the relation between minimum temperature or UTCI in relation to health outcomes in the sense that high minimum temperatures could have an adverse effect on individuals that need to cool down during night time.

Preface

This thesis is written as a degree project in the risk management and safety engineering masters program at Lunds university, faculty of engineering. It was also written adjacent to the international Belmont collaborative AWARD-APR project coordinated by Prof. Amir Sapkota at University of Maryland. The Swedish team in the AWARD-APR project had the main task of investigating the relation between extreme weather and ENSO. As I joined this team I decided on looking closer at high temperatures. I find health studies particularly interesting and after discussing what I could do, my supervisor Chuansi Gao and I agreed that I could also look at health risks in relation to climate conditions to make a connection to risk management. Writing a project like this has been challenging and difficult but at the same time I have learned a lot. The main challenge has been that all the decisions and details have been up to me, which I am not used to. I think it is an important experience to do a project like this and to learn to delimit a study to what is most relevant. Whether I have managed to do so is up to the reader to decide. As I was taking another course in parallel with this project I needed more time than one semester to finish it and I am grateful that I got the opportunity to do so.

I want to say thank you to my supervisor Chuansi Gao who has guided me and helped me through this project. I also want to thank my examiner Åsa Ek for giving valuable comments. Further, I want to thank the team from Taiwan led by Prof Yu-Chun Wang at Chung Yuan Christian University in the AWARD-APR project for providing data and helping me with my results.

Jag vill rikta ett stort tack till min familj som har stöttat mig genom den här processen. Jag vill även tacka mina vänner som har sett till att jag har kommit ut och hittat på saker även ifall jag har haft en begränsad fritid den senaste tiden. Slutligen vill jag rikta ett särskilt tack till Elias Fransson som på gott och ont alltid verkar befinna sig i samma sits som mig.

Tack!

Contents

1 Introduction

Climate change is one of the largest challenges of our time. The average global temperature has been steadily increasing over the last half century which is raising concerns about the potential consequences this might have on health, ecological and socio-economical systems [1][2][3]. As the average global temperature is rising, extreme weather events such as extreme heat, extreme precipitation, flooding, cold spells and storms may become more frequent [2]. The number of extreme weather events increase and the effects on lives and health can already be observed [4]. The increased risk of dying during extreme heat events has been observed for a long time and is quite well described. Groups that already have a preexisting health condition are especially exposed to increased risk of health complications related to climate conditions [4]. There are many different factors that affect the climate and weather conditions in a region. A climate phenomenon that has an impact in the pacific ocean region is the El Niño Southern Oscillation(ENSO) [5][6]. ENSO can be measured in several ways. A common way to describe ENSO is the Oceanic Niño Index(ONI) [7]. Depending on what phase of ENSO is in, different weather variables such as temperature, humidity, precipitation and winds will behave differently [6]. Since ENSO affects the climate and the climate affects human health, it can be of interest to investigate how these are related and if it is possible to make any predictions regarding climate and health outcomes. An effective way to describe the climate conditions is by using a thermal climate index such as universal thermal climate index (UTCI). So far, there has been limited research on health outcomes related to weather, ENSO and UTCI in regions with subtropical climate [8]. A country in the subtropical region that is interesting in this context is Taiwan.

1.1 Study area: Taiwan

In this particular study, the thermal climate in Taiwan will be investigated more closely. Taiwan is situated in the east pacific region and has a population of roughly 23.5 million people [9]. The living patterns have changed considerably during the 20th century. Up until after the second world war the largest portion of the population lived in rural settings [9]. However, in the early 1950s, half of the population lived in cities with a population over 50 000 [9]. This urbanization trend continued up until recent years where it has started to recess as some people move to suburban areas instead of city environments [9]. The largest city is New Taipei City which is one of six cities in Taiwan with a population larger than 1 million inhabitants [9]. A general trend during the 20th century has been a steadily increasing population. However, this trend has seemed to stop in recent years as the population growth is small or even zero [9].

When it comes to the Taiwanese climate it is mostly subtropical except for the southernmost parts of the island where the climate is classified as tropical [9]. The climate is controlled by a current called Kuroshio which is flowing on the east side of the island [9]. The summer is characterized by warm weather and usually lasts from April to September or October. In the northern parts of the island the summer tends to be dry with little precipitation while the southern parts are humid and have more precipitation [9]. The average temperature is expected to be between 8 - 33 °C during the year [8].

Figure 1: Map of Taiwan with the spatial distribution of the regions that are investigated in this study [10].

1.2 ICD10 codes

International Classification of Diseases(ICD) is a classification system for different diseases and health outcomes [11]. The system is used worldwide for statistical analysis of lives and health [11]. In this study the data that will be used is divided according to the version called ICD10. The following five ICD10 codes will be investigated in this study: X30: exposure to excessive natural heat, X32: exposure to sunlight, I50.0: Congestive heart failure, I50.1: Left ventricular failure and I50.9: Heart failure, unspecified. The codes that begin with X are related to exposure to natural conditions and the codes that begin with I are related to heart failure.

1.3 Aim

Previously, there has been limited research about how the thermal environment affects health risks in the subtropical region, where Taiwan is situated. Since UTCI is a rather new thermal climate index there is limited knowledge about the relation between ENSO, UTCI and health outcomes. This study has two aims that attempt to increase the understanding in this area. One aim is related to the relation between thermal environment and ENSO and one is related to mortality and UTCI. The two aims are connected in the sense that ENSO may influence the thermal environment and thermal environment may influence mortality. The aims can be found below:

- The first aim is to describe the relation between 95th percentile average daily air temperature and ONI and the relation between 95th percentile maximum daily air temperature and ONI for the following 15 regions in Taiwan: New Taipei, Taipei, Taoyuan, Hsinchu, Miaoli, Taichung, Chunghua, Chiayi, Nantou, Tainan, Kaohsiung, Pingtung, Yilan, Hualien and Taitung. This will be done by using linear regression. Also, this aim includes additional analysis of monthly average air temperature, UTCI and elevation.
- Additionally, the aim is to use UTCI as a basis to predict the mortality for the following ICD10 codes:
  - X30: exposure to excessive natural heat
  - X32: exposure to sunlight
  - I50.0: Congestive heart failure
  - I50.1: Left ventricular failure
  - I50.9: Heart failure, unspecified

  The mortality will be predicted by estimating a RR for different intervals of UTCI by using Poisson regression. This aims to increase the understanding on how the health outcomes for the ICD10 codes mentioned above are affected by different UTCI levels and how UTCI can be used as a means to predict health outcomes.

1.4 Reading guide

In the following section(2 Theory) some background information and basic concepts that are central to this thesis will be introduced. First there will be a description of ENSO and different aspects of the phenomenon. Then there will be an introduction to extreme heat, UTCI and the potential consequences of extreme heat. This is followed by risk metrics and a background to risk perception and risk perspective. Thereafter, the method is presented in section 3. The method contains a description of the data collection and processing. This is followed by a subsection about linear regression and time series analysis respectively. The method section is followed by the results(section 4) which is divided into two major parts: The analysis of temperature, UTCI and ENSO and the analysis of the health outcomes.

The results and the thesis as a whole is then discussed in the discussion(section 5) followed by conclusions(section 6). In appendix A there is a popular science summary which summarizes the thesis in a more intelligible way.

2 Background

In this section background information and basic concepts that are relevant for the study will be introduced.

2.1 ENSO

ENSO is a climate variation that consists of two major phenomena, namely, El niño and the southern oscillation. El niño was first recorded in the 16th century in Peru where fishermen noticed an unusual rise in the sea water temperature, reoccurring with a certain interval [5]. This was called El niño since it coincided with the Christmas celebration at times, with the name El niño referring to Christ [5]. The other phenomenon that constitutes ENSO is the southern oscillation, which is a variation in the atmospheric pressure that occurs in the pacific region [5]. The counterpart of El niño is called La niña and is characterized by unusually cold water in the eastern part of the pacific and unusually high humidity and warmth in the western parts of the pacific [6].

2.1.1 The southern oscillation

The southern oscillation is part of the same phenomenon as the El niño and La niña. It is described as the variation in the sea-level atmospheric pressure between the eastern parts and the western parts of the pacific ocean [5]. During an El niño event, the Australian and Indonesian region of the pacific is colder than in the normal phase. This makes the sea-level pressure drop below the usual pressure. Meanwhile, the western pacific is warmer than usual and experiences an abnormally high pressure [5].

2.1.2 Normal phase

The normal state in ENSO is characterized by the trade winds blowing strongly westward causing the tropical waters in the pacific to flow west. This brings the heavier and colder water to the surface in the eastern pacific [6]. This in combination with cold currents flowing from the south along South America's coast bring the temperature down in this region [5]. The thermocline(a layer that separates warm surface waters from cold water) in the pacific is therefore tilted and warm surface water accumulates in the western parts of the pacific making the cold water stay deep below the thermocline. In the western region, warm water also drives the so-called Walker circulation consisting of convection and subsidence as a result of the high temperature [6]. The Walker circulation further increases the slope of the thermocline and strengthens the pattern of warm surface water flowing westward [6]. When the trade winds and the thermocline in the Pacific behaves in the way described above, the conditions are considered normal. However, if there is a deviation from this normal pattern an El niño or La niña phase is approaching.

2.1.3 El niño and La niña

If there is a decline in westwards trade winds, the currents of warm surface water flowing westward will slow down. The trade winds are a driving force in the system and a decline in these causes the thermocline to not be tilted as much as in the normal state. Due to this, the surface waters in the east Pacific become unusually warm which causes warm climate and rainfall [5]. This also causes a low pressure in the eastern pacific that weakens the trade winds even further [6]. This becomes a positive feedback loop causing even higher sea surface temperatures in the eastern parts of the Pacific [6]. In the western pacific however, the reduced flow of warm surface water causes a decline in rainfall and does therefore result in dry weather in the Australian-Indonesia region [5]. In these conditions the thermocline is not as tilted as usual and the layer of warm water in the eastern pacific is not as deep as usual [6]. This is what is called El niño [5][6].

La niña on the other hand, is the counterpart of El niño. If the thermocline is tilted unusually much instead of a smaller tilt, the waters in the easter pacific will get more upwelling cold water and the western pacific will experience even more warm surface water causing humid conditions [5]. This results in that south America experiences drought, while western pacific region experiences intensified rainfall and possibly even flooding [5].

2.1.4 ENSO index

ENSO index is a way of describing what phase the system is currently in [5]. This is usually done by measuring anomalies in sea surface temperature(SST) in a specified region [7]. A region that is commonly used is the niño 3.4 region. When the SST deviates from the normal temperature with +0.5 or -0.5°C, this is considered an anomaly according to the Oceanic Niño Index(ONI) (a type of ENSO index) [7]. The definition of an El niño or la niña phase is defined by the national oceanic and atmospheric administration(NOAA) as when "a minimum of five consecutive 3-month running averages of SST anomalies in the Niño 3.4 region surpassing a threshold of +/- 0.5°C" [7]. This is the definition that will be used for this project and the deviation from the temperature considered ENSO normal phase will henceforth be called ONI.

2.1.5 Global impact of ENSO

ENSO does not only impact the region where its major mechanisms take place. Through something called teleconnections, ENSO can affect weather systems around the world [6]. In the normal phase the trade winds force warm surface waters to the west parts of the pacific which induces rainfall and humid climate in southeast Asia. However, during El niño the warm surface water pool is moved more east. This contributes to dry climate in Asia, which may even result in forest fires and severe droughts [6]. Meanwhile the warm surface waters that have moved eastward lead to cloud formation and rainfall over South America. However, what phase ENSO is in may also affect weather in other parts of the world as well. For example, there has been observations made of an effect on the hurricane frequency in the Atlantic ocean. Therefore, great efforts have been made to describe this phenomenon [6].

2.2 Extreme heat

Extreme weather events have become more abundant due to climate change and extreme heat events are a type of extreme weather that have increased significantly in frequency [1] [12]. There have been studies that have shown a significant increase in both maximum and minimum temperatures in Euroasia since the 1950s [12]. An increasingly common phenomenon is heat waves. These events are characterized by unusually high temperatures during several days in a row and often have an adverse impact on mortality and morbidity [13]. This type of heat event also typically has a large impact on infrastructure and ecological systems. The public health is affected in several ways as for example, heat stress and a decline in thermal comfort [13]. When analyzing the relationship between extreme heat and mortality the conclusions from the analysis depend on how extreme heat events are defined [14]. Also, there are several confounding factors that can affect the outcome of the analysis. For example urbanization, living conditions, personal factors and personal protection can influence the results. Another factor that can have an influence is the air pollution which can affect the mortality in a region [14]. Cities tend to experience the effects of extreme heat events to a larger extent than the countryside. Since a global trend is an increased urbanization this may add an extra element of vulnerability during extreme heat events [13]. In recent years there has been an successive increase in literature describing preventative measures such as city planning and early warning systems [13].

2.2.1 Urban heat islands

The phenomenon of higher air temperatures in urban areas than in the surrounding countryside is called urban heat islands [13]. Urbanization comes with several advantages that have improved overall living standards, but it has also been a driving factor in climate change [15]. There is an increased vulnerability and increased risks regarding urban heat islands. This is associated with urbanization and the trend of urbanization seems to be increasing in the future [13]. Urban heat islands are characterized by high temperatures in the urban area and then progressively decreasing temperatures as one moves further away from the city [13] [15]. There are several reasons why this pattern can be observed. The thermal properties of the fabric in urban areas (concrete and asphalt) has a better ability to store heat than naturally occurring materials. This leads to that on warm summer days, the temperature of roofs and roads can be between 27 and 50 °C higher than the air temperature, thus heating the air. Moist surfaces and shaded areas on the other hand, tend to have the same temperature as the surrounding air, which is typical for rural areas [15]. Further, vegetation plays a large role in cooling during warm days. In an urban environment vegetation is usually not a common feature. Evapotranspiration and shade are both contributing to cooling effects compared to concrete surfaces that have the opposite effect [15]. Additionally, the buildings have a heating effect as well. Canyon radiative geometry refers to the fact that heat is trapped between buildings. When long wave radiation is emitted from concrete surfaces for example, it bounces back and forth between buildings and is ultimately absorbed into different urban materials. This lowers the effective albedo of the area and contribute to increasing temperatures since energy is absorbed into the materials, heating the air [15].

Some other effects contributing to the urban heat island phenomenon are anthropogenic heat sources and urban greenhouse effect. Anthropogenic heat sources include for example different combustion processes but also metabolic heat from animals and humans. Urban greenhouse effect refers to the fact that there is an increased level of air pollutants in the atmosphere above a city. These pollutants can contribute to the greenhouse effect by absorbing long wave radiation and emitting it again in random directions[15]. For example, carbon dioxide and methane are both greenhouse gasses that contribute to heating the surroundings.

2.2.2 UTCI

Many previous studies have used air temperature to investigate how climate change and heat waves affect mortality [16]. Though air temperature is a suitable and easy way to measure thermal climate, it does not provide all the details as other variables also have an impact on the body's heat balance and heat exchange with the environment. Some indices such as Physiologically equivalent temperature(PET), Wet-bulb globe temperature(WBGT) and also the universal thermal climate index(UTCI) have been used in other studies [16]. When it comes to the climate in Taiwan, it is suitable to include several meteorological factors rather than using only air temperature for example [17]. UTCI is calculated with several variables and is based on how the human body experiences the atmospheric conditions [18]. The thermal climate variables used to calculate the index are the following: air temperature, wind, radiation and humidity [18]. The way these atmospheric conditions affect the human body is then coupled to the air temperature of a reference environment that produces the same body heat strain. This index could be a more suitable metric than air temperature for predicting the effects of heat on health outcomes. Since the human body experiences temperature differently depending on other factors than temperature alone, UTCI can extend the model and include more variables that may affect human health. On the other hand, UTCI includes several weather variables that can be difficult to acquire [16]. This can cause some limitations and is mainly due to incomplete historical records from the weather stations [16]. The historical records do usually not include such detailed information as cloud coverage, wind speed and radiation. Further, a common problem is that weather stations are located by the city's airport and not in the city. Thereby the thermal climate that is observed at the weather station may not be completely representative for the inner city [16]. Due to the urban heat island effect, thermal climate in the inner city usually differs from the thermal climate outside the city core [15]. A way to avoid this problem is by using reanalysis data which is data complemented with modern weather forecasting methods. This is usually detailed enough to describe the thermal conditions in urban areas for an epidemiological study [16]. UTCI based on reanalysis data can be a suitable way of avoiding the problem of data availability which is what was done in this study.

2.2.3 Impact on human health

Human health is affected to a large extent by extreme heat and this has been known for centuries [19]. The incidence of mortality tend to increase during heat waves. For example, in Europe 2003 around 70 000 deaths are believed to have been caused by the extreme heat during the summer [19]. In 1995 there was a disastrous heat wave in Chicago that also had large consequences [20]. Further, previous studies have shown that a longer duration heat wave comes with a slight increased risk of mortality [20]. However, the main risk contribution comes from the peak temperature even if it is during a short duration [20] which also results in that mortality related to extreme heat has a short lag period [14]. This can be seen as a result of a harvest effect when a part of the population that is susceptible to an exposure is deceased in an early stage, giving a lowered incidence of mortality in the following period [20]. Additionally, the thermoregulation of the body can adapt during periods of heat, making it easier for the population to cope with the heat after a few days. The risk of mortality also depends on how the extreme heat event is defined [8]. If the extreme heat event is defined more as a heat wave the relative risk(RR) tends to be increased. Also, if high percentiles are used to define extreme heat the RR seems to be increased as well [8]. Further, the risk of mortality related to temperature has different characteristics depending on the geographical location investigated [8]. In the US studies have found that cold extremes have a larger effect in southern parts of the country while northern parts are more affected by the heat extremes [8]. This pattern has been observed in Taiwan as well [8].

The body dissipates heat in several different ways. One of the main ways is by dilating blood vessels in the skin which mediates heat dissipation through convection, radiation, evaporation and conduction. Another way the body dissipates heat is by the sweating function where the evaporation process of water takes away energy from the body [21]. The cooling effectiveness of the sweating and evaporation function is dependent on the water vapor pressure(absolute humidity) between the skin and the air. In humid and hot conditions where the water vapor pressure gradient disappears no heat can be dissipated through evaporation of sweat [17]. As mentioned previously, humidity and air temperature in the southeast region of the pacific is dependent on ENSO which may be a significant indicator of the state of these variables.

2.2.4 Extreme heat in Taiwan

Taiwan is located in a subtropical region and has a rather humid climate [14]. Temperature related mortality has been less researched in subtropical and tropical regions [14]. The summer months are hot while the winter is characterized by mild weather [14]. In the period 1994 to 2003 the maximum daily temperature in the capital, Taipei, ranged from 20.6 to 38.8°C and a total of 13 heat events were identified when analysing the period [14]. In urban areas it is common that buildings have air conditioning which can have an effect on reducing mortality [14]. Wu et al. [14] studied the mortality incidence related to extreme temperatures (both hot and cold) and found an increased RR during extreme weather events. Another finding was that rural areas had a higher RR than the more urban areas which could be explained by the accessibility to healthcare resources and living conditions [14]. Diseases such as ischaemic heart disease, cerebrovascular diseases and hypertensive diseases constitute around 20% of the total deaths in Taiwan. Vulnerable subpopulations that have preexisting conditions are most of the times more susceptible to mortality when it comes to extreme incidents as heat waves and it is therefore important to identify these groups [14].

In a study done by Sung et al. [17] it was found that the 95th percentile heat index had a significant increase in the RR for mortality of various causes between 1995 and 2008 in the six largest cities in Taiwan. When investigating how the older population(people with an age over 65 years) was affected it was found that in five of the six cities there was an increased RR of dying due to heat exposure compared to the general population [17]. The highest increased RR due to heat exposure was found in Chiayi in west Taiwan. There the RR was found to be 1.21 when heat waves struck with a 95% confidence interval between 1.09 to 1.34 [17]. Some other factors that were identified to have an impact on the RR are urbanization and the related availability of medical supplies, age(old or very young) and ethnic group(for example aboriginal) [17]. Wu et al. [14] also concluded that the availability of medical resources was a contributing factor to the outcome of heat related illnesses. Further, low income populations were also found to have an increased RR, although, there were some deviations from the expectations of how much this would affect the outcome. This small deviation could be explained by that low income areas was found in smaller cities that may not experience as large heat island effects [17]. Additionally the use of heat index was a suitable choice compared to average ambient temperature since this becomes a better prediction of how the body dissipates heat in the type of climate that is typical for Taiwan [17]. A weakness with the study that Sung et al. [17] identified is that environmental differences between regions have not been taken into account. Thereby, the 95th percentile of heat index could be different in the different regions in Taiwan [17].

In a study by Lin et al. [8] there was no significant increase in RR for mortality caused by respiratory and circulatory diseases during heat events among elderly while using a confidence interval of 95%. Although there was no significance, the risk was found to be larger for circulatory diseases than respiratory [8]. The results indicated a V-shaped relation between RR and temperature. The least risk was found at a temperature between 25-27 °C with an average of 26 °C in the four cities investigated[8]. The mortality for elderly was found to be larger for extreme cold than warm temperatures. The authors also discussed that other causes of death may overshadow circulatory and respiratory illnesses during extreme temperature events [8].

2.2.5 Risk groups

The elderly population is more susceptible to heat related illnesses. However, there is an increased risk for all different age categories [19] [21]. The reason for the increased risk among elderly is that the ability to dissipate heat is reduced when we get older [21]. This is due to the sweating function and the pumping function of the heart being reduced with increasing age[21]. Blood vessels in the skin are dilated to exchange the heat with the environment when it is warm. The reduced pumping function of the heart leads to lowered dissipation of heat since the blood flow in the skin is consequently reduced as well [21]. Further, children are also susceptible to heat related illnesses since the sweating function does not develop fully until teenage years [21]. The majority of deaths related to heat stress occur in the home environment [21]. Therefore, socio-economic factors can play an essential role. The outcome may depend on factors such as air conditioning, type of building and social isolation [21]. This makes low and middle class homes face a larger risk of heat related mortality. Another factor that also plays a major role is , as mentioned above, whether an individual has any underlying conditions or not. Respiratory illnesses may impair the ability to dissipate heat through respiration, which tends to result in hyperventilation [4]. Diabetes can also lead to complications in the case of extreme heat [4]. The blood flow in the skin may be affected by this condition and thereby also the ability to dissipate heat this way. There are also some metabolic complications associated with diabetes that may further increase the susceptibility to hyperthermia [4]. Cardiovascular diseases makes individuals more sensitive to changes in blood viscosity which may increase the risk of mortality. This is also true for various diseases affecting specifically the heart [4]. Additionally, psychiatric diagnoses can increase the susceptibility to heat illnesses. The individual may not have the same awareness of the situation or the medications can have some influence on the ability to dissipate heat [4].

2.3 Risk metrics

An usual definition of risk is to answer the so-called risk triplet that consists of three simple questions. These are usually defined as following: “What can happen?”, ”How likely is it?”, and ”What will the consequences be, should this happen?” [22]. An important aspect when communicating risks is how to measure it and display it. There are several ways to describe risk with metrics and the choice of risk metric is dependent on who the receiver of the information is. Depending on if it is someone familiar with risk sciences and the current subject or if it is someone who is not as familiar with the concepts the risk needs to be presented differently. Risk metrics can be divided into three different categories namely: qualitative, semi-quantitative and quantitative risk metrics [22].

2.3.1 Qualitative risk metrics

Qualitative risk metrics are describing risk without any specific numbers but more in a comparative sense. This type of metric can be useful to visualize different risks and to give an understandable overview of different scenarios. One type of qualitative risk metric is the risk matrix. This type of matrix is usually divided into five steps on the x-axis and five steps on the y-axis [22]. The scales are then graded. The x-axis contains consequences described qualitatively as for example: mild, somewhat severe, severe and catastrophic etc. The y-axis is usually divided into different categories regarding frequency such as rarely, moderate, frequent etc. Thereby, scenarios that are depicted in the top right corner of the matrix are both frequent and of catastrophic character. Therefore, these need to be prioritized [22]. An example of what a risk matrix can look like is found in the following figure:

Likelihood	Consequence: Negligible 1	Minor 2	Moderate 3	Major 4	Catastrophic 5
5 Almost certain	Moderate 5	High 10	Extreme 15	Extreme 20	Extreme 25
4 Likely	Moderate 4	High 8	High 12	Extreme 16	Extreme 20
3 Possible	Low 3	Moderate 6	High 9	High 12	Extreme 15
2 Unlikely	Low 2	Moderate 4	Moderate 6	High 8	High 10
1 Rare	Low 1	Low 2	Low 3	Moderate 4	Moderate 5

Figure 2: A standard type of risk matrix which can be used to illustrate what scenarios should be prioritized when deciding on preventative measures after a risk analysis [23].

2.3.2 Semi-quantitative risk metrics

This type of risk metrics are similar to the qualitative metrics but some kind of estimation of frequency and consequences is being used [22]. This could for example be a similar risk matrix as mentioned above but the y-axis includes numeric estimations of the frequency such as times per year and the x-axis has some estimation of the consequences such as number of fatalities. An example of an semi-qualitative risk matrix is shown in the figure below:

Likelihood or frequently	Severity or consequence: Insignificant or no impact – Rating: 1	Minor compliance impact – Rating: 2	Moderate aesthetic impact – Rating: 3	Major regulatory impact – Rating : 4	Catastrophic public health impact – Rating: 5
Almost certain/ Once a day – Rating: 5	5	10	15	20	25
Likely / Once a week – Rating: 4	4	8	12	16	20
Moderate / Once a month – Rating: 3	3	6	9	12	15
Unlikely / Once a year – Rating: 2	2	4	6	8	10
Rare / Once every 5 years – Rating: 1	1	2	3	4	5
Risk Score	<6	6-9	10-15	>15	
Risk rating	Low	Medium	High	Very High	

Figure 3: A semi-qualitative risk matrix which includes both qualitative and quantitative scales to describe different scenarios [24].

2.3.3 Quantitative risk metrics

This type of risk metric is on the other hand based on numerical estimations of the risk. This can be done in several ways and can be everything from just one simple number such as the expected number of fatalities for a specific event to rather complicated graphs displaying several scenarios at once. Depending on who the risk is being presented to, different risk metrics are more or less suitable [22].

One of the most comprehensive risk metrics is the *FN-curve* which includes consequences on the x-axis and cumulative frequency on the y-axis. The metric is informative and can provide more detail of the analysis than for example an expected number of fatalities [22]. The cumulative frequency can be viewed as the frequency of a certain consequence or something more severe happening. This means that for the most severe event, the cumulative frequency is simply the frequency for the event itself. For a less severe event, the cumulative frequency is the sum of the frequencies of the more severe events and the frequency of the event itself [22]. This way, the FN-curve provides detailed information about all scenarios included in the risk analysis. This can be a powerful way of communicating risk in reports that have a more technical character. However, when communicating with stakeholders that do not have experience of risk analysis the FN-curve can be too intricate and another more easily understandable metric may be more suitable. Further, a line can be drawn in the FN-curve (usually from top left corner to bottom right corner) to represent a limit that the risk is not allowed to exceed [22]. This can be regarded as the bound to the unacceptable risk area [25] (see figure 4). If the FN-curve exceeds the acceptable risk, some risk mitigating measures need to be applied before the analysis can be done again to see if the risk is acceptable this time. Another line which delimits the area in which the risk is acceptable can be drawn. The area in between the acceptable and the unacceptable risk area is called the "as low as reasonably possible(ALARP)" area [25]. An example of a FN-curve is shown below:

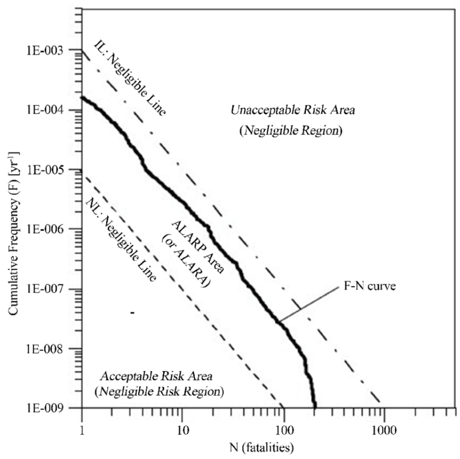

Figure 4: An example of what an FN-curve can look like [25].

Another commonly quantitative risk metric is *location specific individual risk.* This metric displays the risk associated with one or several scenarios tied to a specific geographical location [22]. It could be the risk of an individual dying, risk of the area being flooded or risk of the area experiencing extreme heat as a couple of examples. Usually, individual risk is presented on a map which means that the frequency or probability need to be converted into this format instead [22]. If a certain part of the map is exposed to several scenarios then the location specific individual risk for that particular area is the sum of these scenarios. The unit is usually given as per year(or another time unit) or simply as a probability [22]. If the frequency is given per year, this can be viewed as the risk for an individual to experience the unwanted scenario when staying on the location for one year.

2.3.4 Risk metrics in basic epidemiology

Furthermore, it is of interest in this theory section to define some epidemiological basic concepts. Two key concepts that are usually common in these contexts are prevalence and incidence. Prevalence can be defined as the number of people that have a certain condition at a specific time. This can be modified to prevalence density which is how many people have this condition per 1 000, 10 000, 100 000 etc. people [26]. Incidence is a similar concept but is defined as the rate that people become ill. This can be expressed as the number of people that get a certain condition per day. This is usually also normalized to be expressed per 1 000, 10 000, 100 000 etc. people [26]. When calculating prevalence and incidence it is important to remember that the population may change over time. If so, the value in the midst of the time period is used as the population size [26] or the data needs to be normalized against the population size with as high resolution as is available.

Additionally, it is relevant to define mortality rate since it is a term that is frequently used in this context. Mortality usually refers to deaths of all causes. This is more useful if it is described as a density as well [26]. The mortality rate(or sometimes crude death rate) is in this case the same as incidence although the outcome is death rather than only contracting a disease or a specific health condition. Mortality rate can refer to all deaths regardless of cause per time unit. However, it can also be for a specific cause of death, for example heart failure [26].

There are several ways to characterize differences in mortality or disease in an exposed and an unexposed group. An important concept that is commonly used is the relative risk(RR). The risk of dying in a group of exposed individuals can be defined as the number of cases divided by the number of exposed individuals [26]. Where D in this case denotes deaths and E exposed individuals. Then the risk of dying can be described mathematically as following:

$$p = \frac{D \cap E}{E} \tag{1}$$

Similarly the risk of death in an unexposed group can be described in the same way. Here the denotation U is the unexposed group.

$$p' = \frac{D \cap U}{U} \tag{2}$$

Where p' is the risk of death in the unexposed group U. This can be used to calculate the RR [26]:

$$RR = \frac{p}{p'} \tag{3}$$

Hence, the RR is defined as the ratio between the risk of dying when exposed and the risk of dying when not exposed [26]. If the relative risk is greater than 1 the exposure increases the risk of death. If one wishes to express the difference in risk level between exposure and non exposure this can be done by simply subtracting the two risks according to the following equation [26]:

$$\Delta Risk = p - p' \tag{4}$$

Where $\Delta Risk$ in this case represents the risk difference. Another common way of describing risk is odds. Normally this is expressed as an odds ratio(OR) between the odds of death for an exposed group and an unexposed group [26]. To clarify, the odds, q, will be described below for the exposed group:

$$q = \frac{p}{1-p} \tag{5}$$

The odds for the unexposed group, q' is calculated in the same way as q. Then the OR can be described as following:

$$OR = \frac{\frac{p}{1-p}}{\frac{p'}{1-p'}} = RR \cdot \frac{1-p'}{1-p} \tag{6}$$

In a similar sense as for the RR, the value of OR tells how exposure affects the population. If $OR > 1$ the exposure increases the risk of death (or sickness). If $OR < 1$ the risk of death is decreased by the exposure [26]. The OR is not as suitable for public health surveys as the RR [26]. OR is most suited for case-control studies where the disease that is investigated is rare. Additionally, if the OR is small the value will be close to the RR [26].

2.4 Risk perception and risk perspective

How risk is perceived can be complex and vary greatly between different groups in society. Many factors play in and affect the way the public perceive a specific risk [27]. Thereby, there is not a consensus regarding what risks are considered "high" and should be prioritized. The risk perception in society is often complex and depends on different qualitative factors. This has led to some misunderstandings between professionals and laymen during the years since a common way of communicating risk is in a quantitative manner with probabilities and expected numbers of fatalities [27]. Thereby, the public's view is many times not compatible with the view of the professionals which results in a conflict between these groups [29]. This conflict leads to a belief from the professional side that the public's view is built on ignorance and irrationality. However, this is not necessarily true but several psychological factors that are not included in the classical risk assessment forms the perception of the public. Factors such as if the exposure to the risk is involuntarily or not, if it is controllable, what groups are exposed, dread and if there is inequity in the distribution of the risk all affect how people perceive the risk [29]. Although quantitative risk analysis is important, other perspectives are needed to answer more complex questions than just the ones regarding probabilities. For example, is it worse when 50 people die in a plane crash or in 50 different traffic related accidents? The general public might perceive the plane crash scenario as worse due to the catastrophic nature of the accident [27]. Thereby, the risk is not always perceived in a way proportional to the quantitative measure of the consequences. Garrick [28] described the concept of "technological stigma" which is when some specific technologies get labeled by the public as specially dangerous even though the risk for the unwanted scenario is small [28]. Such stigma can be induced by extensive media coverage which tends to be put together by people who are not familiar with the nature of the risk and the context in which it is acting [28]. The public's risk perception is in many cases determining where resources used for prevention are directed which can be in another direction than where experts think [29]. Again, this can be exemplified with traffic where many people are killed each year and the safety investments are relatively small compared to the safety investments made to prevent fatalities from chemical toxins, which causes fewer deaths in total [29]. When it comes to natural disasters such as floods and storms the public risk perception seems to be that this risk is not extensive and thereby there is a low demand for protection [29]. Additionally, the public's risk perception will be affected by the way the risk is "framed" [29]. Framing refers to the way the risk is presented and this can influence decision makers in different ways. Slovic [29] exemplifies this issue by referring to previous studies where different ways of framing were presented. The risk of mortality compared to the chance of survival or the risk of contamination compared to the chance of no contamination happening exemplifies different ways of framing the same risk. In a previous study the framing made a significant difference and the test subjects were more prone to accept the risk if it was presented as the chance of survival rather than risk of dying [29].

There is already a subjective dimension in the risk assessment itself. The assumptions and structures that make up the theoretical models used to estimate risk are already, in a way, subjective [29]. For example defining consequences and deciding on what risk metrics shall be used requires several subjective decisions [29]. The traditional way of communicating risk through probabilities in technological settings has a drawback when it comes to transparency [30]. This way of describing risk does not allow insecurities to be shown to any greater extent. Further there is an element of surprise that is left out. Unexpected events called black swans can happen in such a way that is outside the analyst's control and can not be included in the analysis to begin with [30]. Risk management has in recent years started to head more in the direction of "the new risk perspective" which is a broader definition of risk. In this perspective the focus lies not on the technical probabilistic calculations but rather on the uncertainty regarding the risk [22]. To make the risk perspective broader the opinion of the public also needs to be considered. The definitions of risk, consequences and the way the risk is framed by the analyst will set the priorities for the preventive measures which may affect the public [29]. Thereby, an inclusion of the public makes the process more democratic and can underline the importance of considering subjective factors as well as the more quantitative ones [29].

3 Method

There are a myriad of different methods to analyse both weather data and health data. In this study the relation between air temperature and ENSO index(ONI) was investigated by using linear regression modelling. The relation between the risk for different health outcomes and UTCI was described by using a Poisson regression model. The analysis will be described thoroughly in this following section.

3.1 Data collection

The temperature records of observational data from Taiwan were acquired through the International Belmont AWARD-APR project. The data contained daily average, maximum and minimum air temperature for the different regions in Taiwan during the years 2008 to 2019. Additionally,the ONI time series was also acquired through the AWARD-APR project. This data was given as monthly three months moving average SST in the Niño 3.4 region. The data for health outcomes was acquired through contacts in the AWARD-APR project as well and was given as the daily number of cases of the ICD10 codes in question (see Aim). This data also included population data for the different regions in Taiwan. Also, for the health analysis air pollution data was used which was also acquired through the AWARD-APR project. For some of the regions data from a specific year was missing and therefore this particular year was excluded from the analysis for that region. The UTCI data was acquired from a freely available database provided by Copernicus [18] where UTCI can be downloaded as netcdf files. The data in this study was for the years 2008 to 2019.

3.2 Data processing

Before the analysis of the relation between temperature and ONI was performed the data was processed and sorted in a suitable way. This was done by first extracting the data for the different regions for the period 2008-2019. The reason for choosing this time period was to base the analysis of the relation between air temperature and ENSO on the same time period as the analysis of the health data. Thereafter, the observed air temperature was sorted by season by a sorting algorithm written in MATLAB. The data was divided into four categories: JJA, SON, DJF and MAM which represents four different seasons (each letter in the acronyms representing a month). The next step was to extract the values that exceeded the 95-percentile heat in each seasonal category with another sorting algorithm. ONI was also sorted after season in the same fashion as the temperature data in a vector of the same order and length. A similar process was done when analyzing the monthly data.

The UTCI data was extracted from NC-files containing hourly data. Each day was represented by one NC-file. The extraction was done using a MATLAB code that can be found in appendix B. The hourly data was processed into average daily UTCI and maximum daily UTCI data since the health data was only available as daily data. The code used to extract and process the UTCI data can be found in appendix B.

3.3 ENSO and linear regression models

To describe the relation between extreme heat and ENSO, linear regression was used. If there is some more simple dependence or a specific trend in the data this can be observed. The relation that is being described is between a dependent variable(temperature) and an explaining variable(ONI) [31]. The explaining variable is assumed to be measured with high precision while the dependent variable has larger variance [31]. A linear regression model is a model where the correlation between the two variables can be described by a straight line [31] and this is what has been done in this study.

Say that the ONI can be described as $x_1, x_2, ..., x_n$ and the temperature as $Y_1, Y_2, ..., Y_n$. The the linear relation can be described as following [31]:

$$y_i = \alpha + \beta \cdot x_i + \epsilon_i \tag{7}$$

Where ϵ_i is a random deviance from the line and has the expected value of 0. This means that the expectation of Y_i can be described by equation 8 [31]:

$$E(y_i) = \alpha + \beta \cdot x_i \tag{8}$$

This is since ϵ is equal to 0 in this case. An important note to make is that y_i should be regarded as an observation of the random variable Y_i [31]. This means that the measured value will somewhat differ from the modelled line and can not be expected to be exactly the same as the value on the line. There are several reasons why a linear model is a reasonable place to start in an analysis. First of all, it is rather straight forward to create the model. Thereby, it can be determined whether there is a correlation between the variables or not [31]. Also, a linear model can be a good approximation over a shorter interval [31].

3.4 Creating the linear model

The method for deriving the linear model is called least squares criterion. The main goal is to make the squares of the distances from the observed values to the line as small as possible [31]. The first step to do this is to calculate the overall mean value of the observed values $y_1, y_2, ..., y_n$. This value is denoted $\bar{y}$ and is used as a horizontal line [31]. Then to quantify the spread of the measured values the total square sum(TSS) is calculated as following [31]:

$$TSS = \sum (y_i - \bar{y})^2 \tag{9}$$

The horizontal line created with $\bar{y}$ is then twisted around the point where the explaining variable has its mean value as well $(\bar{x}, \bar{y})$. The slope, β, where the sum of squares is smallest is the correct one which is supposed to be used. This is given by [31]:

$$\beta = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2} \tag{10}$$

The intersect with the y-axis, α, is given by:

$$\alpha = \bar{y} - \beta \bar{x} \tag{11}$$

The random deviance from the model that was mentioned above, ϵ_i is also called the residuals [31]. The predicted value of y in the model can be labeled $\hat{y}_i$. Then the residuals can be expressed as the difference between the observed value and the predicted value [31]:

$$\epsilon_i = y_i - \hat{y}_i \tag{12}$$

The residuals can then be used to estimate the error square sum(SSE). This is described with the following equations [31]:

$$SSE = \sum (y_i - \hat{y}_i)^2 \tag{13}$$

The third quadratic sum that is necessary for the analysis is the regression square sum(SSR). This is calculated in a similar way [31]:

$$SSR = \sum (\hat{y}_i - \bar{y}_i)^2 \tag{14}$$

The three different square sums that have been described above can be linked together [31]:

$$TSS = SSR + SSE \tag{15}$$

To know if the model is suitable it is necessary to quantify the suitability in some way. This can be done by calculating the coefficient of determination which is also known as the R^2-value [31]. How good the model is to the data can be described by the SSE. However, the SSE will be different for different data sets depending on size. Therefore, it is needed to normalize the SSE in some way. This can be done in the following way [31]:

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2} = 1 - \frac{SSE}{TSS} \tag{16}$$

If the R^2-value is close to 1 the fit is suitable, if it is close to 0 or even negative this model is not a good prediction of the data [31]. R^2 explains how much of the variance is explained by the model. If $R^2 = 0.95$, 95% of the data is explained by the model and 5% is explained by the residuals [31].

Lastly the standard error(SE) was used to create a 95% confidence interval for the correlation coefficient of the linear model. The interval was defined as $CI = \beta \pm SE \cdot 1.96$. The values that were positive or negative through the whole 95% confidence interval(interval does not include 0) were considered to be positive or negative with confidence. The R^2-values were used as a reference to compare how strong the correlation was for the different regions and data sets.

3.5 Time series analysis

The time series analysis requires availability of health data, such as mortality incidence for a specific region. In this study, incidence of death caused by X30: exposure to excessive natural heat, X32: exposure to sunlight, I50.0: Congestive heart failure, I50.1: Left ventricular failure and I50.9: Heart failure (unspecified) was used. To describe the time series in an adequate way a generalized linear model was applied. Poisson regression was used in a similar fashion of how Oudin Åström et al. used it to analyze the mortality in relation to heat in Stockholm during the 20th century [19].

Since the size of the population is changing along with other demographic changes such as improved health care, habits and living conditions, the mortality rate is also changing. Therefore, the model needs to be able to vary to describe the long term changes in the mortality rate [19]. The model can be regarded as a baseline for the mortality [19]. However, more short term variations in the data can not be described by the model but rather by other factors such as extreme heat events or possibly some other confounding factor [19]. Overdispersion is when the variability of the empirical data is higher than the variation of the model. Ideally, possible confounders should be identified and excluded, although, such data might be hard to obtain [33]. Overdispersion can be a consequence of relevant variables not being included in the model. Other causes of overdispersion can be that the outcome variable does not have a relation to the explanatory variable that is well captured by the model [33]. In this study air pollution (NOx and PM10) was included in the model to account for the effects that this might have on the health outcomes.

3.5.1 Poisson regression

Regression models are used among many disciplines[32] and can as mentioned above be useful in this context as well [19]. Poisson regression is commonly used for a data set of the discrete counting type [34][32]. A dependent variable Y_i is influenced by several factors that affect the number of counts. These factors $x_{1,i}, x_{2,i}, ..., x_{k,i}$ all impact the dependent variable [34] [32]. A generalized way of describing the Poisson regression model can be seen in equation 17:

$$ln(\mu_i) = \beta_0 + \beta_1 x_{1,i} + \beta_2 x_{2,i} + ... + \beta_k x_{k,i} \tag{17}$$

In equation 17 μ_i is the expected value, or the mean value. The β-coefficients are estimated by maximum likelihood estimations and is usually done by a computer software [34]. In this study MATLAB was used to perform this task. Each x vector is used as a predictor and the index, i, is referring to a specific position in each vector. When the model is plotted the expected value, μ, is not logarithmic but instead displayed according to the following equation:

$$\mu_i = e^{\beta_0 + \beta_1 x_{1,i} + \beta_2 x_{2,i} + ... + \beta_k x_{k,i}} \tag{18}$$

Where each symbol in equation 18 is the same as in equation 17.

3.5.2 The Poisson regression model in this study

In this study the Poisson regression model will be based on UTCI, daily average temperature, air concentration of NO_x substances and the air concentration of PM10. Since UTCI includes several atmospheric parameters, these will also be accounted for in the model indirectly. The model can be written as following:

$$ln(incidence) = \beta_0 + \beta_1 \cdot UTCI + \beta_2 \cdot Temp + \beta_3 \cdot [NOx] + \beta_4 \cdot [PM10] \tag{19}$$

Where β_0, β_1, β_2, β_3 and β_4 are coefficients estimated in MATLAB and *incidence* is the total number of cases per day of the chosen ICD10 codes per 100 000 inhabitants($\frac{cases \cdot 100000}{day \cdot person}$). All individuals have different follow up time. By normalizing the count with the time and the number of inhabitants, the rate is described as an average without losing information [33]. The model which was created in MATLAB is shown below:

```
X1 =[utci avgT PM10 NOx]; %input data

b = glmfit(X1,incidence,'poisson');%model

yfit = glmval(b,X1,'log'); %values to the model
```

3.5.3 Estimation of relative risk

To estimate the relative risk the Poisson regression model was used. The model provided a time series of incidence estimations. These estimations were divided into different categories depending on what the UTCI level was during each day. The seven categories of UTCI were arbitrarily decided to <5, 5-10, 10-15, 15-20, 20-25, 25-30 and >30 °C. Then the mean incidence with accompanying 95% confidence interval was calculated for each category. To make an estimation of the RR the lowest mean incidence in each region was used as a reference point for that region. The other mean incidences were divided by this value. This was done for each of the 15 regions. For some of the regions there were no values in some of the UTCI intervals. Therefore, no risk could be estimated for this particular interval. For example in Nantou, there were no values for UTCI in the intervals <5 and >30 °C. Therefore these intervals had to be excluded for this particular region. In figure 5 a histogram showing how the UTCI data is distributed for Nantou can be seen.

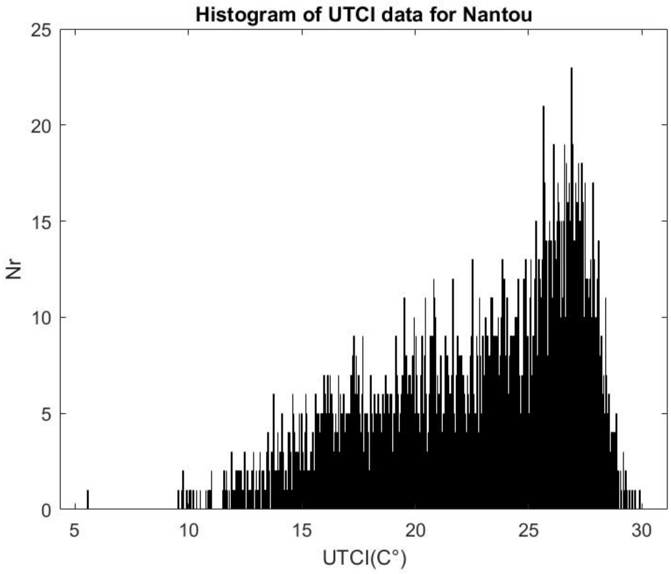

Figure 5: Histogram showing the distribution of UTCI data in Nantou.

Also, an analysis was made based on the categories defined as different levels of thermal stress based on UTCI. The categories included were slight cold stress(0 - 9 °C), no thermal stress (9 - 26 °C), moderate heat stress(26 - 32 °C) and strong heat stress(32 - 38 °C) [18]. The definition of the different categories can be seen in figure 6. The RR was based on the incidence in the category defined as "no thermal stress" in comparison in each of the regions.

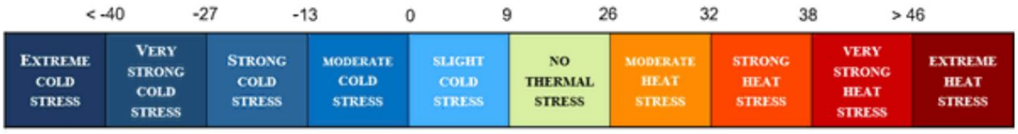

Figure 6: Different categories of thermal stress defined for given UTCI intervals [18].

3.5.4 Assumptions of the model

There were several assumptions made for the Poisson regression model. It was assumed that the variables included in the model describe the incidence in a suitable way. This is most likely not completely true as the relationship between number of cases and different factors is highly complex and cannot be described accurately with few variables. Further it is assumed that all individuals are exposed to the same level of risk which might not be true. Some may have access to air conditioning, heating or some other protection while others may be more vulnerable to high temperatures. Additionally there could be many different confounders that are not included that affect the outcome. Since these are not included in the model they are assumed to not influence the outcome variable to any larger extent. Although it is outside the scope of this study, it could improve the accuracy of the model to include more explanatory variables describing living conditions of the inhabitants.

4 Result

In the following section the results from the analysis will be presented. First, the relation between extreme heat and ONI and thereafter the relation between the health outcomes specified by the ICD10 codes and different UTCI intervals is shown. Also, there is an additional analysis between 95th percentile UTCI and ONI, monthly average air temperature and some more detailed analysis for the health outcomes in Hualien specifically.

4.1 Relation between 95th percentile average daily air temperature and ONI

The result from the analysis made with linear regression is seen below. The number of correlation coefficients between 95th percentile average daily air temperature and ONI that are positive or negative on a 95% confidence level is summarized in table 1. More detailed tables with all coefficients from the linear regression analysis can be found in the appendix C (Table 17 - 20).

Table 1: Correlation coefficients between 95th percentile average daily air temperature and ONI that are positive and negative respectively on a 95% confidence level. The analysis includes 15 regions in the time period 2008-2019.

Season	Number of positive correlations	Number of negative correlations
Summer	4	0
Autumn	2	3
Winter	0	0
Spring	0	0

During the summer months there is a positive correlation in Chunghua, Chiayi, Nantou and Pingtung on a 95% confidence level. For the other regions no trends at this confidence level were found. In the autumn there is 95% confidence for both positive and negative correlations. For Changhua and Taitung a positive correlation was found and for Chiayi, Tainan and Kaohsiung a negative correlation was found. For the winter and spring seasons it can be seen that no correlations are either positive or negative on a 95 % confidence level.

4.2 Relation between 95th percentile maximum daily air temperature and ONI

In this section the relation between 95th percentile maximum daily air temperature and ONI is displayed. The number of correlation coefficients that are positive or negative on a 95% confidence level is summarized in table 2 below. More detailed tables with all correlation coefficients for this analysis can be found in appendix C (Table 21 - 24).

Table 2: Correlation coefficients between 95th percentile maximum daily air temperature and ONI that are positive and negative respectively on a 95% confidence level. The analysis includes 15 regions in the time period 2008-2019.

Season	Number of positive correlations	Number of negative correlations
Summer	0	1
Autumn	1	2
Winter	0	0
Spring	1	0

In the summer, Taipei is the only region that has a correlation coefficient with a slope at 95% confidence. This correlation is negative. In the autumn Chiayi and Tainan have negative correlation and Hualien has a positive correlation on this confidence level. During the winter months non of the correlations are either positive or negative with confidence. For spring months Taoyuan exhibits a positive trend with confidence.

4.3 Relation between 95th percentile average daily UTCI and ONI

In the following section the relation between 95th percentile average daily UTCI and ONI will be presented. The number of correlation coefficients at 95% confidence are presented below. A more detailed representation of the correlations can be observed in appendix C (Table 25 - 28).

Table 3: Correlation coefficients between 95th percentile average daily UTCI and ONI that are positive and negative respectively on a 95% confidence level. The analysis includes 15 regions in the time period 2008-2019.

Season	Number of positive correlations	Number of negative correlations
Summer	0	1
Autumn	0	1
Winter	0	0
Spring	1	0

In the summer months there is one region that has a correlation on a 95% confidence level. This is Tainan which has a negative correlation. During the autumn months Kaohsiung has a negative correlation on a 95% confidence level. The winter season has no trends that are significant and during the spring the correlation coefficient for Hualien is positive on a 95% confidence level.

4.4 Relation between 95th percentile maximum daily UTCI and ONI

The following section contains the results from the analysis of the relation between 95th percentile maximum daily UTCI and ONI. The number of correlation coefficients that are positve or negative on a 95% confidence level is given below. More detailed analysis can be found in appendix C (Table 29 - 32).

Table 4: Correlation coefficients between 95th percentile maximum daily UTCI and ONI that are positive and negative respectively on a 95% confidence level. The analysis includes 15 regions in the time period 2008-2019.

Season	Number of positive correlations	Number of negative correlations
Summer	0	0
Autumn	0	0
Winter	0	1
Spring	0	0

In this analysis only one region has a correlation coefficient of 95% confidence and that is a negative correlation for Chiayi during the winter season.

4.5 Relation between monthly average temperature and ONI

The analysis found no correlation coefficients that were positive or negative with 95 % confidence. However, the correlation was strongest for the winter months(December, January and February) and for spring months(March, April and May) which can be observed in table 33 - 36 in appendix C. The mean correlation coefficient was found to be positive for all locations during the winter and during the spring. This indicate a positive trend between monthly average air temperature and ONI during winter and spring, although, this trend is very weak.

4.6 Monthly average temperature, elevation and ONI

In this section results for a fitted surface using a cubic spline are presented. This to display how elevation and ONI both together affects the monthly temperature.

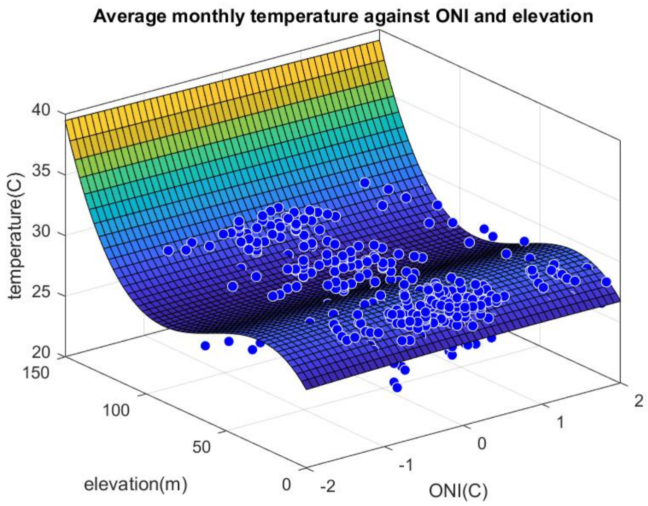

Figure 7: Monthly temperature against ONI and the elevation of each station together with a fitted surface. The figure is for summer months.

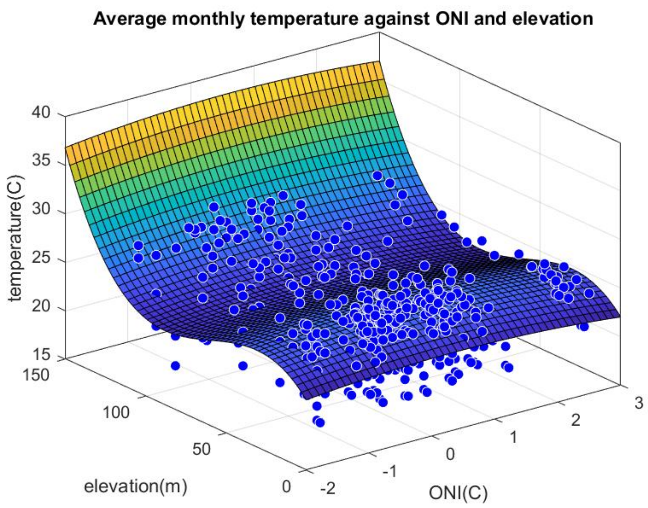

Figure 8: Monthly temperature against ONI and the elevation of each station together with a fitted surface. The figure is for autumn months.

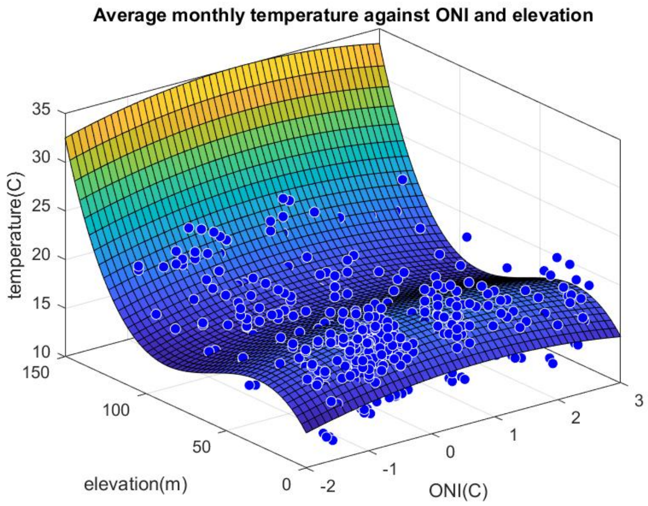

Figure 9: Monthly temperature against ONI and the elevation of each station together with a fitted surface. The figure is for winter months.

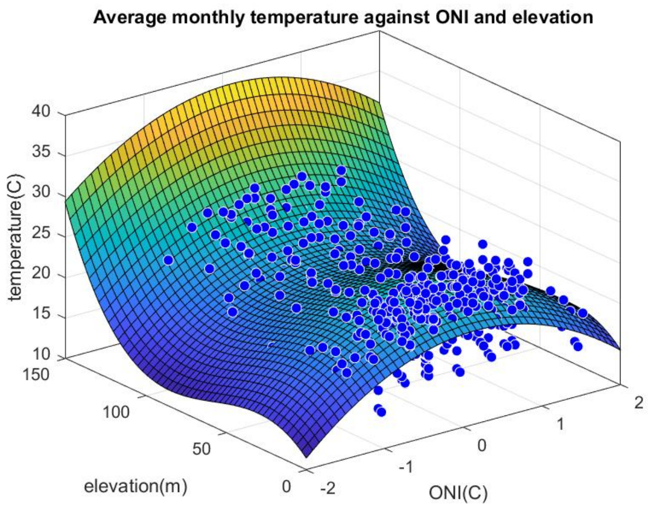

Figure 10: Monthly temperature against ONI and the elevation of each station together with a fitted surface. The figure is for spring months.

There seems to be no apparent pattern to be found. However, the temperature in the spring months (figure 10) seem to be higher when ONI is in a neutral state, i.e. around 0 °C. Elevation seems to not affect the temperature to any greater extent other than a tendency of higher elevation giving higher temperature. However, this high peak in temperature in the figures could be caused by the fitted spline having a positive slope which is due to the region Nantou having considerably lower temperatures than the other regions. Also, during the winter months a small positive trend between temperature and ONI can be seen in figure 9 which was also indicated in section 4.5.

4.7 Monthly average UTCI, elevation and ONI

In this section a cubic spline has been fitted for UTCI against ONI and elevation to visualize how these three variables interact.

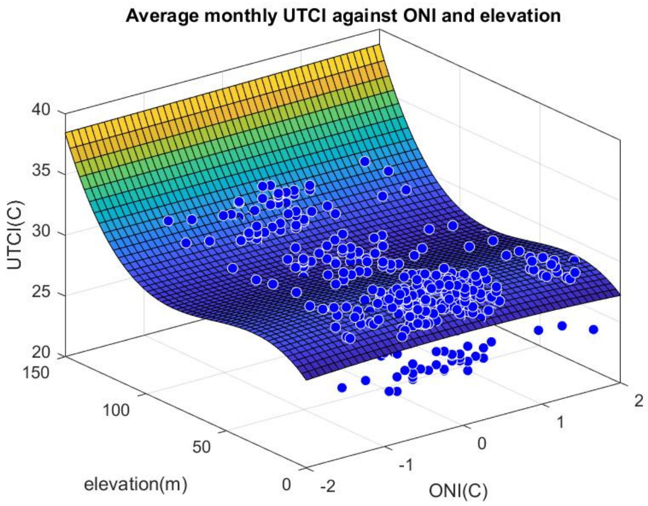

Figure 11: Monthly average UTCI against ONI and elevation with a fitted surface for all weather stations. The figure represents the summer months.

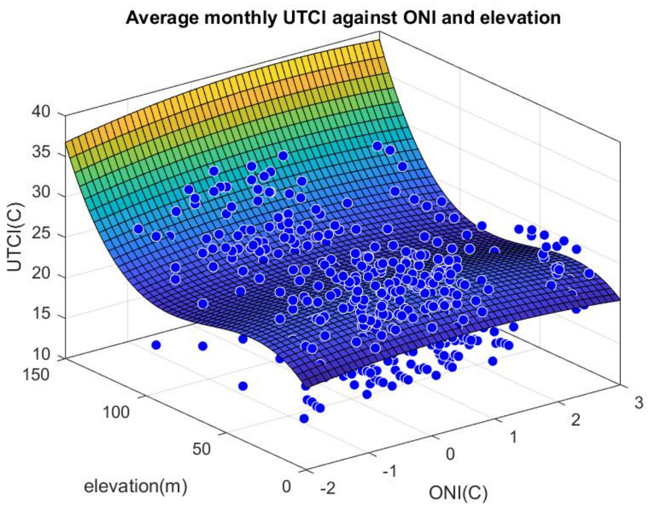

Figure 12: Monthly average UTCI against ONI and elevation with a fitted surface for all weather stations. The figure represents the autumn months.

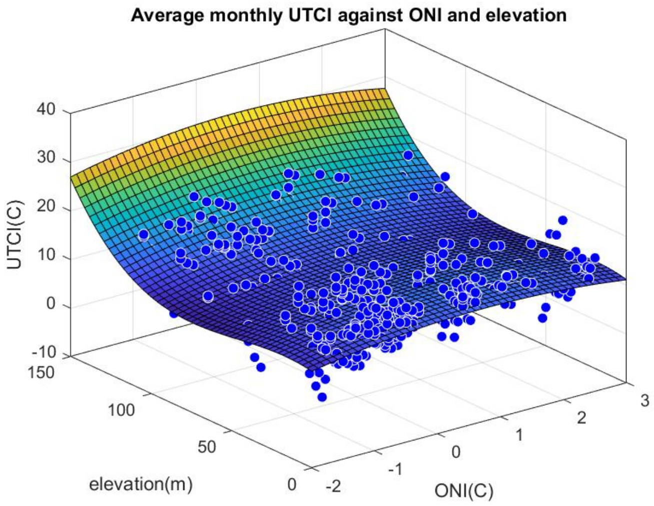

Figure 13: Monthly average UTCI against ONI and elevation with a fitted surface for all weather stations. The figure represents the winter months.

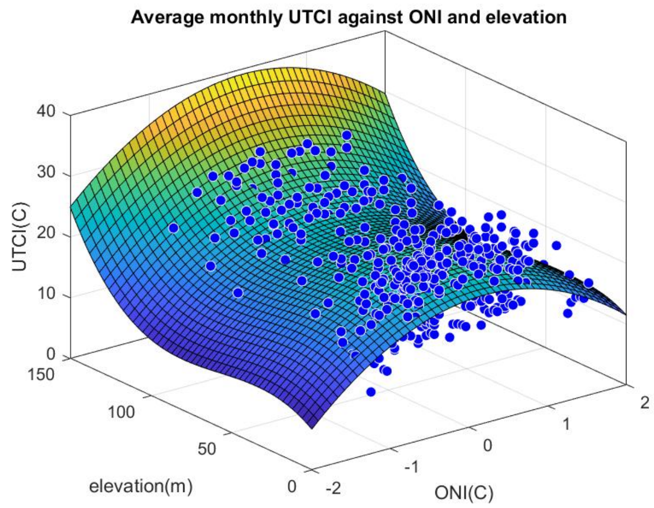

Figure 14: Monthly average UTCI against ONI and elevation with a fitted surface for all weather stations. The figure represents the spring months.

It seems that there is a slight tendency that higher elevation indicates higher UTCI. During the spring months it appears that neutral ONI yields higher UTCI. For UTCI, like temperature, Nantou has a lower average value than the other regions at similar elevation.

4.8 Health analysis

The results from the health analysis done with Poisson regression is presented in the following section. The RR is presented for different intervals of UTCI. The step of the intervals are 5 °C wide. The analysis is done for the regions New Taipei, Taipei, Taoyuan, Hsinchu, Miaoli, Taichung, Chunghua, Chiayi, Nantou, Tainan, Kaohsiung, Pingtung, Yilan, Hualien and Taitung. The RR is based on the lowest incidence in each region. This region can be distinguished since the RR for that region is equal to 1.

Table 5: RR suggested by the Poisson regression model presented for different UTCI intervals by region. In this table the results for New Taipei, Taipei, Taoyuan, Hsinchu and Miaoli are presented. The RR is based on the lowest incidence.

Location	UTCI interval(°C)	RR
New Taipei	< 5	1.2184 [0.7285 2.0396]
	5 - 10	1.2151 [0.6940 2.0886]
	10 - 15	1.1580 [0.6540 2.0027]
	15 - 20	1.0911 [0.6079 1.9012]
	20 - 25	1.0545 [0.5803 1.8495]
	25 - 30	1.0000 [0.5966 1.6763]
	$30 <$	1.0005 [0.6123 1.6513]
Taipei	< 5	1.1605 [0.7131 1.8054]
	5 - 10	1.1951 [0.7294 1.8665]
	10 - 15	1.1574 [0.6605 1.8739]
	15 - 20	1.0794 [0.6386 1.7150]
	20 - 25	1.0404 [0.6444 1.6112]
	25 - 30	1.0185 [0.6803 1.5060]
	$30 <$	1.0000 [0.6936 1.4417]
Taoyuan	< 5	1.3982 [1.1948 1.6243]
	5 - 10	1.3258 [1.0984 1.5787]
	10 - 15	1.2718 [1.0709 1.4953]
	15 - 20	1.2195 [0.9815 1.4842]
	20 - 25	1.1501 [0.9533 1.3689]
	25 - 30	1.0460 [0.8971 1.2115]
	$30 <$	1.0000 [0.8993 1.1120]
Hsinchu	< 5	1.3263 [1.1492 1.5177]
	5 - 10	1.2469 [1.1016 1.4040]
	10 - 15	1.2113 [1.0674 1.3668]
	15 - 20	1.1725 [1.0006 1.3584]
	20 - 25	1.1126 [0.9544 1.2836]
	25 - 30	1.0317 [0.9162 1.1566]
	$30 <$	1.0000 [0.9251 1.0810]
Miaoli	< 5	1.5176 [1.1844 1.9165]
	5 - 10	1.4347 [1.1078 1.8260]
	10 - 15	1.3884 [1.0229 1.8261]
	15 - 20	1.3316 [0.9142 1.8315]
	20 - 25	1.2030 [0.8421 1.6351]
	25 - 30	1.0401 [0.7797 1.3520]
	$30 <$	1.0000 [0.8351 1.1974]

Table 6: RR suggested by the Poisson regression model presented for different UTCI intervals by region. In this table the results for Taichung, Chunghua, Chiayi, Nantou and Tainan are presented. RR is based on the lowest incidence. "-" indicates no data.

Location	UTCI interval(°C)	RR
Taichung	< 5	1.2571 [1.1301 1.3944]
	5 - 10	1.2110 [1.0923 1.3392]
	10 - 15	1.1931 [1.0459 1.3523]
	15 - 20	1.1596 [0.9908 1.3419]
	20 - 25	1.0936 [0.9454 1.2538]
	25 - 30	1.0268 [0.9170 1.1454]
	$30 <$	1.0000 [0.9254 1.0806]
Chunghua	< 5	1.2217 [0.8437 1.7294]
	5 - 10	1.1249 [0.7540 1.6231]
	10 - 15	1.0527 [0.6727 1.5629]
	15 - 20	1.0206 [0.6478 1.5214]
	20 - 25	1.0001 [0.6658 1.4490]
	25 - 30	1.0091 [0.7242 1.3916]
	$30 <$	1.0000 [0.7446 1.3429]
Chiayi	< 5	1.2900 [0.9462 1.6740]
	5 - 10	1.2178 [1.0036 1.4571]
	10 - 15	1.1477 [0.9439 1.3753]
	15 - 20	1.0770 [0.9035 1.2707]
	20 - 25	1.0325 [0.8590 1.2263]
	25 - 30	1.0162 [0.8777 1.1708]
	$30 <$	1.0000 [0.8954 1.1168]
Nantou	< 5	-
	5 - 10	1.5123 [0.9109 2.2562]
	10 - 15	1.2809 [0.9412 1.7012]
	15 - 20	1.1535 [0.8573 1.5199]
	20 - 25	1.0641 [0.7750 1.4218]
	25 - 30	1.0000 [0.8085 1.2369]
	$30 <$	-
Tainan	< 5	1.6004 [0.6318 3.5945]
	5 - 10	1.3730 [0.6616 2.8379]
	10 - 15	1.1961 [0.5455 2.5357]
	15 - 20	1.0591 [0.4897 2.2314]
	20 - 25	1.0000 [0.4857 2.0589]
	25 - 30	1.0484 [0.5735 2.0260]
	$30 <$	1.0793 [0.6602 1.9420]

Table 7: RR suggested by the Poisson regression model presented for different UTCI intervals by region. In this table the results for Kaohsiung, Pingtung, Yilan, Hualien and Taitung are presented. *The model in Pingtung and Hualien only had one value in the category <5 °C and therefore no confidence interval could be given. RR is based on the lowest incidence. "-" indicates no data.

Location	UTCI interval(°C)	RR 95% CI
Kaohsiung	< 5	1.3461 [1.1157 1.5919]
	5 - 10	1.2248 [1.1025 1.3552]
	10 - 15	1.1738 [1.0703 1.2842]
	15 - 20	1.1157 [1.0206 1.2172]
	20 - 25	1.0645 [0.9815 1.1530]
	25 - 30	1.0257 [0.9454 1.1112]
	30 <	1.0000 [0.9378 1.0663]
Pingtung	< 5	1.4294*
	5 - 10	1.2694 [1.0599 1.4936]
	10 - 15	1.1562 [1.0367 1.2841]
	15 - 20	1.0966 [0.9911 1.2094]
	20 - 25	1.0529 [0.9501 1.1629]
	25 - 30	1.0231 [0.9381 1.1140]
	30 <	1.0000 [0.9345 1.0701]
Yilan	< 5	1.0921 [0.8767 1.3434]
	5 - 10	1.0687 [0.8436 1.3311]
	10 - 15	1.0677 [0.8263 1.3493]
	15 - 20	1.0693 [0.8029 1.3799]
	20 - 25	1.0486 [0.7901 1.3502]
	25 - 30	1.0050 [0.8057 1.2374]
	30 <	1.0000 [0.8574 1.1663]
Hualien	< 5	1.3880*
	5 - 10	1.2738 [1.1759 1.3771]
	10 - 15	1.1978 [1.0976 1.3036]
	15 - 20	1.1276 [1.0283 1.2322]
	20 - 25	1.0412 [0.9479 1.1396]
	25 - 30	1.0000 [0.9477 1.0552]
	30 <	-
Taitung	< 5	1.0000 [0.7494 1.3345]
	5 - 10	1.0218 [0.7420 1.3952]
	10 - 15	1.0300 [0.7658 1.3827]
	15 - 20	1.0447 [0.7753 1.4042]
	20 - 25	1.0555 [0.8155 1.3757]
	25 - 30	1.0492 [0.7870 1.3991]
	30 <	1.0605 [0.8421 1.3519]

As can be observed in table 5 - 7 the RR for the ICD10 codes in question seems to increase with decreasing UTCI. However, for Tainan the RR is lowest in the UTCI interval 20 - 25 °C and for Taitung the RR seems to increase with with increasing UTCI. Another representation of the RR is presented in figure 15 below:

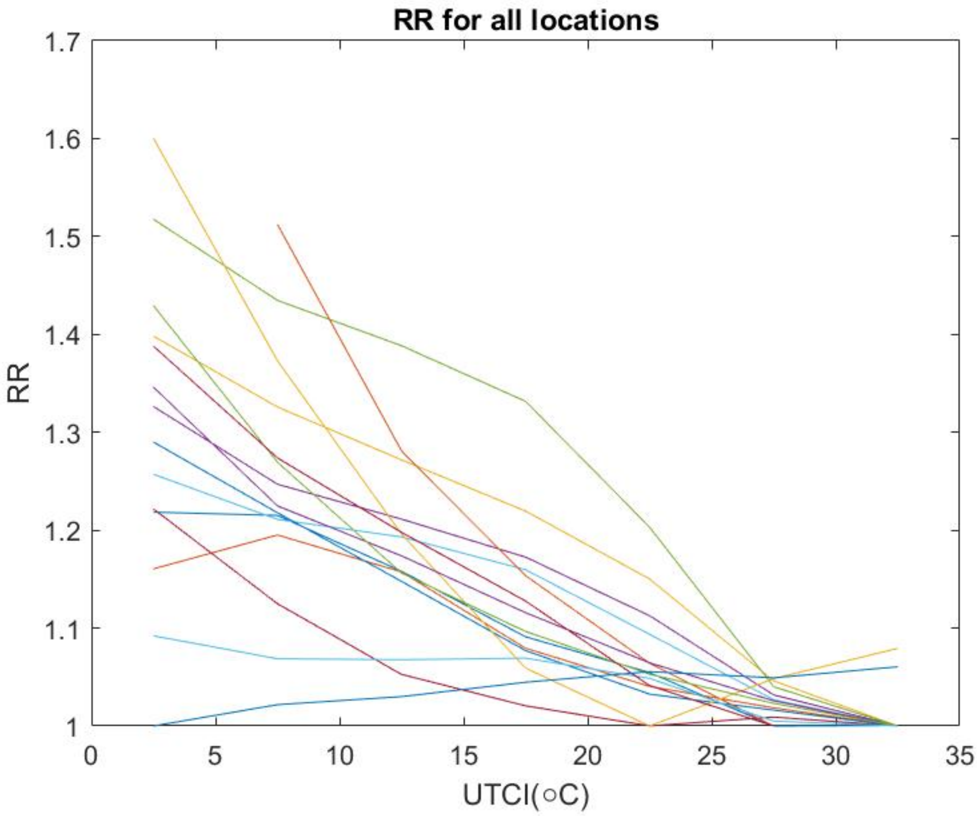

Figure 15: Mean RR for the different regions shown at the same time. Each location's RR is based on the lowest incidence in that specific region and therefore the comparison between the locations can not be made in this figure. This is meant to illustrate the general trend of how the RR is affected by UTCI.

4.8.1 RR for UTCI categories defined by thermal stress

In this section the RR for the UTCI categories defined in figure 6 is presented for each of the regions. In Taiwan, 4 categories of UTCI are occurring according to this definition: slight cold stress, no thermal stress, moderate heat stress and strong heat stress. In table 8 - 10 the results are presented for this definition of thermal stress with the category "no thermal stress" used as a comparison.

Table 8: RR suggested by the Poisson regression model presented for UTCI intervals by region. In this table the results for New Taipei, Taipei, Taoyuan, Hsinchu and Miaoli are presented. The RR is based on the interval that is defined as "No thermal stress" in each region. No data is indicated by "-".

Location	UTCI interval(°C)	RR 95% CI
New Taipei	slight cold stress(0 - 9)	1.1231 [0.6182 2.0867]
	no thermal stress(9 -26)	1.0000 [0.5240 1.9085]
	moderate heat stress(26 - 32)	0.9129 [0.5291 1.6455]
	strong heat stress(32 - 38)	-
Taipei	slight cold stress(0 - 9)	1.1030 [0.6152 2.0218]
	no thermal stress(9 -26)	1.0000 [0.5309 1.8837]
	moderate heat stress(26 - 32)	0.9378 [0.5695 1.6315]
	strong heat stress(32 - 38)	-
Taoyuan	slight cold stress(0 - 9)	1.1236 [0.8676 1.4834]
	no thermal stress(9 - 26)	1.0000 [0.7119 1.4048]
	moderate heat stress(26 - 32)	0.8524 [0.6678 1.1118]
	strong heat stress(32 - 38)	0.8153 [0.6639 1.0281]
Hsinchu	slight cold stress(0 - 9)	1.1005 [0.8905 1.3729]
	no thermal stress(9 -26)	1.0000 [0.7712 1.2966]
	moderate heat stress(26 - 32)	0.8794 [0.7294 1.0739]
	strong heat stress(32 - 38)	0.8570 [0.7389 1.0101]
Miaoli	slight cold stress(0 - 9)	1.1318 [0.7579 1.7813]
	no thermal stress(9 -26)	1.0000 [0.5758 1.7368]
	moderate heat stress(26 - 32)	0.7936 [0.5297 1.2520]
	strong heat stress(32 - 38)	0.7657 [0.5672 1.1106]

Table 9: RR suggested by the Poisson regression model presented for UTCI intervals by region. In this table the results for Taichung, Chunghua, Chiayi, Nantou and Tainan are presented. The RR is based on the interval that is defined as "No thermal stress" in each region. No data is indicated by "-". *Only 1 value was in this category and therefore it is not possible to give a CI.

Location	UTCI interval(°C)	RR 95% CI
Taichung	slight cold stress(0 - 9)	1.0802 [0.8954 1.3203]
	no thermal stress(9 -26)	1.0000 [0.7702 1.2984]
	moderate heat stress(26 - 32)	0.8936 [0.7425 1.0898]
	strong heat stress(32 - 38)	0.8719 [0.7490 1.0315]
Chunghua	slight cold stress(0 - 9)	1.1365 [0.7034 1.8670]
	no thermal stress(9 -26)	1.0000 [0.5929 1.6866]
	moderate heat stress(26 - 32)	0.9834 [0.6551 1.5372]
	strong heat stress(32 - 38)	0.9824 [0.6682 1.5123]
Chiayi	slight cold stress(0 - 9)	1.1530 [0.8481 1.5625]
	no thermal stress(9 -26)	1.0000 [0.7445 1.3432]
	moderate heat stress(26 - 32)	0.9453 [0.7609 1.1929]
	strong heat stress(32 - 38)	0.9127 [0.7468 1.1356]
Nantou	slight cold stress(0 - 9)	1.6365*
	no thermal stress(9 -26)	1.0000 [0.6372 1.5694]
	moderate heat stress(26 - 32)	0.9006 [0.6668 1.2676]
	strong heat stress(32 - 38)	-
Tainan	slight cold stress(0 - 9)	1.3568 [0.6176 3.0399]
	no thermal stress(9 -26)	1.0000 [0.4392 2.2768]
	moderate heat stress(26 - 32)	0.9989 [0.5574 2.0041]
	strong heat stress(32 - 38)	1.0279 [0.6293 1.9356]

Table 10: RR suggested by the Poisson regression model presented for UTCI intervals by region. In this table the results for New Taipei, Taipei, Taoyuan, Hsinchu and Miaoli are presented. The RR is based on the interval that is defined as "No thermal stress" in each region. No data is indicated by "-".

Location	UTCI interval(°C)	RR 95% CI
Kaohsiung	slight cold stress(0 - 9)	1.1427 [0.9647 1.3557]
	no thermal stress(9 -26)	1.0000 [0.8360 1.1962]
	moderate heat stress(26 - 32)	0.9330 [0.8172 1.0715]
	strong heat stress(32 - 38)	0.9113 [0.8160 1.0253]
Pingtung	slight cold stress(0 - 9)	1.2824 [0.2506 2.5040]
	no thermal stress(9 -26)	1.0000 [0.8447 1.1838]
	moderate heat stress(26 - 32)	0.9498 [0.8343 1.0866]
	strong heat stress(32 - 38)	0.9149 [0.8180 1.0296]
Yilan	slight cold stress(0 - 9)	1.0139 [0.7317 1.4228]
	no thermal stress(9 -26)	1.0000 [0.6902 1.4488]
	moderate heat stress(26 - 32)	0.9427 [0.7030 1.2900]
	strong heat stress(32 - 38)	-
Hualien	slight cold stress(0 - 9)	1.1711 [0.9746 1.4299]
	no thermal stress(9 -26)	1.0000 [0.7595 1.3167]
	moderate heat stress(26 - 32)	0.9046 [0.7753 1.0750]
	strong heat stress(32 - 38)	-
Taitung	slight cold stress(0 - 9)	0.9669 [0.7040 1.3122]
	no thermal stress(9 -26)	1.0000 [0.7610 1.3140]
	moderate heat stress(26 - 32)	1.0048 [0.7686 1.3151]
	strong heat stress(32 - 38)	1.0118 [0.8218 1.2616]

The trend in table 8 - 10 seems to be of similar character as the one in table 5 - 7. A difference is however that by using this definition of the UTCI intervals it seems that non of the relations are within the confidence limits(95%). For Tainan there is an increased RR for strong heat stress and slight cold stress and for Taitung there seems to be an increased RR with increasing UTCI. For the other regions it seems that lower UTCI indicates higher RR.

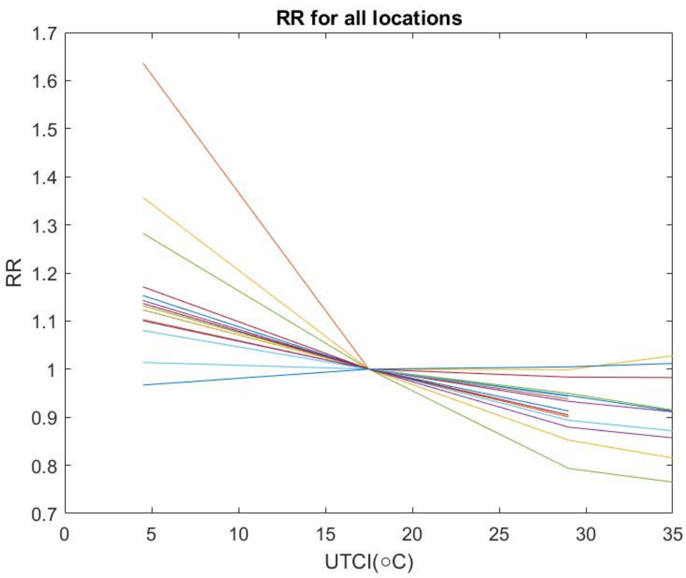

Figure 16: The mean RR for all the regions based on thermal stress categories in figure 6.

4.9 Specific health outcomes in Hualien

The Poisson regression model was also run for the ICD10 codes related directly to heat, X30: exposure to excessive natural heat and X32: exposure to sunlight, to see if there would be a difference in the RR. In table 11 and 12 the RR for these two health outcomes is presented for all ages and for 65+ years respectively.

Table 11: Mean RR suggested by the Poisson regression model presented for different UTCI intervals for Hualien for all ages. There are no confidence intervals given since there was too much variation in the model and therefore these results should be treated with caution and is only an indication of the trend. RR is based on lowest incidence. "-" indicates no data.

UTCI interval(°C)	mean RR
< 5	1.0000
5 - 10	9.5553
10 - 15	44.6183
15 - 20	137.9320
20 - 25	666.4061
25 - 30	919.9143
$30 <$	-

Table 12: Mean RR suggested by the Poisson regression model presented for different UTCI intervals for Hualien for the age group 65+. There are no confidence intervals given since there was too much variation in the model and therefore these results should be treated with caution and is only an indication of the trend. RR is based on lowest incidence. "-" indicates no data.

UTCI interval(°C)	mean RR
< 5	1.0000
5 - 10	26.1431
10 - 15	95.7482
15 - 20	134.0082
20 - 25	742.2089
25 - 30	654.6987
$30 <$	-

It seems that the RR for X30 and X32 increases dramatically when UTCI increases for both all age groups and the age group over 65. However, since the incidence was so low to begin with the model became rather insecure and therefore no confidence limits could be produced. This result should be interpreted carefully.

4.9.1 The influence of cardiovascular health outcomes

An analysis was made on the cardiovascular health outcomes only i.e. I50.0: Congestive heart failure, I50.1: Left ventricular failure and I50.9: Heart failure, unspecified. In table 13 and 14 the results for the Poisson regression can be seen for when the RR is based on the lowest incidence and when it is based on the UTCI interval defined as "No thermal stress in figure 6.

Table 13: Mean RR suggested by the Poisson regression model presented for different UTCI intervals for Hualien for cardiovascular health outcomes only. RR is based on lowest incidence. "-" indicates no data. *For this category there was only one value and therefore no CI could be given.

Location	UTCI interval(°C)	mean RR
Hualien	< 5	1.4125*
	5 - 10	1.2903 [1.1788 1.4089]
	10 - 15	1.2090 [1.0962 1.3290]
	15 - 20	1.1353 [1.0239 1.2538]
	20 - 25	1.0434 [0.9391 1.1543]
	25 - 30	1.0000 [0.9405 1.0633]
	$30 <$	-

Table 14: RR suggested by Poisson regression model for cardiovascular health outcomes only. The RR is based on the category "no thermal stress". "-" indicates no data.

Location	UTCI interval (°C)	RR 95% CI
Hualien	slight cold stress(0 - 9)	1.1808 [0.9683 1.4658]
	no thermal stress(9 -26)	1.0000 [0.7457 1.3410]
	moderate heat stress(26 - 32)	0.9006 [0.7629 1.0852]
	strong heat stress(32 - 38)	-

Also, the plot from the Poisson regression model is shown below for different health outcomes. First only with X30: exposure to excessive natural heat and X32: exposure to sunlight included and then with I50.0: Congestive heart failure, I50.1: Left ventricular failure and I50.9: Heart failure, unspecified.

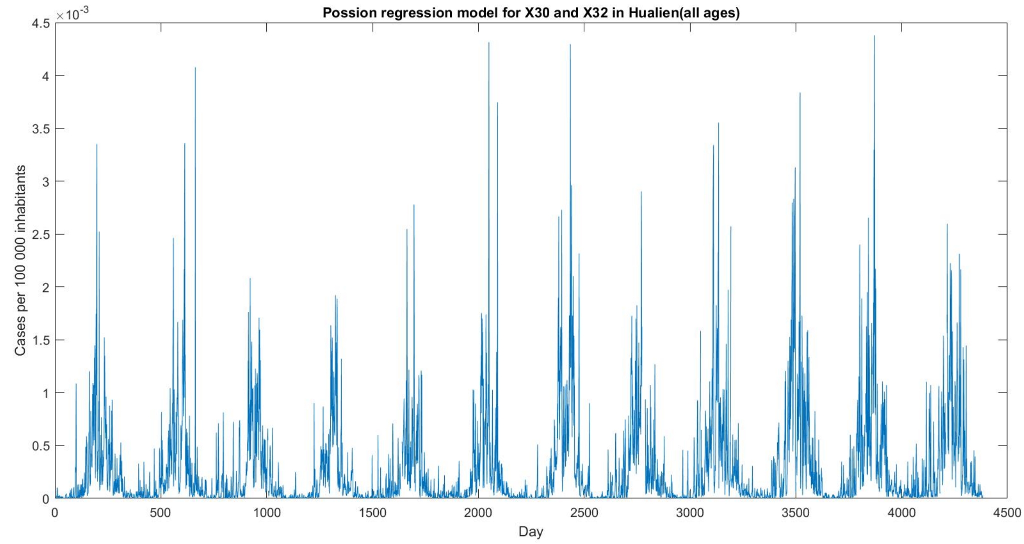

Figure 17: Poisson regression model for X30 and X32 in Hualien.

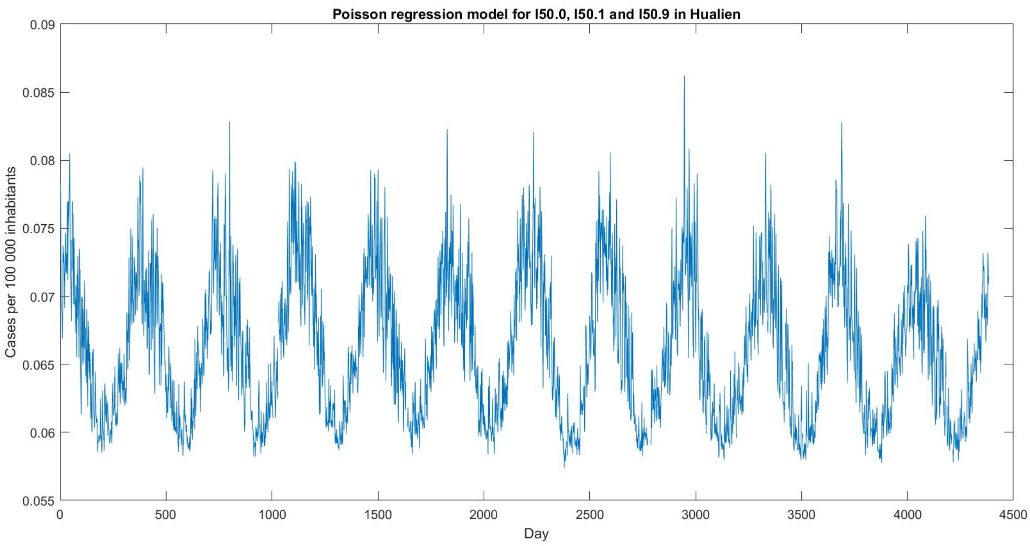

Figure 18: Poisson regression model for the cardiovascular health outcomes(I50.0, I50.1 and I50.9) in Hualien.

When comparing figure 17 and 18 it can be seen that the relation seems to be displaced. The model in figure 17 appears to have its peak in the summer while in figure 18 it seems that the peak is in the winter. Since the models include different health outcomes this is likely the reason. See the discussion for further reasoning regarding health outcomes and this offset in the incidence peaks.

4.10 RR based on sex in Hualien

Also, an analysis of the health outcomes was done based on sex. This was done for Hualien as well. The results can be seen below for males and females respectively:

Table 15: Mean RR suggested by the Poisson regression model presented for different UTCI intervals for Hualien for **males**. RR is based on lowest incidence. "-" indicates no data. *For this category there was only one value and therefore only this value could be presented.

UTCI interval(°C)	RR 95% CI
<5	1.6338*
5 - 10	1.5283 [1.3107 1.7681]
10 - 15	1.3702 [1.1539 1.6085]
15 - 20	1.2285 [1.0400 1.4362]
20 - 25	1.0682 [0.9064 1.2464]
25 - 30	1.0000 [0.9077 1.1017]
$30<$	-

Table 16: Mean RR suggested by the Poisson regression model presented for different UTCI intervals for Hualien for **females**. The RR is based on lowest incidence. "-" indicates no data. *For this category there was only one value and therefore only this value could be presented.

UTCI interval(°C)	RR 95% CI
<5	1.1499*
5 - 10	1.0271 [0.8621 1.2116]
10 - 15	1.0234 [0.8591 1.2071]
15 - 20	1.0200 [0.8628 1.1959]
20 - 25	1.0116 [0.8898 1.1479]
25 - 30	1.0000 [0.8941 1.1185]
$30<$	-

As can be seen in table 15 and 16 there seems to be a larger increase in RR for males with decreasing UTCI than for females. For females there is no confidence for the increase in RR while for males there is confidence at 95% level. The mean RR is presented in the following figure to display how the RR is varying with UTCI for both sexes:

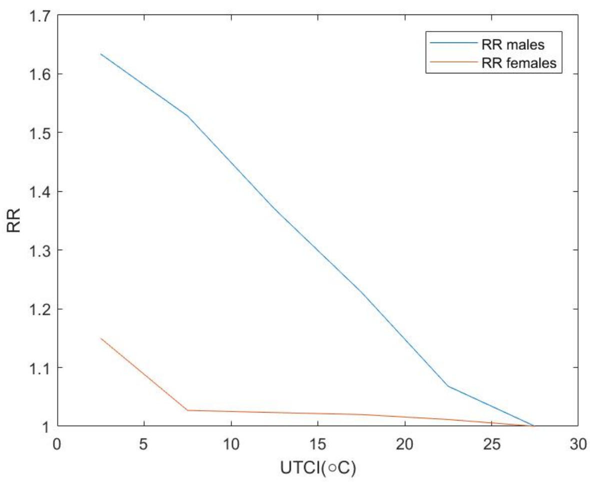

Figure 19: The mean RR for males and females respectively presented for different UTCI intervals as a graph.

5 Discussion

The discussion section will bring up some different aspects of the results and the study as a whole. First the relation between temperature, UTCI and ENSO will be treated followed by a discussion regarding the results of the health outcomes in relation to UTCI. Then there is a discussion about weaknesses in the study and in what direction other studies could continue.

5.1 Relation between 95th percentile air temperature, UTCI and ONI

Overall, the relation between temperature and ONI seems to be quite weak. There are few stations that have a correlation coefficient that is positive or negative with 95 % confidence. However, there are some trends that can be of interest and will thus be discussed.

5.1.1 95th percentile average daily air temperature

The results from the linear regression modelling indicate that the relation between 95th percentile average daily temperature and ONI in general is weak. However, in table 1 it can be seen that in the summer there are 4 out of 15 stations that are positively correlated with ONI with confidence. This is only 27% of the stations which in total is a small portion. The spatial distribution of these stations is on the other hand interesting. Chunghua, Chiayi, Nantou and Pingtung are all located in the mid western and southern parts of Taiwan. This could be interpreted as an indication that the relationship between high temperatures and ONI is positive in southwestern Taiwan during the summer. Also, in table 1 it can be seen that there are no negative correlations at 95% confidence level. In northern and eastern parts, however, the mean correlation coefficients are negative, although there is no confidence. Thereby the indication of a positive correlation is only seen in the south and western parts. This could possibly be used to predict extreme heat events in specifically the southwestern parts of Taiwan. A high ONI value, suggesting El Niño conditions, could indicate that the 95% percentile average daily temperature will be higher than usual.

During the autumn the pattern seems to shift. There are both positive and negative correlations within the confidence limits. The positive ones, Chunghua and Taitung, are located in western and eastern Taiwan respectively. The regions with negative correlation, Chiayi, Tainan and Kaohsiung are located in west, south and south Taiwan respectively. Thereby the pattern that was seen in the summer months is lost during the autumn. The winter and spring seasons seem to have no correlation between 95th percentile average air temperature and ONI and thereby ONI can not be used as a predictor for high average daily temperatures during these seasons.

5.1.2 95th percentile maximum daily air temperature

The relationship between 95th percentile maximum daily temperature and ONI seems to be less pronounced than the relation between the average daily temperature and ONI. In table 2 there is only one negative correlation in the summer, which is Taipei. Taipei did not have 95% confidence for the average temperature in the summer but the mean correlation coefficient was negative (see table 17 in appendix C) indicating a similar pattern for both average and maximum daily air temperature for Taipei. Further, the autumn exhibits both positive and negative correlations. There is a positive correlation for Hualien which is located in eastern Taiwan. The regions with negative correlations are Chiayi and Tainan both located in the western parts of Taiwan. This is in line with the correlations during the autumn for the average temperature as well. Thereby it seems that for western Taiwan there is a weak trend for a negative correlation between daily temperature and ONI. However, it is important to state that the relation is for a small number of weather stations and that the majority of the weather stations that were investigated in this study did not show any significant correlation coefficients. Therefore it might be a coincidence that this pattern is shown as well.

5.1.3 95th average and maximum daily UTCI

The relation between 95th percentile average and maximum daily UTCI and ONI is weaker than the relationship between air temperature and ONI. For the average daily UTCI there are three regions in total that have 95% confidence. One in the summer, one in the autumn and one in the spring (see table 3). Therefore it is difficult to draw any conclusions other than that the relation is weak or non existing. The maximum daily UTCI seems to correlate with ONI even less. As can be seen in table 4 there is only one region that has confidence throughout all four seasons. This is indicating that ONI is not a suitable predictor to be used when modelling UTCI with linear regression.

5.1.4 Monthly average temperature and ONI

The monthly average temperature did not have any correlation coefficients that were positive or negative with confidence. However, the winter and spring had the strongest relation of the seasons. This relation seemed to be positive which could possibly be used to predict cold temperatures. A low ONI value would then indicate colder weather during the winter and spring. However, this should be used with caution as none of the correlation coefficients were within the confidence bound. The correlation is stronger in the winter based on the R^2-values in table 35 when comparing to the R^2-values in table 33, 34 and 36 in appendix C. Although the correlation is stronger than for the other seasons, it is still rather low. This has to be taken into consideration before using ONI as a means to predict the temperature in the winter.

Further, when looking at figure 7 - 14 it can be seen that there is a slight tendency of higher elevation yielding higher average temperature and UTCI. This could be a result of the locations with higher elevation being further away from the ocean and thereby experiencing less cooling effects, although this might only be an explanation during the summer months. Also, the elevation is not very high to begin with suggesting that there might be other factors influencing the average monthly temperature.

5.2 Analysis of the health outcomes in relation to thermal climate

The relation between health outcomes and UTCI seems, in this case, to be that the risk for the analyzed health outcomes increases with lower UTCI. However, as will be discussed below, the relation between the RR and UTCI is heavily dependent on what health outcomes are being investigated and it can be seen that the health outcomes of the cardiovascular character have a large impact on this relation.

5.2.1 Effects of cold stress are more pronounced for the health outcomes

The results of the health analysis indicate a higher sensitivity for cold stress for the health outcomes in question. This might seem a bit contradictory as both X30: exposure to excessive natural heat and X32: exposure to sunlight are included in the total incidence. These health outcomes intuitively would contribute to an increased incidence during hot conditions. However, the opposite can be seen in table 5, 6 and 7. The other three health outcomes investigated in this study, I50.0: congestive heart failure, I50.1: Left ventricular failure and I50.9: Heart failure, unspecified, seem to be more sensitive to cold stress and thereby have an overshadowing effect on the contribution of X30 and X32. This is in line with the findings of Lin et al. (2011) who suggested that cold effects in Taiwan have a greater impact on short term effects on the incidence of cardiovascular diseases than hot temperatures [8]. Although this study investigated the relation to UTCI, the pattern seems to be similar to that of temperature. To confirm if this could be the case, the Poisson regression model was run for Hualien with only X30 and X32. In table 11 and 12 it can be seen that the RR is considerably higher for higher UTCI when compared to lower UTCI.

To confirm this overshadowing effect further, the model was also run for I50.0, I50.1 and I50.9 only. When comparing the RR for Hualien in table 7 and 13 it can be seen that the pattern is the same. However when all health outcomes are included (table 7) the RR in cold conditions are slightly lower than when only the cardiovascular health outcomes are included (table 13). The same difference can be seen when comparing table 10 and 14. This shows that the health outcomes ideally should not be mixed the way they were in this study as the RR might be underestimated for the cardiovascular health outcomes in cold conditions.

When X30 and X32 are the only health outcomes included the effects of heat can be observed to be extremely strong. The reason why the effects of X30 and X32 are overshadowed by the cardiovascular health outcomes might be that there are few reported cases of X30 and X32 compared to I50.0, I50.1 and I50.9. Another explanation could be that there are few cases of heat related health outcomes or that it is more common to report heat related deaths as some other ICD10 code. Other ICD10 codes could be applied when heat stress induces other illnesses that are not necessarily directly associated with heat. This would make the number of reported cases of strictly heat related health outcomes low. However, for Tainan and Taitung(which are located in southern Taiwan) the RR increases with increasing UTCI. This indicates some sensitivity to heat as well for the cardiovascular health outcomes, although, for the majority of the regions the cold effect is more pronounced.

In figure 17 and 18 it can be seen that there is a displacement between the pattern in the two figures. Figure 18 includes the cardiovascular health outcomes and the major effect can be seen during the winter when there are cold conditions. Figure 17 includes only heat related health outcomes and therefore the largest effects that can be seen during hot conditions in the summers. This displacement shows the origin of the overshadowing effect that cardiovascular health outcomes have on the health outcomes related to heat. There might be completely different results from the model depending on what health outcomes are being investigated. Therefore, no general conclusions regarding the health risks of the UTCI intervals can be drawn. However what can be said is that the ICD codes I50.0, I50.1 and I50.9 are more sensitive to cold stress i.e. low UTCI intervals. Also, X30 and X32 can be said to increase with increasing heat although the incidence is always rather low in comparison to the incidence of the cardiovascular health outcomes.

5.2.2 Different categorization of exposure

When the UTCI intervals were defined according to figure 6, the RR estimates are not within 95% confidence(see table 8 - 10). However, the pattern is the same as for when the UTCI intervals were defined with 5 °C steps(see table 5 - 7). The categorisation used in figure 6 is supposed to correspond to the level of thermal stress that is being experienced given the atmospheric conditions. It seems as the health outcomes chosen in this study do not follow these categories in regards to the RR. For the majority of the regions the RR is lowest in the interval "moderate heat stress" or "strong heat stress" and highest in "slight cold stress". This is in line with the previous discussion about the cardiovascular health outcomes being more sensitive to cold.

5.2.3 Health outcomes, ONI and risk perspective

As discussed previously, ONI can potentially be used to predict the temperature during specific seasons and locations. The findings in the health analysis could be integrated with these findings to use ONI as a means to predict when certain health outcomes will increase. Since heat related health outcomes are expected to increase during hot conditions, the relation between extreme heat and ONI found in the south and western parts of Taiwan can be used to predict when these health outcomes are expected to increase. However, the heat stress related health outcomes in this study already have quite low incidences. When it comes to the cardiovascular health outcomes, the correlation between average monthly air temperature and ONI could potentially be used. This since this relation had its highest correlation during the winter although, this correlation was rather weak as well. In this case, a trend of lower ONI could indicate cold temperatures in the winter which in turn can give an increase in the number of cases of I50.0, I50.1 and I50.9. Therefore, ONI can potentially be used to predict when resources need to be put in place to reduce the number of cases of these diseases.

Looking at the risk of contracting the illnesses investigated, it can be concluded that there is a relatively small risk of an individual being diseased by X30 and X32. Out of all the cases that were investigated, only 5 in total were X30 or X32. Compared to I50.0, I50.1 and I50.9 that adds up to 43 500 cases the incidence of X30 and X32 is disappearingly small. Therefore, it might not be possible to reduce the risk of X30 and X32 to any meaningful extent. These health outcomes appear to be more of a freak accident that do not occur regularly. Further,the reason that they have such a high increase in hot conditions is due to the fact that they simply can not occur in cold conditions. Therefore, resources might be better suited to reduce the risk of cardiovascular health outcomes. The incidence for those is considerably higher and the same resources might contribute to a larger reduction of risk for these illnesses than for X30 and X32. From a strictly probabilistic view it is more efficient to try to mitigate the risk of I50.0, I50.1 and I50.9. As mentioned above however, there are many factors playing in, and a strictly probabilistic approach may in some cases not be the best way to manage risks of these characteristics.

Another aspect is how dreaded this risk is by the public. If the public's view on deaths caused by X30 and X32 is that these diseases are abominable the willingness of allocating resources to reduce the risk will be higher. Another aspect that is mentioned above is how controllable the risk is. X30 and X32 could be argued to be rather controllable in the sense that it can be avoided by staying out of direct sunlight or extreme heat. On the other hand, it might be less avoidable in the sense that one can be exposed to extreme heat in their own home. Also, even though it is hot outside, some work has to be done regardless of the health risks as for example firefighting and rescuing work. When exposed to the risk in one's own home or at the workplace there might be inequity in the distribution of the risk in the population, which tends to increase the willingness to reduce it. The inequity comes from that people have different economical prerequisites to decide whether they want to have air conditioning and other devices that may protect them from the risks of heat. There might also be limited knowledge about the risk. For example, Oudin Åström et al. (2015) described how the knowledge about the risk for negative health outcomes related to elevated temperatures is rather limited in Stockholm [4]. A way to get a more comprehensive understanding of the public's view on the risk of the diseases mentioned in this study is by doing an opinion poll. The results from such polls can then be used as a basis for how the resources should be distributed.

5.2.4 Comparison to UTCI studies in other places of the world

Urban et al. (2021) found the risk of various causes of death to increase with increasing UTCI, although, the study itself was more focused on evaluating the use of reanalysis based UTCI. The study was done for several cities in Europe [36]. Additionally, Oudin Åström et al. (2013) investigated the mortality risk during extreme temperature events in Stockholm and also found that the risk of mortality was more pronounced for heat extremes than for cold [19]. However, the study found a declining sensitivity to heat extremes over the decades, which corresponded with several other studies in Europe, which could be a result of gradually improving healthcare and living conditions [19]. A study conducted in Poland found decreased mortality risk over time due to cold stress as the number of cold events have been declining. The ratio between extreme cold events and extreme heat events has been reduced in the last decades. However, there are still more cold events than heat events in Poland [37]. Mortality due to circulatory diseases was found to be considerably higher for men than for women during cold stress. This finding is consistent with what was found in this study for Hualien. In this study the RR for the different health outcomes(mainly cardiovascular) was found to increase faster with decreasing UTCI for men than for women. As can be seen in table 15 and 16 the RR increased from 1.0000 to 1.6338 for males and 1.0000 to 1.4990 for females when UTCI decreased from 25 - 30 °C to below 5 °C. Additionally, in the polish study, higher mortality among elderly was found during the studied period in comparison to the whole population during heat events. The same pattern was seen in Helsinki during the same time period [37]. The heightened mortality for heat stress found in some studies and for cold in others might be caused by different climate in different regions. In Nantou in Taiwan for example, the most extreme cases of heat seem to be indicating only moderate heat stress (see figure 5) and the cold extremes do not seem particularly extreme either, indicating slight cold stress according to the categories in figure 6. If compared with another region, for example, Ahmedabad in India (figure 20) there are a fair amount of data points indicating strong heat stress which might make the effects of heat more pronounced for that region. The climate in Taiwan is overall not extreme. This could be due to the closeness to the pacific ocean which can contribute with cooling and heating effects, evening out the climate.

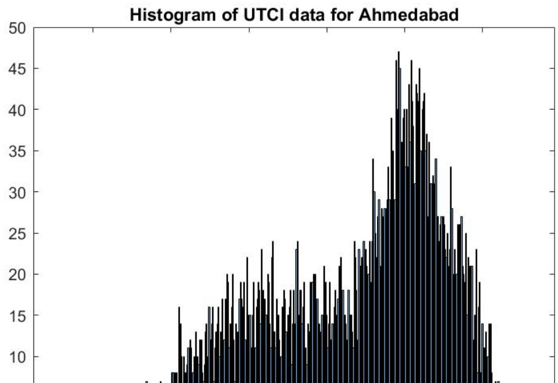

Figure 20: Histogram of UTCI data in Ahmedabad between 2002 and 2019. The histogram depicts the number of days with a certain average UTCI.

5.3 Weaknesses and strengths in the study

In the model for the relation between 95th percentile temperature and ONI the use of linear regression might be limiting. The relationship between these variables may be more complex and a linear approximation might not capture actual relation in a suitable way. Although a more complex analysis was outside the scope of this study, it could have contributed to the understanding on how temperature is influenced by ONI. Also, the study is limited to specific regions in Taiwan and if more regions would be included a more comprehensive view of the relation between temperature and ENSO could appear.

When it comes to the time period studied, 2008 - 2019, it might be a drawback. This is a rather limited time period which could make it more difficult to distinguish patterns. In a longer time period the trends can be more distinguishable and this could partly explain why the results in this study indicate a weak correlation between 95th percentile air temperature and ONI. Also, a longer study period could consolidate the results further by indicating that the trends that are found are not simply a temporal anomaly but rather a pattern found over long time periods.

The Poisson regression model is rather limited as there are few variables included. To get a more comprehensive picture of the situation more environmental, socioeconomic and health related variables should be included. There might be confounding factors that are not included in the study. Different seasons may exhibit varying risks associated with other variables than just atmospheric ones. Living habits such as alcohol consumption, smoking and exercise all affect the risk of contracting illnesses. Since this study included three cardiovascular complications the results could be influenced by such factors. Although it is impossible to include all potential confounders, it could be useful to include some variables that are known to have a large impact on people's lives. However, such data might be difficult to obtain and the quality may be poor. Further the intervals of UTCI that were used to derive a RR had quite low resolution as only seven different categories were created. The pattern could have been highlighted more clearly if there would have been a finer sectioning of the different categories. In this study the UTCI intervals were decided to be 5°C. If the interval would have been for example 1°C instead there would have been considerable increase in the number of categories. Further, the RR was estimated with temperature, UTCI and air pollution data from one measurement point or estimation in each region. Thereby, the data was assumed to be the representative for the whole region which is not true. Different areas within the region might be more or less affected by the levels of UTCI. Therefore, this assumption could lead to overestimating or underestimating the RR depending on the circumstances. Urban heat island effects could make specific areas of the region more exposed to extreme heat for example. This cannot be captured with the current model. Other areas within the regions may be protected from extreme heat to a larger extent which could also have an impact in the estimations of the RR. Further, UTCI is not necessarily valid for physical activity and thereby in working environments this may also contribute to an underestimation of the RR.

The use of outdoor conditions might not be completely representative to describe and predict the risk of health complications. As Oudin Åström et al. (2015) discussed, there are several factors affecting the relation between indoor and outdoor temperature [4]. The indoor climate conditions might also have an effect on the RR which is not captured in this study. Another aspect that Oudin Åström et al. (2015) mentioned is that some individuals could be affected by the possibility to cool down during the night [4]. For those individuals the daily minimum temperature might be more important for the risk associated with certain health outcomes. Since this study only focused on the average temperature, maximum temperature and average UTCI these possible effects are not accounted for.

On the other hand a strength of this study is the use of UTCI. UTCI includes several variables at once which thereby indirectly accounts for several possible confounders. As heat and cold stress is dependent on many things such as wind speed, relative humidity, solar radiation, physical activity and clothing the use of an index that includes several such variables can be a suitable representation of the atmospheric conditions. The use of only air temperature can be useful but does not take into account these aspects. Since UTCI is optimized to describe how the human body experiences the atmospheric conditions it can give a broader picture of how these conditions affect health outcomes. The use of UTCI in this study thereby increased the accuracy of the model without needing to include all these variables separately. Since UTCI indicates both heat stress and cold stress it is useful to analyze both cold and heat which became convenient in this study as the cold effects were more distinguishable.

Urban et al. (2021) concluded that UTCI seems to have lower values at low percentile than the corresponding percentile of temperature in a given time series. This since UTCI includes wind speed which has a large impact on the perceived thermal environment at lower temperatures [36]. Further, the use of reanalysis data for UTCI is a strength since it includes all necessary variables. UTCI is calculated with, among others, wind speed and this variable is commonly not available in station data. Thereby, the reanalysis data can provide an alternative way of solving the problem when data is not available. Exposure response relations seem to be quite similar when using reanalysis and station based data which further support the use of this type of data [36].

5.4 Continued studies

An interesting study to continue with would be to investigate the relation between extreme cold events and ONI. As this study was limited to only investigating heat, a cold study could complement the findings. The cold study could use a similar approach with linear regression to describe the relationship between 5th percentile temperature and ONI. If done for the same regions that were used in this study, a comparison between heat and cold extreme's relation to ONI could be made. Further, as the health outcomes that were investigated indicated that there is a sensibility to cold stress, the relationship between cold spells and ONI would be interesting in the context of predicting extreme colds. This was unfortunately outside the scope of this study but could be an interesting continuation. Further, different ENSO indexes could be used to describe this relationship. For example, Lin et al. (2015) used an ENSO index called the El Niño Modoki index (EMI) which is a weighted average of sea surface temperature anomalies from three regions. Different ENSO indexes with different definitions of El Niño seemed to predict a contrasting rainfall pattern [35]. Allthough it was used to predict rainfall, the EMI could possibly be used to predict temperature patterns as well which in turn can be compared to the pattern that is derived from using ONI. The EMI could be used in a similar fashion as ONI was used in this study.

Further, it could be interesting to investigate how the RR is affected when other ICD10 codes (other health outcomes) are included. The susceptibility for heat or cold spells could differ for different sets of health outcomes. As this study included three cardiovascular health outcomes, cold effects seemed to have a greater impact on health. However, if the study would have included only the health outcomes directly linked to heat stress the effects of heat could have been more obvious. Further, an interesting aspect could be to investigate different ICD10 codes to identify what health outcomes are more susceptible to heat stress and cold stress respectively.

An aspect that could also be interesting to investigate could be to include more socioeconomically related factors in the model. As Wu et al. (2010) discussed, vulnerable subgroups may experience higher risk for some health outcomes [14]. Therefore, using more factors in the model related to living standards could give insight into what factors increase the risk of illnesses. Additionally, this study did not include any distinction for different age groups which has been observed to have an impact on the risk of different health outcomes. If this distinction would be made it could increase the understanding on how UTCI affects different age groups. Also, it could be interesting to include other climate indexes. For example, Ueno et al. (2021) used wet bulb globe temperature(WBGT) to predict the number of heat related ambulance transports in Japan [21]. If a similar study would be made in Taiwan, a comparison could be made between the effects of UTCI and WBGT.

In this study, the incidence was investigated in relation to the average daily UTCI value on the same day. Other studies usually include analysis of the lag effects. Lag effects could show effects of a heat event several days after the event occurred. This could be interesting as some effects of varying weather conditions are presented later than the actual weather event itself. All effects are not immediately acute as exposure to excessive natural heat and exposure to sunlight. Such delayed effects could better be captured if lag was incorporated in the model.

Another aspect that could be interesting to investigate further is, as mentioned above, the relation between the RR for different health outcomes and minimum daily UTCI and temperature. As some individuals might be more vulnerable to not being able to cool down during night time, high minimum temperatures might contribute to the effects of heat waves. Thereby, using the minimum temperature and UTCI as a way of defining heat events could bring another perspective and possibly show effects that are not identifiable when using average or maximum temperature and UTCI. It may be relevant to investigate what health outcomes are sensitive to high minimum temperature.

6 Conclusions

- 95th percentile average daily air temperature has a positive correlation with ONI in south and mid-western parts of Taiwan during the summer months.
- The results suggest a positive correlation between average monthly air temperature and ONI in Taiwan during the winter and spring months although these correlations are rather weak.
- There is no correlation between average daily or maximum daily UTCI and ONI.
- The health outcomes investigated in this study are more sensitive to cold stress and the RR seem to increase with lower UTCI levels(where >30 °C has lowest RR and <5 °C has the highest RR). However, the cardiovascular health outcomes are the main reason that this pattern appears since their incidence is increasing in cold conditions. On the other hand, two regions in southern Taiwan have increased RR when UTCI is increasing(the RR in Tainan increases above UTCI levels of 25 °C and the RR for Taitung increases when UTCI levels are above 5 °C) which might be a sign of the cardiovascular health outcomes being sensitive to heat as well.
- There seem to be increasing RR for the heat related health outcomes with increasing UTCI(from <5 to >30 °C). This effect is overshadowed by the effects of cardiovascular health outcomes when all health outcomes are included in the Poisson regression model as the incidence for the heat related health outcomes is rather low.

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A Popular science summary

The health risks when the climate is changing in Taiwan

Is the risk of dying in heart failure the same all year around? Diseases occur with varying frequency throughout the year. To be able to prevent them from happening, it is important to be able to predict when they will happen and under what circumstances. Climate change is making extreme weather events more common, which could increase the occurrence of some health conditions. In this study, different ways of predicting the weather and how the weather is affecting the health in Taiwan have been investigated.

Every year, many people die from different illnesses that are to some extent related to the atmospheric conditions around us. The human body is vulnerable to extreme environmental conditions such as high or low temperatures and intense sunlight. Some atmospheric conditions such as radiation from the sun may not be noticed in a short-term perspective but are presented much later as for example skin cancer. Other atmospheric conditions such as temperature can have more acute effects which can become life threatening if ignored. To be able to prevent such awful events it is important to predict when they will occur. In this study, a climate phenomenon called El Niño Southern Oscillation(ENSO) was used to try predicting when hot conditions that can cause disease may occur in Taiwan. ENSO is affecting the climate in the Pacific region. It also influences the climate in the whole world to some extension. ENSO drives the global weather and can be forecasted with 6-12 month lead time. Understanding the link between ENSO and extreme weather provides an opportunity to develop early warning systems. Also, a climate index called the Universal Thermal Climate Index(UTCI) was used to predict how likely different diseases are to occur. UTCI is like temperature, but it is integrated with several atmospheric variables and can therefore better predict how the body will be affected. This is because temperature is not the only variable affecting the human body's response to heat. What is hot also depends on how easily our bodies can get rid of heat. Imagine lying under a thick blanket or doing intense exercise. You will be rather warm without the temperature in the room necessarily being particularly high. The blanket is trapping heat under it. It is the same with conditions in the atmosphere. For example, if it is humid outside little heat can be lost through sweating as water will not evaporate as easily as on a dry day. The humid day may be perceived as warmer than the dry day even though the temperature was the same both days. This is where UTCI comes in handy as it is a representation of how the body will respond to the atmospheric conditions, in a more accurate and complete way than temperature.

So, what was found in the study? First, it seems that ENSO can be used to predict high temperatures in specific locations during specific seasons. In the south and mid-western parts of Taiwan there seems to be a positive relation between temperature and ENSO index in the summer, meaning that higher values of the ENSO index give higher temperature. Also, it seems that diseases related to the heart and circulatory system are more sensitive to cold conditions in Taiwan. Therefore, these kinds of diseases will increase when the weather is unusually cold. In south Taiwan the diseases related to the heart and circulatory system are sensitive to heat stress as well. Diseases that are related to heat stress directly seem, as one would expect, to increase when it is hot outside. However, these diseases occur rarely to begin with. The climate is complex, and it is tricky to predict the weather. UTCI is a useful tool that can make it easier to determine if the atmospheric conditions will be dangerous. It is important to continue working with these issues to better be able to prevent diseases from happening. As cold stress was found to affect the number of cases of the diseases related to the heart and circulatory system, an interesting direction continued studies look at is how ENSO can be used to predict when temperatures will be unusually cold. Also, some individuals could be particularly sensitive to high minimum temperatures which could also be an interesting continuation of this study.

B Matlab Code

In this section the MATLAB codes used in the study are presented. The codes presented are the most relevant ones.

B.1 UTCI data extraction

The following code was used to extract data from the NC-files containing UTCI data.

```
clear all

%location inneh ller alla koordinater f r de olika regionerna. Vissa
% verlappar d uppl sningen r begr nsad. filenames r filens namn(string-vektor).

%files r ett direktiv som refererar till alla filer av typen .nc i mappen
%som denna .m-filen r sparad i.

files = dir('*.nc');

filenames_cell = {files.name};
filenames = char(filenames_cell);

utci_mean_all = zeros(15,length(filenames));
utci_max_all = zeros(15, length(filenames));

for w = 1:length(filenames)

location = [25 121.5
            25 121.5
            25 121.25
            24.75 121
            24.5 120.75
            24.25 120.75
            24 120.5
            23.5 120.5
            23 120.75
            23 120.25
            22.75 120.25
            22.75 120.5
            24.75 121.75
            24 121.5
            22.75 121.25];





  utci = ncread(filenames(w,:),'utci');
  lon = ncread(filenames(w,:),'lon');
  lat = ncread(filenames(w,:),'lat');


  utci_mean =[];
  utci_max = [];
  for i = 1:15
```

```
        lon_pos = 0;
        for k = 1:length(lon)
            if(lon(k) == location(i,2))
                lon_pos = k;
            end
        end

        lat_pos = 0;
        for k = 1:length(lat)
            if(lat(k) == location(i,1))
                lat_pos = k;
            end
         end

        utci_location = squeeze(utci(lon_pos,lat_pos,:));
        utci_mean = [utci_mean; mean(utci_location)];
        utci_max = [utci_max; max(utci_location)];
    end
utci_mean_all(:,w) = utci_mean;
utci_max_all(:,w) = utci_max;
end

%utci_all  r genomsnittet f r dagen f r alla st llen i ordningen som  r
%angiven i rapporten.

utci_mean_transpose = utci_mean_all';
utci_max_transpose = utci_max_all';
```

B.2 Preparation of data set used in health analysis

The code below was used to prepare the different sets of data into one matrix before a Poisson regression model was created according to the code presented in the method section. See page 22 for the basis of this model.

```

%Script f r att ligera tv  dataset med d dsfall uppdelade efter k n

clear

data = readtable('HualienDeathsDailyX_65.xlsx'); %Fil med d dsfall uppdelad efter k n
%Denna filen m ste f rberedas enligt samma format som chiayiDeathsDaily.xlsx.
%Annars f s en felkod
%Chiayi saknar 2013, New Taipei saknar 2012, Taipei saknar 2012
yearMale = table2array(data(:,2));
monthMale = table2array(data(:,3));
dayMale = table2array(data(:,4));
casesMale = table2array(data(:,5));

yearMale = yearMale(~isnan(yearMale)); %Skala bort NaN v rden p slutet av vektorn
monthMale = monthMale(~isnan(monthMale));
dayMale = dayMale(~isnan(dayMale));
casesMale = casesMale(~isnan(casesMale));
```

```
yearFemale = table2array(data(:,6));
monthFemale = table2array(data(:,7));
dayFemale = table2array(data(:,8));
casesFemale = table2array(data(:,9));

yearFemale = yearFemale(~isnan(yearFemale));
monthFemale = monthFemale(~isnan(monthFemale));
dayFemale = dayFemale(~isnan(dayFemale));
casesFemale = casesFemale(~isnan(casesFemale));


weatherData = readtable('avgTempTaitung2008-2019.xlsx'); %L s in temperaturfilen f r platsen

allYear = table2array(weatherData(:,2));
allMonth = table2array(weatherData(:,3));
allDay = table2array(weatherData(:,4));
tempLocation = str2double(table2array(weatherData(:,5)));

utciData = readtable('utciFinal.xlsx');

utciLocation = str2double(table2array(utciData(:,18))); %utci f r den aktuella platsen

popData = readtable('populationByYear.xlsx');

popYear = table2array(popData(:,1));
popLocation = table2array(popData(:,17)); %befolkningsdata f r den aktuella platsen

%% sortering av data
%Skapa vector som inneh ller manliga och kvinliga fall som sker samma dag
%Medf ljande datumvektorer

doubleCases = [];
doubleDay = [];
doubleMonth =[];
doubleYear = [];

for i = 1:length(casesMale)

    for k = 1:length(casesFemale)

        x1 = 0;
        date = 0;
        month = 0;
        year = 0;
        if(yearMale(i) == yearFemale(k) && monthMale(i) == monthFemale(k) && dayMale(i) == dayFemale(k))

            x1 = casesMale(i) + casesFemale(k);
            date = dayFemale(k);
            month = monthFemale(k);
            year = yearFemale(k);
```

```
                doubleCases = [doubleCases; x1];
                doubleDay = [doubleDay; date];
                doubleMonth = [doubleMonth; month];
                doubleYear = [doubleYear; year];

            end
        end
    end


%Ta bort v rden som inkluderats i dubbelvektorn(manlig och kvinnliga fall
%samma dag) fr n vektorn f r kvinnor
w = length(casesFemale) - length(doubleCases);

for i = 1:w

    for k = 1:length(doubleCases)

        if(yearFemale(i) == doubleYear(k) && monthFemale(i) == doubleMonth(k) && dayFemale(i) == doubleDay(k))

            yearFemale(i) = [];
            monthFemale(i) = [];
            dayFemale(i) = [];
            casesFemale(i) = [];

        end
    end
end

%Ta bort dubbeldatumf r manliga vektorn med
 for i = 1:length(casesMale)-length(doubleCases)

    for k = 1:length(doubleCases)

        if(yearMale(i) == doubleYear(k) && monthMale(i) == doubleMonth(k) && dayMale(i) == doubleDay(k))

            yearMale(i) = [];
            monthMale(i) = [];
            dayMale(i) = [];
            casesMale(i) = [];


        end
        if(isnan(yearMale(i))) %skala bort tomma element i vektorn
             yearMale(i) = [];
            monthMale(i) = [];
            dayMale(i) = [];
            casesMale(i) = [];
        end
    end
 end

```

```
%H r g rs datum om till nummer om i matlab representerar ett datum
allDates = datenum(allYear,allMonth,allDay);


dateMale = datenum(yearMale, monthMale,dayMale);
dateFemale = datenum(yearFemale, monthFemale, dayFemale);
doubleDate = datenum(doubleYear, doubleMonth, doubleDay);

totYear = [yearMale
           yearFemale
           doubleYear];
totYear = sort(totYear);

totDate_osort = [dateMale
       dateFemale
       doubleDate];

totDate = sort(totDate_osort); %alla datum med ett eller fler fall i ordning

totCases = zeros(1,length(totDate))'; %alla fall i ordning
for i = 1:length(totDate)
    for k = 1:length(dateMale)
        if(dateMale(k) == totDate(i))
            totCases(i) = casesMale(k);
        end
    end
end
 for i = 1:length(totDate)
    for k = 1:length(dateFemale)
        if(dateFemale(k) == totDate(i))
            totCases(i) = casesFemale(k);
        end
    end
end
 for i = 1:length(totDate)
    for k = 1:length(doubleDate)
        if(doubleDate(k) == totDate(i))
            totCases(i) = doubleCases(k);
        end
    end
 end

%Ta ut relevanta v rden ur utcivektorn. Dvs. v rden som motsvarar en dag
%d det finns fall av ICD-codes

utciCases = zeros(1,length(totCases))';
for i = 1:length(allDates)

    for k = 1:length(totCases)
        if(allDates(i) == totDate(k))
            utciCases(k) = utciLocation(i);
        end
    end
end
```

```
 totCasesNoCases = zeros(1,length(allDay))'; %Alla dagar med 0 eller
     fler fall

 for i = 1:length(allDay)

     for k = 1:length(totCases)
         if(totDate(k) == allDates(i))

             totCasesNoCases(i) = totCases(k);

         end
     end
 end


count = zeros(1,length(allDay))';

for i = 1:length(allDay)
    count(i) = i;
end

popByYear = zeros(1,length(allYear))'; %vektor med  rlig  population
%formaterad f r att kunna dividera hela tidsserien

for i = 1:length(allYear)
    for k = 1:length(popLocation)
        if(allYear(i) == popYear(k))
            popByYear(i) = popLocation(k);
        end
    end
end



incidence = (totCasesNoCases./popByYear)*100000; %incidencen per 100
    000 inv nare
utciLocation = utciLocation - 273.15;
aa = [incidence utciLocation tempLocation];
```

C Relationship between temperature, UTCI and ONI in more detail

Appendix C contains some more details about the relationship between temperature, UTCI and ONI. The values of the correlation coefficients are given with a 95% confidence interval. Additionally, R^2-values are given to visualize how well the model fit the data.

C.1 Relation between 95th percentile average daily air temperature and ONI

In this section, results from the analysis of the relation between 95th percentile average daily air temperature and ONI are presented in more detail. All the correlation coefficients and some additional analysis can be seen below.

C.1.1 Summer

The correlation between 95-percentile average daily air temperature and ONI during the summers 2008-2019 can be seen in table 17. The values are altering between positive and negative correlations for the different locations. The R^2-values indicate that the majority of the variance is not explained by the models. For Chunghua, Chiayi, Nantou and Pingtung the correlations are positive with 95% confidence. For the rest of the regions no trends are positive or negative with 95% confidence.

Table 17: Linear relation between 95th percentile average daily air temperature and ONI in the different regions with accompanying 95% confidence interval and R^2-value. The analysis includes the months June, July and August between 2008 and 2019.

Region	Correlation coefficient 95% CI	R-square value
New Taipei	-0.04866 [-0.1591 0.0618]	0.0139
Taipei	-0.064724 [-0.1723 0.0428]	0.0251
Taoyuan	0.0070787 [-0.0898 0.1039]	0.000133
Hsinchu	-0.028886 [-0.1706 0.1128]	0.00275
Miaoli	-0.028886 [-0.1706 0.1128]	0.00275
Taichung	0.020837 [-0.0757 0.1173]	0.00283
Chunghua	0.096057 [0.0093 0.1828]	0.055
Chiayi	0.20747 [0.0905 0.3245]	0.175
Nantou	0.44899 [0.1923 0.7057]	0.157
Tainan	0.051026 [-0.0273 0.1294]	0.0273
Kaohsiung	-0.035234 [-0.1296 0.0591]	0.00948
Pingtung	0.089754 [0.0237 0.1558]	0.116
Yilan	0.01168 [-0.1653 0.1886]	0.000288
Hualien	-0.030307 [-0.1272 0.0666]	0.00583
Taitung	0.047117 [-0.1204 0.2146]	0.00504

The correlation coefficients in table 17 were also plotted against the elevation of each weather station which can be seen in the following figure:

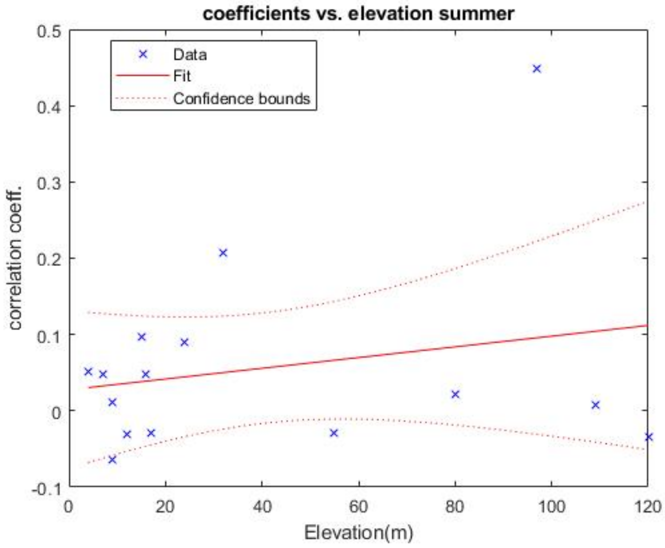

Figure 21: Linear relation between correlation coefficients and the elevation of corresponding weather station. The relation has the correlation coefficient 0.00070219[-0.0009622 0.0024] and the R^2-value 0.05.

C.1.2 Autumn

When it comes to the values during the autumn there is 95% confidence for both positive and negative correlation coefficients. For Changhua and Taitung there is a positive correlation coefficient with confidence. For Chiayi, Tainan and Kaohsiung there is confidence for negative correlation coefficients. When looking at the R^2-values it becomes apparent that the majority of the variance in the data is not explained by the model for any of the regions.

Table 18: Linear relation between 95th percentile average daily air temperature and ONI in the different regions with accompanying 95% confidence interval and R^2-value. The analysis includes the months September, October and November between 2008 and 2019.

Region	Correlation coefficient 95% CI	R-square value
New Taipei	-0.10338 [-0.2923 0.0855]	0.0201
Taipei	-0.028389 [-0.2326 0.1758]	0.0014
Taoyuan	-0.056234 [-0.3709 0.2584]	0.00188
Hsinchu	0.10703 [-0.1648 0.3788]	0.0105
Miaoli	0.10703 [-0.1648 0.3788]	0.0105
Taichung	-0.065107 [-0.2283 0.0981]	0.00993
Chunghua	0.28181 [0.1035 0.4602]	0.14
Chiayi	-0.23698 [-0.4011 -0.0728]	0.113
Nantou	-0.24792 [-0.6223 0.1264]	0.0282
Tainan	-0.16553 [-0.3122 -0.0189]	0.0754
Kaohsiung	-0.20098 [-0.3356 -0.0664]	0.118
Pingtung	0.15138 [-0.0051 0.3079]	0.0635
Yilan	0.046478 [-0.1201 0.2131]	0.00561
Hualien	0.13478 [-0.0369 0.3065]	0.0399
Taitung	0.21226 [0.0185 0.4060]	0.0761

The correlation coefficients in table 18 plotted against the elevation can be seen in the following figure:

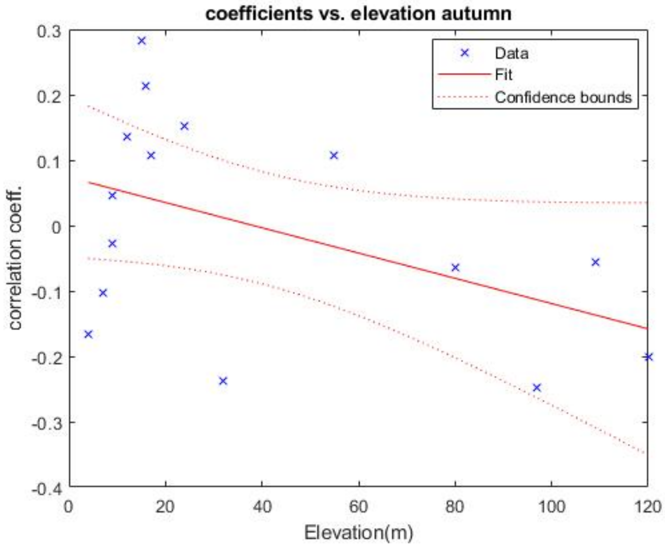

Figure 22: Linear relation between correlation coefficients and the elevation of corresponding weather station. The relation has the correlation coefficient -0.0019319[-0.0039 0.000039664] and the R^2-value 0.221.

C.1.3 Winter

The results from the analysis of the winter season does not show any trend at 95% confidence for any of the regions. The R^2-values are all rather low as well, suggesting that most of the variation is not described by the model. Additionally, the average correlation coefficients of the linear models indicate both positive and negative trends.

Table 19: Linear relation between 95th percentile average daily air temperature and ONI in the different regions with accompanying 95% confidence interval and R^2-value. The analysis includes the months December, January and February between 2008 and 2019.

Region	Correlation coefficient 95% CI	R-square value
New Taipei	-0.08887 [-0.2449 0.0672]	0.0234
Taipei	0.069851 [-0.1138 0.2535]	0.0104
Taoyuan	0.017166 [-0.1477 0.1821]	0.000639
Hsinchu	0.077753 [-0.0983 0.2538]	0.0132
Miaoli	0.077753 [-0.0983 0.2538]	0.0132
Taichung	-0.034056 [-0.2418 0.1736]	0.00198
Chunghua	0.2188 [-0.0374 0.4750]	0.0511
Chiayi	-0.015658 [-0.2719 0.2406]	0.000271
Nantou	-0.13564 [-0.3263 0.0550]	0.0341
Tainan	0.08137 [-0.1629 0.3257]	0.08137
Kaohsiung	0.10504 [-0.0243 0.2344]	0.0412
Pingtung	0.037757 [-0.0761 0.1516]	0.00791
Yilan	-0.015768 [-0.1675 0.1360]	0.000754
Hualien	-0.041434 [-0.1988 0.1160]	0.00509
Taitung	0.064564 [-0.0901 0.2192]	0.0116

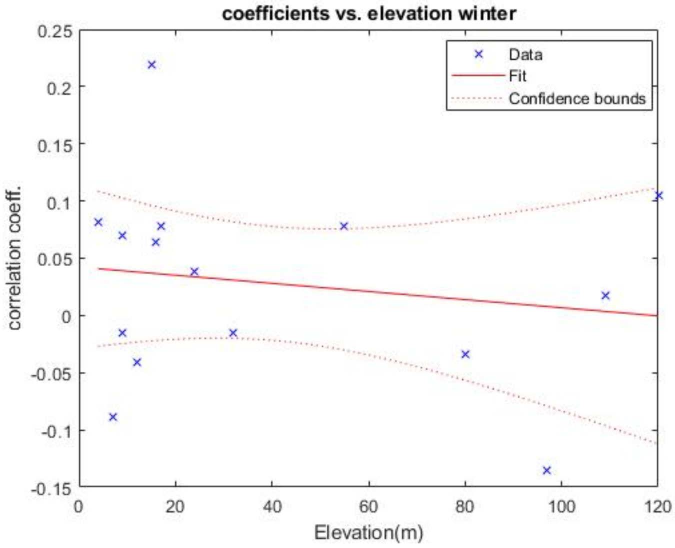

Figure 23: Linear relation between correlation coefficients and the elevation of corresponding weather station. The relation has the correlation coefficient -0.0003554[-0.0015 0.00078806] and the R^2-value 0.0278.

C.1.4 Spring

When it comes to the analysis of the spring it appears that there is no confidence at 95% for any positive or negative correlation coefficient. As for the R^2-values the values are rather low; it indicates that most of the variation can not be described by the model. The average correlation coefficients indicate both positive and negative relations, although none are significant.

Table 20: Linear relation between 95th percentile average daily air temperature and ONI in the different regions with accompanying 95% confidence interval and R^2-value. The analysis includes the months March, April and May between 2008 and 2019.

Region	Correlation coefficient 95% CI	R-square value
New Taipei	0.12235 [-0.2778 0.5225]	0.00673
Taipei	0.1203 [-0.2599 0.5005]	0.00682
Taoyuan	0.32298 [-0.0181 0.6640]	0.0423
Hsinchu	0.18812 [-0.2032 0.5795]	0.0165
Miaoli	0.18812 [-0.2032 0.5795]	0.0165
Taichung	-0.043796 [-0.4176 0.3300]	0.000958
Chunghua	0.10013 [-0.2318 0.4321]	0.0062
Chiayi	0.092184 [-0.3244 0.5087]	0.00347
Nantou	-0.11051 [-0.3449 0.1239]	0.0156
Tainan	0.042488 [-0.2395 0.3245]	0.00164
Kaohsiung	-0.013767 [-0.2755 0.2480]	0.000197
Pingtung	-0.059181 [-0.3084 0.1901]	0.00407
Yilan	-0.22935 [-0.5898 0.1311]	0.0275
Hualien	-0.32146 [-0.6258 -0.0171]	0.0667
Taitung	0.26609 [-0.0998 0.6320]	0.0363

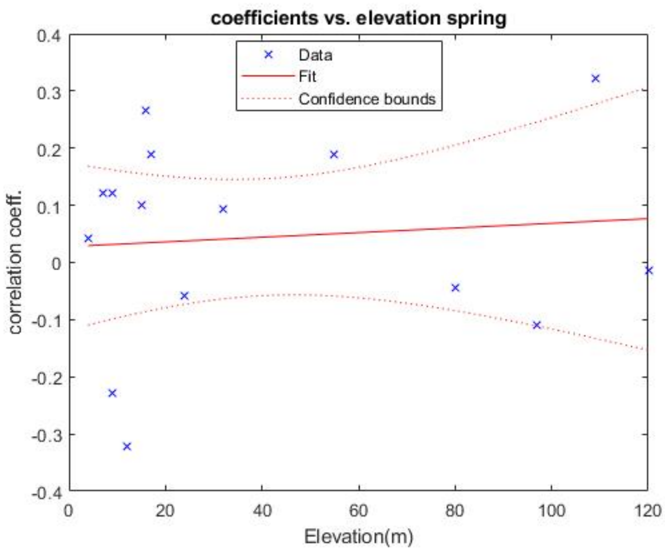

Figure 24: Linear relation between correlation coefficients and the elevation of corresponding weather station. The relation has the correlation coefficient 0.00040631[-0.0019 0.0028] and the R^2-value 0.00877.

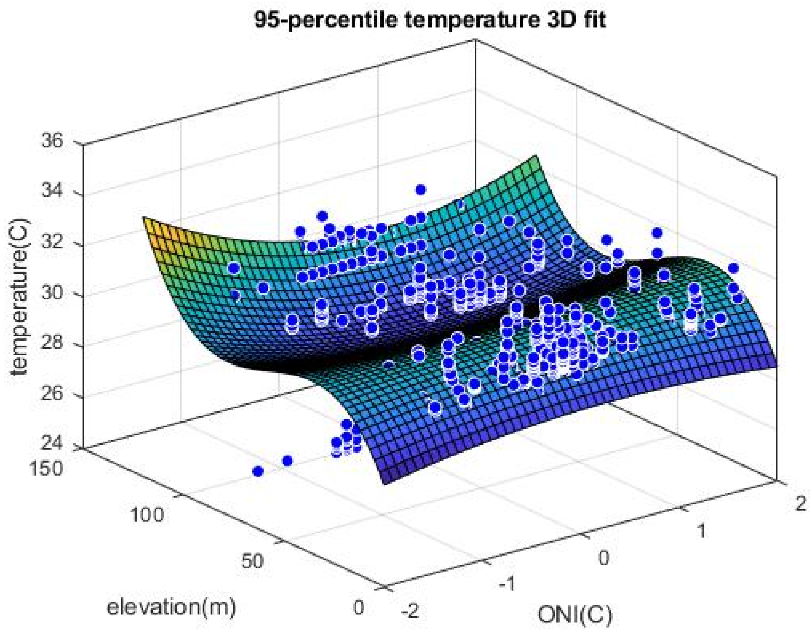

Figure 25: 3D surface fit for 95th percentile average daily temperature against ONI and elevation during the summer season. There seems to be a slight increase in temperature with increasing ONI. There seems to be no apparent relation between temperature and elevation though. This might be since the elevation is in a rather limited interval where such correlations can not appear.

C.2 Relation between 95th percentile maximum daily air temperature and ONI

In this section the analysis of the relation between 95th percentile maximum daily air temperature and ONI is presented in more detail. Below, the correlation coefficients and some other analysis is presented.

C.2.1 Summer

For the summer the mean values of the correlations coefficients have both positive and negative values. There is one region that has negative correlation at 95% confidence which is Taipei. Other than for Taipei none of the locations have a positive or negative slope at this confidence level. Further, the R^2-value for Taipei is relatively high, although, the majority of the variance still is not explained by the model.

Table 21: Linear relation between 95th percentile maximum daily air temperature and ONI in the different regions with accompanying 95% confidence interval and R^2-value for the months June, July and August between 2008 and 2019.

Region	Correlation coefficient 95% CI	R-square value
New Taipei	-0.11276 [-0.2927 0.0672]	0.0277
Taipei	-0.33793 [-0.5272 -0.1487]	0.185
Taoyuan	0.054524 [-0.1499 0.2590]	0.00309
Hsinchu	0.049394 [-0.2757 0.3745]	0.00164
Miaoli	0.049394 [-0.2757 0.3745]	0.00164
Taichung	-0.0077174 [-0.1369 0.1214]	0.000229
Chunghua	0.11382 [-0.0802 0.3078]	0.0231
Chiayi	0.070718 [-0.0981 0.2395]	0.0126
Nantou	0.23487 [-0.0623 0.5321]	0.0391
Tainan	0.025853 [-0.1213 0.1730]	0.00223
Kaohsiung	-0.026065 [-0.2018 0.1497]	0.00138
Pingtung	0.090441 [-0.0438 0.2247]	0.0297
Yilan	-0.11591 [-0.4069 0.1751]	0.0106
Hualien	0.12007 [-0.1335 0.3736]	0.0139
Taitung	0.081025 [-0.1646 0.3267]	0.00782

C.2.2 Autumn

The analysis of the relation between maximum daily air temperature and ONI during the autumn indicate both positive and negative correlations. For Chiayi and Tainan the correlation coefficients of the linear models are negative with 95% confidence and for Hualien the correlation is positive at this confidence level. Overall, most of the variance in the data is not explained by the models which can be seen in the low R^2-values.

Table 22: Linear relation between 95th percentile maximum daily air temperature and ONI in the different regions with accompanying 95% confidence interval and R^2-value for the months September, October and November between 2008 and 2019.

Region	Correlation coefficient 95% CI	R-square value
New Taipei	-0.11192 [-0.3193 0.0955]	0.0207
Taipei	0.022858 [-0.2010 0.2467]	0.000741
Taoyuan	0.054201 [-0.3184 0.4268]	0.00153
Hsinchu	0.3133 [-0.1872 0.8138]	0.0266
Miaoli	0.3133 [-0.1872 0.8138]	0.0266
Taichung	-0.10978 [-0.4111 0.1915]	0.00791
Chunghua	0.17097 [-0.0392 0.3812]	0.0394
Chiayi	-0.54971 [-0.9142 -0.1852]	0.142
Nantou	-0.026912 [-0.3311 0.2773]	0.000537
Tainan	-0.25369 [-0.5020 -0.0053]	0.0703
Kaohsiung	-0.066002 [-0.3006 0.1686]	0.00513
Pingtung	0.12536 [-0.0369 0.2877]	0.0393
Yilan	-0.024436 [-0.1993 0.1505]	0.00141
Hualien	0.27796 [0.0170 0.5390]	0.071
Taitung	0.12879 [-0.2264 0.4840]	0.0091

C.2.3 Winter

When it comes to the relations for the winter months none of the correlation coefficients of the linear models are positive or negative with 95% confidence. The mean values of the correlation coefficients indicate both positive and negative relations. When looking at the R^2-values it can be seen that most of the variance is not explained by the model.

Table 23: Linear relation between 95th percentile maximum daily air temperature and ONI in the different regions with accompanying 95% confidence interval and R^2-value for the months December, October and November between 2008 and 2019.

Region	Correlation coefficient 95% CI	R-square value
New Taipei	0.0472 [-0.2184 0.3128]	0.00233
Taipei	0.0081844 [-0.2337 0.2500]	8.46e-05
Taoyuan	0.11174 [-0.1880 0.4115]	0.00944
Hsinchu	0.21015 [-0.1077 0.5280]	0.0313
Miaoli	0.21015 [-0.1077 0.5280]	0.0313
Taichung	-0.026399 [-0.3009 0.2481]	0.000683
Chunghua	-0.016623 [-0.3269 0.2937]	0.000208
Chiayi	0.017042 [-0.2036 0.2376]	0.000424
Nantou	-0.14246 [-0.3823 0.0974]	0.0245
Tainan	-0.016034 [-0.2121 0.1800]	0.000451
Kaohsiung	0.012286 [-0.1589 0.1835]	0.000347
Pingtung	-0.090117 [-0.2059 0.0257]	0.0428
Yilan	0.094252 [-0.0573 0.2458]	0.0268
Hualien	0.038272 [-0.1137 0.1903]	0.00433
Taitung	0.10421 [-0.1149 0.3233]	0.0164

C.2.4 Spring

The relations for the spring months indicate both positive and negative correlation coefficients. However, for Taoyuan the correlation coefficient of the linear model is positive with 95% confidence. The models do not explain the majority of the variance during this season either.

Table 24: Linear relation between 95th percentile maximum daily air temperature and ONI in the different regions with accompanying 95% confidence interval and R^2-value for the months March, April and May between 2008 and 2019.

Region	Correlation coefficient 95% CI	R-square value
New Taipei	0.18443 [-0.1763 0.5452]	0.0183
Taipei	-0.07971 [-0.4905 0.3311]	0.00258
Taoyuan	0.32234 [0.0255 0.6192]	0.0787
Hsinchu	-0.091256 [-0.4539 0.2714]	0.0044
Miaoli	-0.091256 [-0.4539 0.2714]	0.0044
Taichung	0.018685 [-0.3698 0.4071]	0.000146
Chunghua	-0.12176 [-0.4942 0.2506]	0.00755
Chiayi	0.11128 [-0.3390 0.5615]	0.00441
Nantou	-0.16228 [-0.5911 0.2665]	0.0103
Tainan	0.06377 [-0.2160 0.3435]	0.00362
Kaohsiung	0.010925 [-0.1770 0.1989]	0.000209
Pingtung	-0.17579 [-0.4596 0.1080]	0.0271
Yilan	-0.17121 [-0.5422 0.1998]	0.0149
Hualien	-0.27939 [-0.6228 0.0640]	0.0434
Taitung	-0.47262 [-1.3200 0.3747]	0.0221

C.3 Relation between 95th percentile average daily UTCI and ONI

The analysis of the relation between 95th percentile average daily UTCI and ONI is presented in more detail in this section.

C.3.1 Summer

The summer season has one correlation coefficient that is negative with 95% confidence, Tainan. The other correlation coefficients do not exhibit positive or negative values at this confidence level.

Table 25: Linear relation between 95th percentile average daily UTCI and ONI in the different regions with accompanying 95% confidence interval and R^2-values for the months June, July and August between 2008 and 2019.

Region	Correlation coefficient 95% CI	R-square value
New Taipei	-0.0389 [-0.1434 0.0656]	0.00995
Taipei	-0.0389 [-0.1434 0.0656]	0.00995
Taoyuan	0.1297 [-0.0682 0.3276]	0.0302
Hsinchu	0.0180 [-0.1666 0.2025]	0.000699
Miaoli	0.0055 [-0.1952 0.2063]	5.53e-05
Taichung	0.0491 [-0.1542 0.2524]	0.00421
Chunghua	0.0052 [-0.1390 0.1494]	9.59e-05
Chiayi	0.0874 [-0.0457 0.2205]	0.0303
Nantou	0.0105 [-0.1577 0.1787]	0.000282
Tainan	-0.1318 [-0.2561 -0.0075]	0.0767
Kaohsiung	-0.0279 [-0.1701 0.1144]	0.00282
Pingtung	0.0349 [-0.1333 0.2030]	0.00311
Yilan	-0.0389 [-0.1434 0.0656]	0.00995
Hualien	0.0458 [-0.1171 0.2086]	0.00569
Taitung	-0.2446 [-0.5076 0.0183]	0.0601

C.3.2 Autumn

The correlation coefficient for Kaohsiung is the only one that is positive or negative with 95% confidence during the autumn. This value is negative.

Table 26: Linear relation between 95th percentile average daily UTCI and ONI in the different regions with accompanying 95% confidence interval and R^2-values for the months September, October and November between 2008 and 2019.

Region	Correlation coefficient 95% CI	R-square value
New Taipei	-0.0310 [-0.2625 0.2004]	0.00133
Taipei	-0.0310 [-0.2625 0.2004]	0.00133
Taoyuan	0.1476 [-0.1357 0.4308]	0.0197
Hsinchu	-0.0109 [-0.2116 0.1898]	0.000218
Miaoli	-0.0449 [-0.2833 0.1936]	0.00261
Taichung	-0.0777 [-0.2884 0.1331]	0.00993
Chunghua	-0.1410 [-0.3351 0.0531]	0.0375
Chiayi	-0.2341 [-0.5069 0.0388]	0.0516
Nantou	-0.0262 [-0.2095 0.1572]	0.0015
Tainan	-0.1037 [-0.2870 0.0796]	0.0231
Kaohsiung	-0.2357 [-0.4649 -0.0064]	0.0724
Pingtung	-0.0288 [-0.2363 0.1786]	0.00143
Yilan	-0.0310 [-0.2625 0.2004]	0.00133
Hualien	0.1087 [-0.0557 0.2730]	0.0313
Taitung	-0.0858 [-0.2674 0.0957]	0.0162

C.3.3 Winter

During the winter there is no correlation coefficient that is either positive or negative on a 95% confidence level.

Table 27: Linear relation between 95th percentile average daily UTCI and ONI in the different regions with accompanying 95% confidence interval and R^2-values for the months December, January and February between 2008 and 2019.

Region	Correlation coefficient 95% CI	R-square value
New Taipei	-0.1461 [-0.3872 0.0950]	0.0264
Taipei	-0.1461 [-0.3872 0.0950]	0.0264
Taoyuan	0.0163 [-0.2391 0.2718]	0.000302
Hsinchu	-0.0516 [-0.3233 0.2202]	0.00265
Miaoli	-0.0444 [-0.3443 0.2555]	0.00162
Taichung	-0.2694 [-0.5567 0.0180]	0.061
Chunghua	-0.1240 [-0.4353 0.1874]	0.0116
Chiayi	-0.1466 [-0.3711 0.0779]	0.0306
Nantou	-0.1016 [-0.2607 0.0574]	0.0293
Tainan	-0.0539 [-0.3192 0.2114]	0.00304
Kaohsiung	-0.0311 [-0.2436 0.1815]	0.00158
Pingtung	-0.0890 [-0.2863 0.1083]	0.0148
Yilan	-0.1461 [-0.3872 0.0950]	0.0264
Hualien	-0.0872 [-0.3383 0.1639]	0.00883
Taitung	0.0596 [-0.1147 0.2339]	0.00856

C.3.4 Spring

In the spring there is one correlation coefficient that is positive with 95% confidence and that is the one of Hualien. Other than Hualien none of the locations exhibit any significant trends.

Table 28: Linear relation between 95th percentile average daily UTCI and ONI in the different regions with accompanying 95% confidence interval and R^2-values for the months March, April and May between 2008 and 2019.

Region	Correlation coefficient 95% CI	R-square value
New Taipei	0.2012 [-0.2305 0.6329]	0.0155
Taipei	0.2012 [-0.2305 0.6329]	0.0155
Taoyuan	-0.4871 [-1.0764 0.1022]	0.0472
Hsinchu	0.2840 [-0.4047 0.9727]	0.0122
Miaoli	0.1791 [-0.5585 0.9166]	0.00425
Taichung	-0.0107 [-0.5368 0.5155]	2.98e-05
Chunghua	-0.3225 [-0.8465 0.2015]	0.0267
Chiayi	-0.1082 [-0.4684 0.2520]	0.00649
Nantou	0.0192 [-0.2562 0.2947]	0.000353
Tainan	0.2284 [-0.2112 0.6680]	0.0192
Kaohsiung	-0.1771 [-0.5743 0.2200]	0.0142
Pingtung	-0.2836 [-0.6907 0.1235]	0.034
Yilan	0.2012 [-0.2305 0.6329]	0.0155
Hualien	0.3397 [0.0316 0.6478]	0.081
Taitung	0.3272 [-0.1167 0.7710]	0.0379

C.4 Relation between 95th percentile maximum daily UTCI and ONI

The analysis between 95th percentile maximum daily UTCI and ONI is presented in more detail in this section.

C.4.1 Summer

During the summer no trends on a 95% confidence level were found.

Table 29: Linear relation between 95th percentile maximum daily UTCI and ONI in the different regions with accompanying 95% confidence interval and R^2-values for the months June, July and August between 2008 and 2019.

Region	Correlation coefficient 95% CI	R-square value
New Taipei	0.0766 [-0.1116 0.2648]	0.0119
Taipei	0.0766 [-0.1116 0.2648]	0.0119
Taoyuan	0.2408 [-0.1001 0.5818]	0.0349
Hsinchu	0.1614 [-0.0743 0.3971]	0.0329
Miaoli	-0.0228 [-0.1923 0.1468]	0.0013
Taichung	-0.1062 [-0.3533 0.1409]	0.0132
Chunghua	0.1203 [-0.0807 0.3214]	0.0253
Chiayi	-0.0718 [-0.1768 0.0332]	0.0328
Nantou	0.0298 [-0.1519 0.2114]	0.00194
Tainan	-0.0712 [-0.1935 0.0511]	0.024
Kaohsiung	0.1165 [-0.0374 0.2703]	0.0399
Pingtung	-0.0645 [-0.3025 0.1734]	0.0053
Yilan	0.0766 [-0.1116 0.2648]	0.0119
Hualien	-0.0213 [-0.1967 0.1541]	0.00107
Taitung	0.1310 [-0.2387 0.5007]	0.00902

C.4.2 Autumn

During the autumn no trends on a 95% confidence level were found.

Table 30: Linear relation between 95th percentile maximum daily UTCI and ONI in the different regions with accompanying 95% confidence interval and R^2-values for the months September October and November between 2008 and 2019.

Region	Correlation coefficient 95% CI	R-square value
New Taipei	0.0185 [-0.2424 0.2793]	0.00037
Taipei	0.0185 [-0.2424 0.2793]	0.00037
Taoyuan	0.2309 [-0.2998 0.7615]	0.0138
Hsinchu	0.0421 [-0.1775 0.2616]	0.0027
Miaoli	-0.0056 [-0.1855 0.1744]	7.12e-05
Taichung	-0.1596 [-0.3662 0.0471]	0.0422
Chunghua	0.0165 [-0.2205 0.2535]	0.000359
Chiayi	-0.0225 [-0.3150 0.2701]	0.000435
Nantou	-0.0602 [-0.1961 0.0757]	0.0143
Tainan	-0.0615 [-0.2876 0.1647]	0.00543
Kaohsiung	-0.2279 [-0.4818 0.0260]	0.0562
Pingtung	-0.1433 [-0.3557 0.0691]	0.0325
Yilan	0.0185 [-0.2424 0.2793]	0.00037
Hualien	-0.0538 [-0.2091 0.1016]	0.00878
Taitung	0.0181 [-0.1341 0.1704]	0.00105

C.4.3 Winter

During the winter season Chiayi was found to have a negative relation at 95% confidence. No positive trends were found at this confidence level.

Table 31: Linear relation between 95th percentile maximum daily UTCI and ONI in the different regions with accompanying 95% confidence interval and R^2-values for the months December, January and February between 2008 and 2019.

Region	Correlation coefficient 95% CI	R-square value
New Taipei	-0.0236 [-0.2437 0.1964]	0.000851
Taipei	-0.0236 [-0.2437 0.1964]	0.000851
Taoyuan	0.0631 [-0.1496 0.2757]	0.00646
Hsinchu	-0.0186 [-0.3681 0.3310]	0.000208
Miaoli	-0.0303 [-0.3660 0.3054]	0.000601
Taichung	-0.0844 [-0.3190 0.1502]	0.00947
Chunghua	0.0148 [-0.2519 0.2815]	0.000227
Chiayi	-0.2442 [-0.4168 -0.0716]	0.129
Nantou	-0.1009 [-0.2605 0.0586]	0.0287
Tainan	0.0250 [-0.2478 0.2978]	0.000621
Kaohsiung	-0.0825 [-0.3076 0.1427]	0.00981
Pingtung	0.0085 [-0.1725 0.1896]	0.000164
Yilan	-0.0236 [-0.2437 0.1964]	0.000851
Hualien	-0.0670 [-0.2565 0.1226]	0.00914
Taitung	0.0471 [-0.1694 0.2636]	0.00349

C.4.4 Spring

No correlation coefficients were found to have confidence in the spring season.

Table 32: Linear relation between 95th percentile maximum daily UTCI and ONI in the different regions with accompanying 95% confidence interval and R^2-values for the months Mars, April and May between 2008 and 2019.

Region	Correlation coefficient 95% CI	R-square value
New Taipei	-0.1285 [-0.4114 0.1545]	0.0147
Taipei	-0.1285 [-0.4114 0.1545]	0.0147
Taoyuan	0.1434 [-0.3088 0.5957]	0.00724
Hsinchu	0.2348 [-0.4124 0.8820]	0.00945
Miaoli	0.3080 [-0.2995 0.9156]	0.0183
Taichung	0.3160 [-0.0969 0.7290]	0.0407
Chunghua	-0.1089 [-0.5946 0.3769]	0.00363
Chiayi	-0.1725 [-0.5259 0.1809]	0.017
Nantou	-0.0014 [-0.2332 0.2303]	2.81e-06
Tainan	0.0413 [-0.2806 0.3631]	0.00119
Kaohsiung	-0.1700 [-0.5367 0.1967]	0.0153
Pingtung	0.2149 [-0.2675 0.6973]	0.0142
Yilan	-0.1285 [-0.4114 0.1545]	0.0147
Hualien	0.1736 [-0.2404 0.5876]	0.0126
Taitung	0.3919 [-0.1559 0.9397]	0.0358

C.5 Relation between average monthly temperature and ONI

In this section the relationship between monthly average temperature and ONI is presented. Although there are no correlation coefficients positive or negative with 95 % confidence there are some patterns that can be seen. The most clear pattern is that all mean correlation coefficients during the winter months and spring months are positive and the R^2-values are relatively large compared to the ones for the other seasons.

C.5.1 Summer

Table 33: Linear relation between average monthly temperature and ONI in the different regions with accompanying 95% confidence interval and R^2-values for the months June, July and August between 2008 and 2019.

Region	Correlation coefficient 95% CI	R-square value
New Taipei	0.1043 [-0.3786 0.5871]	0.00524
Taipei	0.0274 [-0.4445 0.4993]	0.000381
Taoyuan	-0.0548 [-0.5977 0.4880]	0.00115
Hsinchu	0.0740 [-0.3797 0.5277]	0.003
Miaoli	0.0740 [-0.3797 0.5277]	0.003
Taichung	0.0479 [-0.2926 0.3885]	0.00223
Chunghua	-0.0080 [-0.3851 0.3691]	5.06e-05
Chiayi	0.1370 [-0.1705 0.4446]	0.0219
Nantou	0.0186 [-0.2335 0.2706]	0.000614
Tainan	0.0130 [-0.3216 0.3476]	0.000171
Kaohsiung	0.0695 [-0.2759 0.4148]	0.00455
Pingtung	0.1358 [-0.1106 0.3821]	0.0332
Yilan	0.0040 [-0.4503 0.4583]	8.78e-06
Hualien	0.1224 [-0.2551 0.4999]	0.0117
Taitung	0.0758 [-0.2756 0.4271]	0.00523

C.5.2 Autumn

Table 34: Linear relation between average monthly temperature and ONI in the different regions with accompanying 95% confidence interval and R^2-values for the months September, October and November between 2008 and 2019.

Region	Correlation coefficient 95% CI	R-square value
New Taipei	-0.0449 [-0.9056 0.8157]	0.000308
Taipei	-0.0817 [-0.9371 0.7737]	0.00103
Taoyuan	-0.1214 [-1.0081 0.7653]	0.00211
Hsinchu	-0.0749 [-0.9550 0.8051]	0.000818
Miaoli	-0.0749 [-0.9550 0.8051]	0.000818
Taichung	-0.0203 [-0.7814 0.7407]	8.04e-05
Chunghua	-0.0233 [-0.8698 0.8233]	8.53e-05
Chiayi	0.0314 [-0.7540 0.8168]	0.000181
Nantou	-0.0142 [-0.5566 0.5282]	7.74e-05
Tainan	0.0839 [-0.6540 0.8217]	0.00146
Kaohsiung	0.0876 [-0.4870 0.6622]	0.00262
Pingtung	0.0090 [-0.5080 0.5260]	3.41e-05
Yilan	-0.1056 [-0.9319 0.7206]	0.00184
Hualien	-0.0351 [-0.7097 0.6395]	0.000306
Taitung	0.0166 [-0.5948 0.6280]	8.33e-05

C.5.3 Winter

Table 35: Linear relation between average monthly temperature and ONI in the different regions with accompanying 95% confidence interval and R^2-values for the months December, January and February between 2008 and 2019.

Region	Correlation coefficient 95% CI	R-square value
New Taipei	0.3053 [-0.1187 0.7293]	0.0553
Taipei	0.2782 [-0.1471 0.7035]	0.0461
Taoyuan	0.2953 [-0.1118 0.7024]	0.0561
Hsinchu	0.2828 [-0.1514 0.7170]	0.0457
Miaoli	0.2828 [-0.1514 0.7170]	0.0457
Taichung	0.2846 [-0.1621 0.7312]	0.0438
Chunghua	0.3335 [-0.1125 0.7796]	0.0594
Chiayi	0.3728 [-0.0947 0.8402]	0.067
Nantou	0.1507 [-0.2621 0.5635]	0.0148
Tainan	0.3241 [-0.1285 0.7767]	0.0548
Kaohsiung	0.3033 [-0.1223 0.7288]	0.0543
Pingtung	0.2924 [-0.0198 0.6045]	0.0902
Yilan	0.2650 [-0.1051 0.6350]	0.0548
Hualien	0.2142 [-0.1363 0.5647]	0.0405
Taitung	0.2334 [-0.1222 0.5891]	0.0464

C.5.4 Spring

Table 36: Linear relation between average monthly temperature and ONI in the different regions with accompanying 95% confidence interval and R^2-values for the months March, April and May between 2008 and 2019.

Region	Correlation coefficient 95% CI	R-square value
New Taipei	0.4436 [-1.1430 2.0303]	0.00875
Taipei	0.4582 [-1.0917 2.0080]	0.00978
Taoyuan	0.3617 [-1.3112 2.0345]	0.00525
Hsinchu	0.4355 [-1.2592 2.1301]	0.0074
Miaoli	0.4355 [-1.2592 2.1301]	0.0074
Taichung	0.3133 [-1.1513 1.7779]	0.00514
Chunghua	0.3930 [-1.2022 1.9882]	0.00681
Chiayi	0.5770 [-0.8846 2.0387]	0.0173
Nantou	0.2836 [-0.7214 1.2886]	0.00892
Tainan	0.2797 [-1.1032 1.6626]	0.0046
Kaohsiung	0.3533 [-0.7473 1.4539]	0.0115
Pingtung	0.5167 [-0.4989 1.5324]	0.0284
Yilan	0.3970 [-0.9381 1.7320]	0.00989
Hualien	0.4451 [-0.7491 1.6392]	0.0155
Taitung	0.4435 [-0.6943 1.5812]	0.0169

C.6 Relation between 95th percentile average daily air temperature and ENSO phase

An analysis was made where the relation between 95th percentile average daily air temperature and ENSO phase was investigated with the ONI translated into a value representing the phase of ENSO. A negative phase(ONI<-0.5 °C) is represented by -1. A positive phase(ONI>0.5 °C) is represented by 1. Anything in between these two is given the value 0 to represent the normal phase. The results can be seen in the tables below:

C.6.1 Summer

Table 37: Linear relation between average 95th percentile average daily air temperature and ENSO phase in the different regions with accompanying 95% confidence interval and R^2-values for the months June, July and August between 2008 and 2019.

Region	Correlation coefficient 95% CI	R-square value
New Taipei	-0.0487 [-0.1913 0.0938]	0.00839
Taipei	-0.0749 [-0.2013 0.0515]	0.0244
Taoyuan	0.0544 [-0.0490 0.1579]	0.00686
Hsinchu	0.0309 [-0.1510 0.2128]	0.00191
Miaoli	0.0309 [-0.1510 0.2128]	0.00191
Taichung	-0.0064 [-0.1180 0.1051]	0.000203
Chunghua	0.0990 [0.0093 0.1887]	0.0547
Chiayi	0.1807 [0.0467 0.3148]	0.109
Nantou	0.3581 [0.0594 0.6568]	0.0806
Tainan	0.0614 [-0.0297 0.1525]	0.0292
Kaohsiung	-0.0415 [-0.1728 0.0898]	0.0068
Pingtung	0.0805 [0.0026 0.1584]	0.0707
Yilan	-0.1662 [-0.3437 0.0113]	0.0549
Hualien	-0.0225 [-0.1430 0.0980]	0.00209
Taitung	0.0130 [-0.2033 0.2293]	0.000231

C.6.2 Autumn

Table 38: Linear relation between average 95th percentile average daily air temperature and ENSO phase in the different regions with accompanying 95% confidence interval and R^2-values for the months September, October and November between 2008 and 2019.

Region	Correlation coefficient 95% CI	R-square value
New Taipei	-0.1128 [-0.3083 0.0827]	0.0223
Taipei	0.0298 [-0.2084 0.2679]	0.00113
Taoyuan	-0.1081 [-0.3624 0.1462]	0.0106
Hsinchu	-0.0416 [-0.2548 0.1717]	0.0026
Miaoli	-0.0416 [-0.2548 0.1717]	0.0026
Taichung	-0.0996 [-0.2373 0.0380]	0.0319
Chunghua	0.1373 [-0.0150 0.2895]	0.0547
Chiayi	-0.2035 [-0.3382 -0.0688]	0.122
Nantou	-0.2923 [-0.5946 0.0099]	0.0583
Tainan	-0.0937 [-0.2111 0.0237]	0.0392
Kaohsiung	-0.1100 [-0.2413 0.0213]	0.0404
Pingtung	0.1794 [0.0582 0.3006]	0.137
Yilan	0.1033 [-0.1023 0.3089]	0.018
Hualien	0.0489 [-0.0960 0.1937]	0.00761
Taitung	0.1382 [-0.0289 0.3052]	0.0448

C.6.3 Winter

Table 39: Linear relation between average 95th percentile average daily air temperature and ENSO phase in the different regions with accompanying 95% confidence interval and R^2-values for the months December, January and February between 2008 and 2019.

Region	Correlation coefficient 95% CI	R-square value
New Taipei	-0.1631 [-0.3632 0.0371]	0.0468
Taipei	0.0123 [-0.2146 0.2393]	0.000215
Taoyuan	0.0254 [-0.2052 0.2560]	0.000776
Hsinchu	0.1064 [-0.1238 0.3367]	0.0145
Miaoli	0.1064 [-0.1238 0.3367]	0.0145
Taichung	-0.0805 [-0.3404 0.1794]	0.00704
Chunghua	0.3172 [-0.0002 0.6346]	0.0687
Chiayi	-0.1127 [-0.4018 0.1764]	0.0109
Nantou	-0.1745 [-0.3595 0.0105]	0.0585
Tainan	0.0509 [-0.2298 0.3317]	0.00243
Kaohsiung	0.0907 [-0.0441 0.2255]	0.0286
Pingtung	0.0466 [-0.0903 0.1835]	0.00833
Yilan	-0.0964 [-0.2797 0.0868]	0.019
Hualien	-0.1122 [-0.3022 0.0778]	0.0251
Taitung	0.0504 [-0.1294 0.2302]	0.00527

C.6.4 Spring

Table 40: Linear relation between average 95th percentile average daily air temperature and ENSO phase in the different regions with accompanying 95% confidence interval and R^2-values for the months March, April and May between 2008 and 2019.

Region	Correlation coefficient 95% CI	R-square value
New Taipei	0.0420 [-0.3380 0.4220]	0.000884
Taipei	0.0236 [-0.3261 0.3733]	0.000313
Taoyuan	0.3264 [0.0056 0.6472]	0.0485
Hsinchu	0.1052 [-0.2452 0.4557]	0.00649
Miaoli	0.1052 [-0.2452 0.4557]	0.00649
Taichung	-0.1153 [-0.4753 0.2447]	0.00711
Chunghua	-0.0066 [-0.3189 0.3056]	3.11e-05
Chiayi	-0.0507 [-0.4670 0.3656]	0.00106
Nantou	-0.0219 [-0.2457 0.2020]	0.000679
Tainan	-0.0440 [-0.3074 0.2193]	0.00202
Kaohsiung	-0.1052 [-0.3722 0.1617]	0.0109
Pingtung	-0.1650 [-0.4252 0.0952]	0.0283
Yilan	-0.1476 [-0.4741 0.1789]	0.0141
Hualien	-0.3108 [-0.5793 -0.0424]	0.0791
Taitung	0.0066 [-0.3933 0.4066]	1.97e-05

During the summer months there are 4 stations that have a positive correlation with the ENSO phase. These are the same stations that were positive when analysing the relationship between 95th percentile average daily air temperature and ONI. During the autumn there is one station that is positive and one that is negative. During the winter there are no relations within the confidence limits and during the spring one station is negative with confidence.