AMERICAN UNIVERSITY OF BEIRUT

THE IMPACT OF CLIMATE CHANGE ON THE PRODUCTION OF WHEAT IN LEBANON

by
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AN ABSTRACT OF THE THESIS OF

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Climate extreme indices were calculated for the Beqaa Valley, Lebanon using weather data that was collected, digitized and cleaned for the first time from the American University of Beirut Agricultural Research and Education Center for the period 1956-2013. The indices were calculated using the RClimDex software which was developed by Xuebin Zhang and Yang Feng as part of an international initiative to develop and analyze a suite of climate extreme indices.

Linear trends were computed using the Theil-Sen estimator which has been widely used in climatic and hydro-meteorological series. Results, although mostly not statistically significant, were in line with trends obtained in previous literature for the Middle East and Lebanon. The growing season length index showed a significant and decreasing trend which can potentially limit the growth of wheat and other crops. A positive trend was noted in the annual count of summer days and tropical nights. Cool days and nights decreased, warm days and nights increased and the cold spell duration index showed a decreasing trend. An increasing but weak trend was observed for all precipitation indices (though not statistically significant).

To further explore the impact of this change in climate and its impact on wheat production, the relationship between wheat yields and three monthly climatic variables (maximum temperature, minimum temperature and precipitation) was evaluated for Lebanon for the period 1961-2008. A series of independent regressions was performed between technology-adjusted residuals and monthly climatic variables. Results of multiple regressions showed that the maximum temperature for March has a high and statistically significant negative effect on yields. The logged precipitation for April and logged precipitation squared for November also showed a significant positive effect and are in line with winter wheat growth stages and water requirements.

The above results should be considered in the larger context where as much as 50-80% of wheat grown in the Beqaa Baalbek-Hermel districts is irrigated. Investing in better irrigation data is therefore crucial for a better understanding of climate-yield relationships and the effect of additional climate-induced impediments on the wheat production sector in Lebanon.

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PART I

TRENDS IN CLIMATE EXTREME INDICES FROM 1960 TO 2008: THE CASE OF THE BEQAA VALLEY, LEBANON

CHAPTER I

INTRODUCTION

The climate system warming the world is facing today is undisputable and many of the observed changes since the 1950s have been unprecedented over decades. According to the Intergovernmental Panel on Climate Change (IPCC), a warming of approximately 0.6°C to 0.7°C over the period 1951 to 2010 has been observed and global surface temperature change for the end of the 21st century is likely to exceed 1.5°C relative to 1850 to 1900 for almost all emission scenarios (IPCC, 2013).

It is estimated that more than half of the increase in global average surface temperature since the mid-twentieth century was caused by an anthropogenic increase in greenhouse gas concentrations and other anthropogenic forcings. The situation is even more critical for the eastern Mediterranean and Middle East regions where warming rates are expected to exceed the global average.

Unfortunately, the lack of both reliable baseline data and climate model consensus for large areas of Africa, Asia, the Middle East, and South America has hindered the accurate projections for these regions. Nevertheless, the Mediterranean basin is one region where climate model consensus is relatively strong, with most models showing on average decreased winter, summer, and annual precipitation totals (Lee, Ashwill, & Wilby, 2013a). Despite the difficulty to access high quality daily data, climate change detection and attribution studies have increasingly focused on studying extreme events (Easterling, Meehl, & Parmesan, 2000).

A recent and notable initiative is the international effort coordinated by the joint World Meteorological Organization Commission for Climatology (CCl) Climate Variability and Predictability (CLIVAR) Expert Team on Climate Change Detection, Monitoring and Indices (ETCCDMI) to develop, calculate, and analyze a suite of indices of climate extremes. These indices are derived from daily temperature and precipitation data and would improve the monitoring of climate extreme change and provide much broader spatial coverage than currently available (Zhang et al., 2005).

Amongst the activities undertaken by the expert team is a workshop that targeted the Middle East and resulted in the development of the first area-wide analysis of climate extremes for the region. The findings of the workshop were reported by Zhang et al. (2005) who examined trends in these indices for the period 1950–2003 obtained from 52 stations covering 15 countries. Results indicated that there have been statistically significant, spatially coherent trends in temperature indices that are related to temperature increases in the region.

Despite being left out of the study, climate extreme indices have increasingly been computed for Lebanon in recent years by various parties and reports such as the Department of Irrigation and Agro-Meteorology (DIAM) of the Lebanese Agricultural Research Institute (LARI), Lebanon's second communication to the UNFCCC and more recently in a report that examines climate change impacts on selected native tree distributions in Lebanon by the Lebanon Reforestation Initiative and the Center for Applied Research in Agroforestry Development. Lastly, UNDP has been creating country-level climate data summaries for developing countries to address the climate change information gap. Lebanon was one of the 52 countries for which UNDP constructed climate extreme indices.

Nevertheless, more effort is required for improving observational data availability and quality in Lebanon, as well as the retrieval and digitization of older data from a larger number of stations.

The thesis aims to respond to these needs through the retrieval and digitization of old climate data for the first time from the American University of Beirut Agricultural Research and Education Center (AREC). The compilation and cleaning exercises of the 1956-2013 weather data was successfully undertaken through the collaboration with AREC, the department of Agriculture, the relentless efforts of a dedicated team of students and a rigorous quality control and cleaning exercise.

The wealth of data collected enabled the calculation of climate extreme indices for the Beqaa that could be used for comparison purposes with other stations in the area. The data and resulting indices would increase AREC's involvement in climate change research in the region by making available for others its own raw data. The data also open doors to future climate and agricultural research at the university.

A first attempt to undertake such agricultural research by using the newly acquired and cleaned data is documented in part two of this thesis which assesses the historical effects of temperature and precipitation on wheat yield in the Beqaa.

CHAPTER II

LITERATURE REVIEW

A. Climate Change and Its Impact on Society

Climate change is one of the most critical environmental challenges faced in the world today, with significant threats to ecosystems, food security, water resources and economic stability overall.

According to the Intergovernmental Panel on Climate Change (IPCC), climate change refers to a change in the state of the climate that can be measured by the observed change in the mean or variability of its properties over an extended period of time, usually decades or longer. This change can be due to natural variability or be the outcome of human activity. Unlike the IPCC, the United Nations Framework Convention on Climate Change (UNFCCC) restricts the definition of the term climate change to a change of climate which is strictly attributed to direct or indirect human activity that alters the composition of the global atmosphere and that is in addition to natural climate variability observed over comparable time periods (IPCC, 2007).

Whether due to natural variability or human activity, the case remains that the climate system warming the world is facing today is unequivocal and many of the observed changes since the 1950s have been unprecedented over decades or more. According to the IPCC, a warming of approximately 0.6°C to 0.7°C over the period 1951 to 2010 has been observed and global surface temperature change for the end of the 21st century is likely to exceed 1.5°C relative to 1850 to 1900 for almost all emission scenarios (IPCC, 2013).

Since the 1980s, each decade has been successively warmer than any preceding decade since the 1850s. It is very likely that on the global scale, the number of cold days and nights has decreased and the number of warm days and nights has increased. This global change in climate has also materialized through warmer oceans, a significant decrease in snow and ice, a rise in sea level and most importantly, the increase in greenhouse gas concentrations (IPCC, 2013).

The main culprit in this warming is anthropogenic as it is hypothesized that more than half of the increase in global average surface temperature since the mid-twentieth century was caused by human-induced increase in greenhouse gas concentrations and other anthropogenic forcings. In fact, global GHG emissions due to human activities have grown since pre-industrial times, with an increase of 70% between 1970 and 2004 (IPCC, 2007).

Although human influences can now be identified and measured, it seems to be a bit too late to reverse the process. According to some climate model projections, decadal-average warming by 2030 is inevitable no matter which emission pathway is chosen and is very likely to exceed natural variability observed during the twentieth century (Lee et al., 2013a).

The situation is even more critical for the eastern Mediterranean and Middle East regions where rates of twenty-first century warming are expected to exceed the global average. Though projected patterns of warming and continuous increases in sea levels are done with high confidence, regional rainfall has been trickier to predict. In general, precipitation is projected to increase at high latitudes and decrease over most subtropical land regions. However, the lack of both reliable baseline data and climate model consensus for large areas of Africa, Asia, the Middle East, and South America has hindered the accurate projections for these regions. Nevertheless, the Mediterranean basin is one region where climate model consensus is relatively strong, with most models showing on average decreased winter, summer, and annual precipitation totals (Lee et al., 2013a).

This adds pressure to the frail agriculture sectors of countries around the Mediterranean basin, such as Lebanon, as the former already suffer from limited water resources, land degradation and the pressure exerted by population growth and urbanization.

B. Importance of Measuring Climate Change

Interest in climate change has been increasing over the past decades due to the potential threats it poses on nature and society (Houghton, Callander, & Varney, 1992). In response to this interest, climate scientists from throughout the world have been analyzing local, regional, and global temperature and other climate records (H. A. Nasrallah & Balling, 1993).

Most analyses of long term global climate changes using observational temperature and precipitation data has focused on changes in monthly mean values (Alexander & Zhang, 2006; AlSarmi & Washington, 2014). Several monthly data sets such as Jones & Moberg (2003) and Peterson & Vose (1997) provided reasonable spatial coverage across the globe. Monitoring and detecting changes in the occurrence of extreme weather and climate events, such as changes in the number of days during which temperature exceeds its long-term 90th percentile, requires high quality daily resolution data in digital form (Alexander & Zhang, 2006) which is unfortunately not readily available and accessible by the international research community for large portions of the world (Folland et al., 2001; Zhang et al., 2005). Also, some institutions are reluctant to part with data for various reasons (Alexander & Zhang, 2006). In addition, the existing and available analyses conducted by researchers in different countries cannot easily be merged into a global data set or used for comparative purposes because the analyses were not all conducted on the same set of indices and did not use the same methods (Zhang et al., 2005).

Despite the difficulty to access high quality daily data, climate change detection and attribution studies have increasingly focused on studying extreme events (Easterling et al., 2000). The current and projected global warming is believed to have direct implications on the occurrence of such extreme events. Understanding how the latter are changing whether on a local or global scale is an important first step for planning appropriate adaption measures for their potential profound impacts on nature and society such as human injury, deaths, property damage and the existence of certain species (Aguilar & Barry, 2009; Zhang et al., 2005).

This shift from measuring the mean climate to measuring the occurrence of extremes has spurred some debates. Some scholars believe that it is unlikely that the mean climate could warm without altering climatic extremes (Aguilar & Barry, 2009; Parmesan, Root, & Willig, 2000; Peterson, 2008) and thus studying changes in means would suffice. While others claim that a rise in the mean would not necessarily lead to a rise in extreme climate events. However, if the change in mean values was related to a shift in distribution, particularly in the extremes, then this could have major repercussions such as fewer frost days and increased heat wave duration (Frich, Alexander, & Della-Marta, 2002). In addition, analyzing extremes can shed light on many everyday problems. Our infrastructure, food, water, energy and transportation systems are all sensitive to extreme meteorological values. For instance, high precipitation amounts can affect sewage systems, dams and bridges and can lead to safety hazards. Measuring such extremes can help us identify the right amount of safety standards that are generally costly but essential for the prevention of major damage to infrastructure (Data, 2009).

Accordingly, no matter what the outcome of the abovementioned debate is, it sheds light on the importance of measuring extreme events and of compiling a global and readily available full resolution daily data set.

To address this issue and to provide better input to the IPCC Fourth Assessment Report, the joint World Meteorological Organization Commission for Climatology (CCl) Climate Variability and Predictability (CLIVAR) Expert Team on Climate Change Detection, Monitoring and Indices (ETCCDMI) coordinated an international effort to develop, calculate, and analyze a suite of indices of climate extremes. These indices are derived from daily temperature and precipitation data and would improve the monitoring of climate extreme change and provide much broader spatial coverage than currently available (Zhang et al., 2005).

The initiative encompassed a series of five regional workshops that were organized in 2004 and 2005 with the aim of addressing gaps in data availability and analysis in previous global studies such as Frich et al. (2002). The workshop targeting the Middle East brought together scientists to produce the first area-wide analysis of climate extremes for the region. The findings of the workshop were reported by Zhang et al. (2005) who examined trends in these indices for the period 1950–2003 obtained from 52 stations covering 15 countries, including Armenia, Azerbaijan, Bahrain, Cyprus, Georgia, Iran, Iraq, Israel, Jordan, Kuwait, Oman, Qatar, Saudi Arabia, Syria, and Turkey.

Results indicate that there have been statistically significant, spatially coherent trends in temperature indices that are related to temperature increases in the region. Unfortunately, Lebanon was left out of this study for reasons that were not explicitly mentioned. Nevertheless, climate extreme indices were widely computed for the country afterwards. The aim of this chapter is to use for the first time the newly retrieved and digitized data from AREC to reproduce the calculation of those climate extreme indices for the Beqaa. Findings would be used for comparative purposes with other station data and computed indices and enrich research and knowledge of climate change in Lebanon.

C. Evidence of Climate Change in the Arab Countries of the Middle East

Arab countries in the Middle East and North Africa are the most vulnerable in the world to the potential impacts of climate change, namely increased average temperatures, less and more irregular precipitation, and sea level rise which aggravate the region's already widespread aridity, recurrent droughts and water scarcity (Arab Forum for Environment and Development, 2010).

The Middle East is an arid to semi-arid region where fresh water is often a scarce and precious resource and the already critical situation is expected to reach severe levels by 2025 (Tolba & Saab, 2009a). The rapid population growth, substantially increases the vulnerability of the region to future climate change. In addition, agricultural demand accounts for 84 percent (30–88 percent for the individual countries) of the water demand in the region and any dwindling in the resource will have a major impact on the already fragile sector (Bou-Zeid & El-Fadel, 2002).

In the AFED Climate Change report, Tolba and Saab (2009a) warn that the Fertile Crescent which includes Iraq, Syria, Lebanon, Jordan and Palestine, would lose all traits of fertility and might disappear before the end of the century because of deteriorating water supply from major rivers. This is mainly due to human-induced problems such as the widespread construction of dams and unsustainable irrigation practices which waste about half of the water resources; in addition to unsustainable and above global average rates of human water consumption. The expected effects of climate change are likely to exacerbate this deterioration. With continuing increases in temperatures, water flow in the Euphrates may decrease by 30 percent and that of the Jordan River by 80 percent before the turn of the century.

It is often assumed that since the Middle East region has very scarce water resources, the impact of climate change would be negligible. But, water resources in the region are under a heavy and increasing stress and any alteration in climatic patterns that would increase temperatures and reduce precipitation would greatly exacerbate existing difficulties (Bou-Zeid & El-Fadel, 2002).

The region will also have to face the potential threats of sea level rise. With most of the region's economic activity, agriculture and population hubs situated on coastal zones, a rise in sea level could lead to flooding, and an increased salinity in the soil and the available freshwater resources such as aquifers. It is believed that Egypt, Tunisia, Morocco, Algeria, Kuwait, Qatar, Bahrain and the UAE will be the most seriously impacted. Egypt's agricultural sector will face the biggest blow where a 1 meter rise would put 12 percent of the country's agricultural land at risk. This rise would also directly affect the lives of 3.2 percent of the Arab population compared to a global percentage of 1.28 percent. It goes without saying that urgent adaptive measures will be required to ensure the sustainability of food production in the region and its resilience to climate change (Tolba & Saab, 2009a). Finally, climate change will also have substantial impact on human health, where increased temperatures would bring way to disease vectors such as mosquitoes and waterborne pathogens. The tourism sector, biodiversity and land use will also be affected.

Simulating the region's climate has been a challenge for climate models (Evans, Smith, & Oglesby, 2004), mainly due to the high natural inter-annual variability, the topography of the region which includes multiple mountain ranges and inland seas, and the presence of a slight cooling trend in recent decades despite the global trend being a warming one (Evans, 2009). Nevertheless, the challenge was addressed by Zhang et al. (2005) who were responsible for the first region-wide analysis of the Middle East extreme indices for 1950–2003, examining 52 stations from 15 countries.

Donat et al. (2014) studied the temporal changes in climate extremes in the Arab region with regard to long-term trends and found consistent warming trends across the region where the increased frequencies of warm days and warm nights, higher extreme temperature values, fewer cold days and cold nights and shorter cold spell durations seemed to be evident since the early 1970s (AlSarmi & Washington, 2014). In earlier work, Nasrallah et al. (2004) studied the summer extreme temperatures in Kuwait over the period ranging from 1958 to 2000 and found that the most significant heat wave events, both in duration and intensity, occurred in the last decade of the 20th century. Almazroui et al. (2012) observed a decrease in precipitation in Saudi Arabia amounting to 35.1mm and 5.5mm per decade during the wet and dry seasons respectively over the years 1994–2009 and a temperature increase of 0.72◦C per decade during the dry season. The authors report that maximum, mean and minimum temperatures have increased significantly at a rate of 0.71, 0.60 and 0.48◦C per decade, respectively.

The northern part of the Mediterranean basin will be facing drier conditions where the most significant reductions in precipitation are projected over the Eastern Mediterranean, namely Jordan and Lebanon. Annual precipitation is expected to decline by more than 100mm annually compared to present averages (Evans 2009) which represents a 24-32 percent reduction in winter precipitation (Lee et al., 2013a).

D. The Case of the Beqaa Valley, Lebanon

Though literature has started to increasingly cover climate change and its impact in the Middle East, it still deficiently covers Lebanon more specifically in aspects related to the computation of climate extreme indicators. As previously mentioned, the IPCC Middle East workshop whose findings were reported by Zhang et al. (2005) examined trends in climate extreme indices for 52 stations covering 15 countries excluding Lebanon. Indices were later calculated for the country by various parties. The aim of this chapter will be to extend the analyses done for the Middle East and more recently Lebanon to the Beqaa Valley using for the first time data from the American University of Beirut Agricultural Research and Education Center.

1. Climate Profile

Lebanon is located on the eastern basin of the Mediterranean Sea with a surface area of 10,452 km2, mainly characterized by mountainous areas constituted of the following parts:

- A narrow coastal plain composed of 2 plains found in the north, Aakar, and in the south, Tyre, and a chain of narrow plains separated by rocky headlands in the center.
- The Mount Lebanon chain which has an average elevation of about 2,200 m.
- The Anti Lebanon chain divided into Talaat Moussa (2,629 m) in the north and Jabal el Sheikh or the Mount Hermon (2,814 m) in the south.
- The Beqaa valley, which is the area of interest for this thesis, a flat basin with a length of about 120 km, located between the Mount Lebanon and the Anti Lebanon chains. Its elevation averages at 900 m, peaking at 1,000 m at its center (Ministry of Environment, 2011).

The country enjoys a Mediterranean climate divided over five distinct agro-climatic zones in the coastal strip, low and middle altitudes of Mount Lebanon, west, central and north Beqaa. It is characterized by a humid to sub-humid wet season and a sub-tropical dry season. A wide distribution of precipitation mainly occurs between the months of October and March. During the four dry months namely June through September, water availability is scarce due to the very low water storage capacity, the challenges of capturing water near the sea, and the inefficient water delivery systems and networks (Ministry of Environment, 2011).

According to Karam (2002) rainfall between November and April can reach averages of 800mm at the coast, 1000mm in the mountains and 400mm in the Beqaa Valley. While the coastal and mountainous areas are characterized by abundant rainfall during the winter season, the Beqaa Valley has a semi-arid to continental climate with unpredictable rainfall and recurrent droughts. In the central part of the Valley, the climate is semi-arid, whereas in the northern part it is almost arid to continental, since it is separated from the sea effect by the presence of a high mountain chain. In the southern Beqaa Valley, a sub-humid Mediterranean climate is dominant, with more consistent rainfall (Karam, 2002).

Mean annual temperature varies on the coast between 19.5 °C and 21.5 °C. It decreases approximately 3°C for each 500 m elevation. At 1000m, where AREC is located, mean annual temperature is around 15 °C and decreases to 9°C at 2000m. The lowest temperatures recorded in January vary from 7°C at the coast to 4°C in the mountains while the highest temperatures are reached in July, where maximum daily temperatures exceed 35°C in the Beqaa Valley (Karam, 2002).

2. Climate Change in Lebanon

Lebanon is located at the border of desert regions and more than 60 percent of its economic activity lies in a narrow coastal plain along the Mediterranean Sea which makes it quite vulnerable to the potential flooding and desertification threats (Bou-Zeid & El-Fadel, 2002) from the projected climate change whose effects are increasingly becoming palpable.

Compared to the rest of the region, Lebanon is well endowed with renewable water resources that were estimated to amount 8,600 million cubic meters per year from 40 major rivers and more than 2000 springs yielding on average 1,200 cubic meters per year per capita. However, this represents a significant decrease from the 1,900 cubic meters per year per capita of freshwater that were available in 1990, putting the country at risk of a critical water deficit in the coming 10–15 years (Halwani, 2009; Shaban, 2009). Despite the long-held view that Lebanon is water rich and that it can, and should, share its excess water resources with its neighbors, the reality is that the country won't be able to satisfy its own local demand by 2025. The water deficit is especially acute in the Beqaa Valley, where potential evapotranspiration exceeds 70 percent of precipitation (Bou-Zeid & El-Fadel, 2002).

The increasing water deficit plaguing the country is believed to be vulnerable to the observed increases in temperatures and alterations in precipitation patterns. According to the UNDP Climate Change Profile for Lebanon, temperature increases of 0.15°C and 0.26°C per decade in MAM (March, April, May) and JJA (June, July, August) were found to be statistically significant. As for precipitation patterns, although not statistically significant, the biggest percentage decrease in precipitation per decade (1960-2006) amounts to 4.3 percent during the months of MAM, when precipitation can play a crucial role in the growth of wheat crops. The biggest percentage increase of 3.5 percent occurs in September, October and November (McSweeney, New, & Lizcano, 2010).

Indeed, precipitation and snow cover over the last 40 years are on the downfall. Between the period spanning from the 1950s to the 1980s precipitation in the Mount Lebanon basin dropped from 1,295 to 1,060mm per year (Khair, Aker, & Haddad, 1994). After the 1980s precipitation further increased by 12 percent across Lebanon, while the average number and intensity of peak rainfalls increased (Shaban, 2009). Satellite measurements indicate that the area of dense snow cover in the Lebanese mountains has declined by 16 percent from 2,280 square kilometers prior to 1990, to an average of 1,925 square kilometers for the years afterwards. Average residence time of dense snow before melting has also decreased from 110 days to less than 90 days over the same period (Lee et al., 2013a).

The change in climate is also contributing along with the human-induced factors to the aggravation of the water deficit. Coastal aquifers are particularly vulnerable to saline intrusion because of the combined effects of drought and abstraction beyond safe yields. Salinity concentrations greater than 5,000mg per litre are now detected in some public and private wells in the greater Beirut area, indicating a mixing of at least 10 percent seawater. Such concentrations make the water unsuitable for public supply and beyond the irreversible contamination limit (Saadeh, 2008). These saline intrusion rates could be exacerbated by any further decline in precipitation, increased evapotranspiration and/or sea level rise.

Hreiche, Najem, and Bocquillon (2007) studied daily runoff and mean snow depth for Nahr Ibrahim over six different climate change scenarios which tested sensitivity to changes in rainfall amount, frequency, wet-spell duration, length of rainy season, and the impact of a temperature rise of 2°C. Results showed that droughts occurred 15 to 30 days earlier, rainfall-induced floods replaced snowmelt events, and peak flows occurred two months earlier.

Simulated warming scenarios showed a decrease of 50 percent in the depth of snow cover. In another study by Bou-Zeid and El-Fadel (2002), four climate model scenarios were evaluated in terms of potential effects on the water budget and soil moisture status in the Beqaa Valley and in Beirut. Evaporation increased in both locations under all scenarios. The results also hint to a possible increase in irrigation demand in the Beqaa Valley of up to 6 percent by the 2020s.

As part of its second communication to the UNFCCC, the Ministry of Environment jointly with UNDP developed climate change scenarios by using the PRECIS model which was developed by the Hadley Centre at the UK Met Office to generate detailed climate change projections. According to the results obtained from the model, by 2040, temperatures in Lebanon will increase by 1°C on the coast and 2°C in the mainland, and in 2090 by 3.5°C to 5°C on the coast and in the mainland respectively. Historical temperature records from the early 20th century indicate that the projected warming is unprecedented. Compared to current precipitation levels, rainfall is projected to decrease by 10-20 percent by 2040, and by 25-45 percent by the year 2090. The decrease in precipitation and increase in temperature will lead to an extended hot and dry climate with intensified extremes. In Beirut, hot summer days with maximum temperatures above 35°C and tropical nights with minimum temperatures below 25°C will last respectively 50 and 34 days more by the end of the century. The drought periods, over the whole country, will become 9 days longer by 2040 and 18 days longer by 2090 (Ministry of Environment, 2011).

According to projections by Kitoh et al. (2008) who use a GCM from the Japan Meteorological Agency, rainfall is expected to decrease by 15 percent for Lebanon under a moderate warming scenario. Evans (2010) who used the MM5 model[1], predicts a 2°C and 6°C increase in temperature in winter and summer respectively and a higher decrease in rainfall of 30 percent by 2100.

3. Computation of Climate Extreme Indices for Lebanon

Despite being left out of the first region wide study conducted by Zhang et al. (2005) for the IPCC, climate extreme indices have increasingly been computed for Lebanon in recent years. The Department of Irrigation and Agro-Meteorology (DIAM) of the Lebanese Agricultural Research Institute (LARI) collects and analyzes large amounts of observed climate data to detect climate trends and identify any significant climate change. DIAM has

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[1] The MM5 model which is short for Fifth-Generation Penn State/NCAR Mesoscale Model is a regional model used for creating weather forecasts and climate projections. It is a community model maintained by Penn State University and the National Center for Atmospheric Research.

already carried out many assessments of the impact of climate change on the agriculture sector and water resources (Karam, 2002).

In the second communication to the UNFCCC, various climate extreme indices were computed for climate change projections using the PRECIS model which represents the country by 17 grid-boxes, a great improvement from the 4 grid-box representation in the initial national communication. The indices were defined and constructed based on the definition set by the joint CCl/CLIVAR/JCOMM Expert Team (ET) on Climate Change Detection and Indices (ETCCDI).

Large increases in temperature extremes were projected by the end of the century, and modest ones for the next 30 years in Lebanon as depicted by the four selected stations in Beirut, Zahle, Cedars and Dahr El Baidar, as depicted in Table 1.1. For the period ranging from 2080 to 2098, hot “Summer Days” will increase by 50-60 days, while hot “Tropical Nights” will increase by 1-2 months. The extremes of maximum and minimum temperatures will increase by several degrees with the largest increase amounting to 5-6°C for the maximum extreme of the minimum temperatures. Precipitation is expected to decrease between 18% and 38%, with the largest reduction occuring in the mountainous stations.

The World Bank Climate Change Knowledge Portal was used to check the results obtained by the PRECIS Model. Although results obtained are inline with those presented in the portal and are in broad agreement with other published studies using different modeling systems, the data used lacks accuracy and requires empirical and statistical downscaling and bias correction methods that were not applied because the data was insufficient spatially and temporally.

In Beirut, minimum temperatures will peak at 30°C leading to very hot night conditions. Precipitation will decrease between 18 to 38 percent with the largest reduction occurring over mountainous stations. The amount of rain falling within 5 consecutive days and the rainfall intensity will decrease as well. The consecutive dry days are projected to increase between 15-20 days (Ministry of Environment, 2011).

Table 1.1 Changes in temperature and rainfall climate extreme indices for 2080-2098 using the 1981-2000 modeled mean

Index	**Beirut**	**Cedars**	**Daher El Baidar**	**Zahleh**
Hot Summer Days SU30 (days)	+50	+62	+60	+53
Hot Tropical Nights TR20 (days)	+34	+53	+18	+62
Precipitation (mm)	-116	-205	-312	-191
Rainfall intensity SDII (%)	-6	-14	-8	-15
Consecutive Dry Days CDD (days)	19	21	15	19

Source: Ministry of Environment, 2011. *Lebanon's Second National Communication to the United Nations Framework Convention on Climate Change.*

Findings from the PRECIS model correspond with other climate studies of the Middle East and the Eastern Mediterranean region using different modeling systems (Evans, 2010; Kitoh et al., 2008). Nevertheless, simulations in higher horizontal resolution than the one that was used in the PRECIS model (25 x 25 km) need to be explored in future studies. For instance the use of a grid box size less than 10 km wold be required but would prove to be a very challenging effort for integrations in climatic time-scales. In addition, observational data availability and quality need to be improved, as well as the collection and digitization of older data from a larger number of stations. This would entail a close collaboration between relevant national departments and international experts with experience in data rescue and homogenization (Ministry of Environment, 2011).

Recently, the Lebanon Reforestation Initiative together with the Center for Applied Research in Agroforestry Development published a report examining likely climate change impacts on selected native tree distributions in Lebanon (Center for Applied Research in Agroforestry Development- University of Cordoba, 2013). For the purpose of this report various climate change scenarios from present to 2050 were derived to assess the impact on major tree species native to Lebanon.

The report used climate data from WorldClim (Hijmans & Cameron, 2005), a set of global climate layers with a 30 arc-second spatial resolution generated through interpolation of real data from weather stations for the period 1950 - 2000. 19 Bioclimatic variables were derived from monthly temperature and rainfall values. The constructed variables overlap with several ETCCDI indices. For instance, temperature of the coldest and warmest month, and precipitation of the wet and dry quarters. Future climatic variables were calculated using a mixed climate model that was generated from predictions made by CCCMA-CGCM3 and ECHAM5 global models.

Lastly, UNDP has been creating country-level climate data summaries for developing countries to address the climate change information gap. They use existing climate data to generate a series these summaries using climate observations and multi-model projections from the WCRP CMIP3. Fortunately, Lebanon was one of the 52 countries for which UNDP constructed climate extreme indices that are reflected in the 2010 country profile. Results show that daily temperature observations displayed statistically significant trends in the frequency of hot and cold nights. In fact, between 1960 and 2003, the average number of hot[2] nights per year in Lebanon increased by 27. The rate of increase is strongest during the months of June, July and August. In parallel, the average number of cold nights[3]

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[2] Hot day or hot night is defined by the temperature exceeded on 10% of days or nights in the current climate of that region and season.

[3] Cold day or cold night is defined as the temperature below which 10% of days or nights are recorded in the current climate of that region and season.

per year in Lebanon decreased by 23. Trends in the frequency of hot and cold days did not turn out to be statistically significant (McSweeney et al., 2010).

CHAPTER III

DATA AND METHODOLOGY

A. Data Source and Compilation

As previously mentioned, this chapter aims to extend the analyses done for the Middle East and Lebanon and more specifically reproduce the exercise of analyzing climate extreme trends for the Beqaa Valley to address gaps in data availability and analyze changes in extreme climate indices.

It is in this light that climate extreme indices were calculated for the Beqaa Valley using data from the American University of Beirut Agricultural Research and Education Center. In the spring of 2012, with the help of AREC, namely Mr. Hilal Dbouk and Mr. Nicolas Haddad, hard copies of weather records collected from 1956 were located at the AREC premises. Only a small part of the data had been already digitized by other members of AREC and the AUB faculty, namely some temperature and rainfall trends for some of the years. However, this is the first attempt to compile and standardize all weather records available at AREC from October 1956 till April 2013. Newer data is available but for the purpose of this exercise the cut-off point was April 2013.

In the summer of 2012, under my supervision, 8 AUB students[4] contributed to the digitization of the data. The data also underwent rigorous cleaning to ensure the standardization of variables, units of measurement and time amongst other details. The total

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[4] Great thanks go to Celine Khoury, Farah Zaweel, Rawand Wehbe, Fatima Mousawi, Reem Mansour, Chafik Abdallah, Rayan Baalbaki and May Ghanem.

variables compiled are listed in Table 1.2 below[5]. For the purpose of this thesis, only minimum and maximum temperatures as well as precipitation will be used for the calculation of the climate extreme indices. A plot of the variables as well as the diurnal temperature can be found in Appendices 1.A, 1.B, 1.C and 1.D.

Table 1.2 List of weather variables

Variable	**Specification**
Atmospheric pressure	600mm, Max and Min
Temperature	Max, Min and Grass min
Hygrometry	Dry Bulb, Wet Bulb, Relative Humidity (Average, Max and Mix)
Evaporation	Measured in mm
Wind	Speed (Km/day) direction (cardinal and degree directions)
Sun	Measured in hours of sunshine
Rain	Total precipitation measured in mm
Grass temperature	Measured at different depths (5 and 10 cm)
Uncovered earth temperature	Measured at different depths (5, 10, 30 and 75cm deep)

B. Station Specificities

The Agricultural Research and Educational Center (AREC) of the American University of Beirut (AUB) is located in Housh Sneid 14 km southwest of Baalbeck in the Central Beqaa Valley. As shown in Figure 1.1, this area falls in the middle of the Beqaa at a latitude of 34° 54” N and a longitude of 36° 45” E, and is 1000 m above sea level.

AREC has been keeping records of rainfall, temperature, soil temperature, wind speed, daily sunshine hours and other weather variables since October 1956. During this period, data was collected either manually or through different weather stations listed in

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[5] The data set is available at FAFS.

Table 1.3 below. This change in stations and record type, created some data inconsistencies which were dealt with in the data cleaning exercise.

Figure 1.1 Location of AREC

Table 1.3 Weather Station Models

Weather Station Model	**Recorded Years**
Manual data collection	October 1956-1999 2005-2008
Organiser II- PSION	1999-2004
WatchDog 700	2007-2011
Campbell Scientific CR1000	2011- till present

C. Station Data Suitability

Before proceeding with the calculation of the climate extreme indices, the suitability of the station data was assessed. The data was considered to be suitable as it met the following criteria:

- Data for daily precipitation, minimum and maximum temperatures which are essential for the calculation of the indices is available.

- Data includes over 45 years of data (minimum is 30 years) and covers the standard reference period of 1971-2000.
- For 85 percent of the years, less than 20 percent of the data is missing as shown in Table 1.4 below. For the years 1976-1977 data is completely missing as the country was under civil war which prevented any data collection. More than 20 percent of the data is missing for 1998, 2002, 2007, 2009, 2010 and 2011 due to problems with the various weather stations and the delay in fixing them. Data is not missing but rather incomplete for the years 1956 and 2013 as they are the years when data collection started and when the data was retrieved from AREC for the purpose of this thesis respectively. Since only 8 years out of 45 had more than 20 percent of data missing, I proceeded with the calculation of the indices.

Table 1.4 Annual percentage of missing data, 1956-2013

	Percentage of missing data per year			
year	**Precipitation**	**Tmax**	**Tmin**	**Comments**
1956	75	75	75	Data recording started in October 1956
1957	0	0	0	
1958	8	0	0	
1959	0	1	1	
1960	0	0	0	
1961	0	1	1	
1962	0	1	1	
1963	1	1	1	
1964	3	2	2	
1965	0	0	0	
1966	0	1	0	
1967	0	2	2	
1968	0	0	0	
1969	0	1	1	
1970	0	1	1	
1971	8	8	8	
1972	0	1	1	
1973	0	2	2	

	Percentage of missing data per year			
year	**Precipitation**	**Tmax**	**Tmin**	**Comments**
1974	0	1	2	
1975	0	0	0	
1976	100	100	100	Data recording was stopped due to civil war
1977	100	100	100	Data recording was stopped due to civil war
1978	16	8	9	
1979	11	8	8	
1980	0	0	0	
1981	0	0	0	
1982	0	0	2	
1983	1	0	2	
1984	0	0	4	
1985	2	0	4	
1986	1	1	3	
1987	2	1	4	
1988	0	1	1	
1989	1	1	1	
1990	0	0	0	
1991	8	8	8	
1992	0	2	2	
1993	0	0	0	
1994	0	0	1	
1995	0	0	0	
1996	1	4	3	
1997	6	13	17	
1998	25	29	24	Possible problems with weather station set-up or repair
1999	9	13	13	
2000	0	0	0	
2001	11	11	11	
2002	46	47	47	Possible problems with weather station set-up or repair
2003	4	5	5	
2004	18	16	16	
2005	7	18	17	
2006	0	6	6	
2007	41	10	10	Possible problems with weather station set-up or repair
2008	16	19	19	
2009	21	21	21	Possible problems with weather station set-up or repair

	Percentage of missing data per year			
year	**Precipitation**	**Tmax**	**Tmin**	**Comments**
2010	28	29	29	Possible problems with weather station set-up or repair
2011	27	27	27	Possible problems with weather station set-up or repair
2012	1	1	1	
2013	68	68	68	Data records obtained from AREC were up to April 2013

D. Data Quality Control and Homogeneity Testing

The data quality control and homogeneity testing was conducted using the RClimDex software which was developed and maintained by Xuebin Zhang and Feng Yang at the Climate Research Branch of Meteorological Service of Canada[6].

The main purpose of the quality control procedure is to identify errors usually caused by data processing such as manual keying. Obviously wrong values, such as nonexistent dates, were checked and removed. The negative daily precipitation amounts were set to missing values, and both daily maximum and minimum temperatures were set to missing values if the daily maximum temperature was found to be less than the daily minimum temperature.

The next step in the quality control procedure is to identify outliers in daily maximum and minimum temperatures and precipitation amounts. Outliers are daily values that lie outside a particular range according to a predefined custom threshold. For example, for temperature series, this range can be defined as the mean value of observations for the day of the year plus or minus four times the standard deviation of the value for that calendar day

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[6] http://etccdi.pacificclimate.org/software.shtml

in the entire series. Daily temperature values outside of these thresholds were marked as potentially erroneous, and manually checked and corrected on a case-by-case basis. After checking all identified outliers, all observations for maximum and minimum temperatures that were outside the range defined above were turned to missing. This led to negligible changes in annual percentage of missing daily values documented in Table 1.4.

The diurnal temperature, the difference between the maximum and minimum temperatures, was also used as a reference to identify outliers. Some observations that were close to this range were kept (plus or minus 2°C). A list of the outliers in the series can be found in Appendix 1.E.

After completing the quality control exercise, testing the data for temporal homogeneity is crucial since climatic time series often exhibit spurious, non-climatic, jumps and/or gradual shifts due to changes in station location, environment (exposure), instrumentation or observing practices. These in-homogeneities may severely affect the extremes and as such, station history metadata are vital for understanding and resolving these issues.

Using the RHtestsV4 data homogenization software package of Xiaolan L. Wang and Yang Feng[7], the weather data, namely maximum/minimum temperatures, was subjected to a two-phase linear regression test for change point detection (Wang, 2003). The package was designed to detect and adjust change points or shifts that could exist in a data series that may have first order autoregressive errors. It is based on the penalized maximal t test and the penalized maximal F test (Wang, Wen, & Wu, 2007; Wang, 2008b), which are embedded in a recursive testing algorithm (Wang, 2008a), while accounting for the lag-1 autocorrelation (if

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[7] http://etccdi.pacificclimate.org/software.shtml

any) of the time series which may have a linear trend or none at all. Although it is preferable to use a homogenous time series that is well correlated with the series being analyzed, it is possible to detect change points without a reference series but with less reliable results, as was done in this thesis.

The RHtestsV4 functions can only handle annual/monthly/daily series of Gaussian errors. Since daily precipitation series are typically non-Gaussian and based on the recommendation of the authors, the functions were applied to a log-transformed monthly total precipitation series. For more in depth analysis, a similar package RHtests_dlyPrcp was created by the authors for the homogenization of precipitation data. It is based on the transPMFred algorithm (Wang et al. 2010), which integrates a data adaptive Box-Cox transformation procedure into the PMFred algorithm (Wang 2008a) mentioned above. This Box-Cox transformation is necessary, because daily precipitation amounts are not normally distributed.

Using the RHtestsV4 package, change points were detected in the daily series and only ones that were deemed to be significant even without metadata were retained (Type 1 change points). Including Type 0 change points, or change points that are only significant in the presence of suitable metadata information in daily series analysis would be time consuming and unnecessary. In addition, the metadata information available for AREC stations (approximate date of setting up or changing stations) corresponded to Type 1 change points identified.

Table 1.5 and Table 1.6 below include the list of the significant Type 1 change points along with any corresponding and available metadata for maximum and minimum temperatures. They are succeeded by Figure 1.2 and Figure 1.3 that graphically depict these change points. No change points were identified for the log-transformed monthly precipitation series. Though it was mentioned by AREC staff that over the years the various weather stations malfunctioned at certain points in time and had to be repaired, as is noticeable from the data gaps, no information is available regarding the exact dates of these malfunctions.

Table 1.5 Tmax significant Type 1 change points

Date	**95% confidence interval of the p-value**	**nominal p-value (confidence level)**	***PT*max**	**95% confidence interval of the *PT*max**	**Metadata information**
19561206	(1.0000-1.0000)	0.950	123.7580	(60.5263-63.8664)	
19570726	(1.0000-1.0000)	0.950	384.4296	(67.1075-70.8777)	
19630221	(1.0000-1.0000)	0.950	459.3082	(86.9952-92.0752)	
19860501	(1.0000-1.0000)	0.950	137.0365	(98.4348-104.2682)	
20041227	(1.0000-1.0000)	0.950	192.1091	(81.1850-85.8823)	Dysfunction of the Organiser II- PSION weather station and start of the manual data collection
20080831	(1.0000-1.0000)	0.950	2443.4144	(66.3381-70.0576)	
20110531	(1.0000-1.0000)	0.950	1267.4007	(63.6219-67.1625)	Dysfunction of the WatchDog700 weather station and its replacement with the Campbell Scientific CR1000
20120402	(1.0000-1.0000)	0.950	85.1817	(62.5884-66.0610)	

Note: Metadata information does not correspond to the exact date of the change point but to a period that surrounds it.

Figure 1.2 Homogeneity test of annual daily maximum temperatures

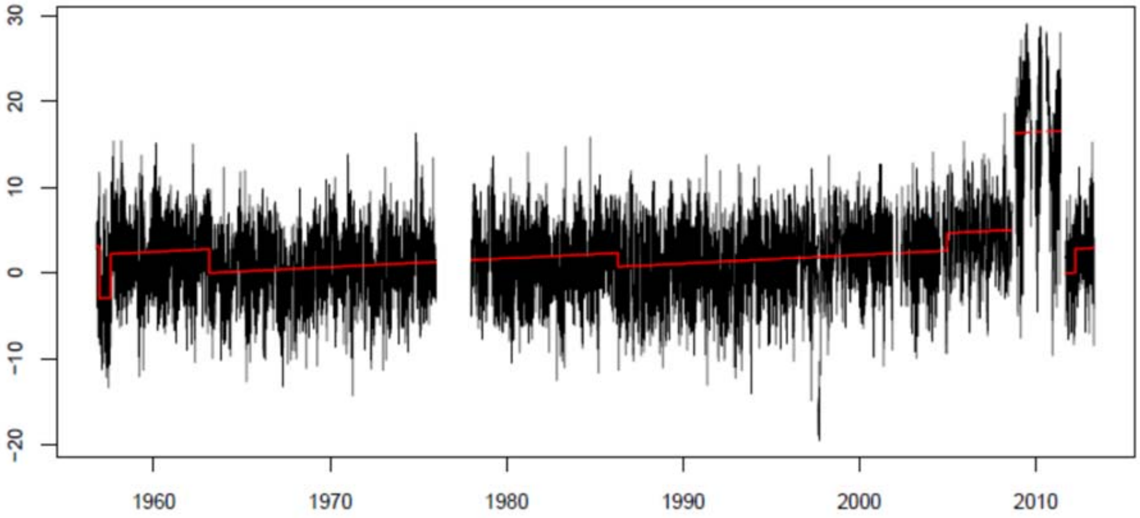


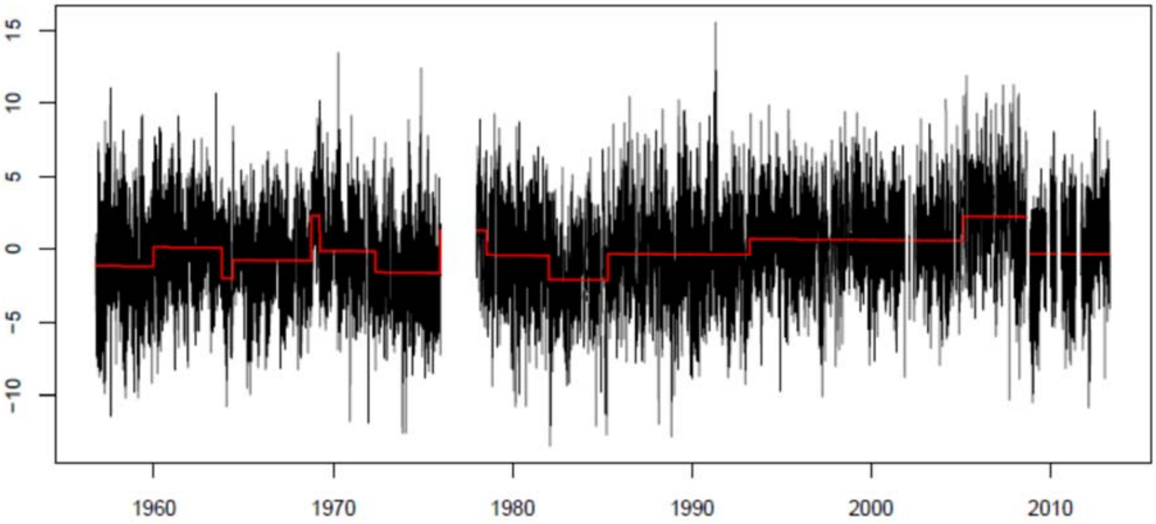
Table 1.6 Tmin significant Type 1 change points

Date	**95% confidence interval of the p-value**	**nominal p-value (confidence level)**	***PT*max**	**95% confidence interval of the *PT*max**	**Metadata information**
19591218	(1.0000-1.0000)	0.950	100.0610	(43.0702-45.6140)	
19631022	(1.0000-1.0000)	0.950	111.5168	(41.5830-44.0178)	
19640531	(1.0000-1.0000)	0.950	46.1951	(41.8842-44.3411)	
19681014	(1.0000-1.0000)	0.950	210.1724	(41.8030-44.2540)	
19690401	(1.0000-1.0000)	0.950	117.3723	(41.0492-43.4449)	
19720509	(1.0000-1.0000)	0.950	121.6739	(42.8346-45.3611)	
19751227	(1.0000-1.0000)	0.950	138.9288	(41.3832-43.8034)	
19780719	(1.0000-1.0000)	0.950	50.3301	(41.2771-43.6895)	
19820114	(1.0000-1.0000)	0.950	164.6011	(42.8205-45.3460)	
19850429	(1.0000-1.0000)	0.950	170.0133	(45.2769-47.9824)	
19930325	(1.0000-1.0000)	0.950	80.5724	(49.4172-52.4261)	
20050216	(1.0000-1.0000)	0.950	212.8220	(46.8859-49.7093)	Dysfunction of the Organiser II- PSION

Date	**95% confidence interval of the p-value**	**nominal p-value (confidence level)**	***PT*max**	**95% confidence interval of the *PT*max**	**Metadata information**
					weather station and switch to the manual data collection
20080831	(1.0000-1.0000)	0.950	366.5188	(43.0452-45.5872)	

Note: Metadata information does not correspond to the exact date of the change point but to a period that surrounds it.

Figure 1.3 Homogeneity test of annual daily minimum temperatures



The data shows several significant shifts with a maximum temperature (tmax) change point in 2008 being the most notable one. However, adjusting daily data to account for step changes is quite complex and according to Aguilar et al. (2003) and Vincent & Zhang (2002) the latter is rarely a fruitful exercise, therefore the most reverted to method is the exclusion of the in-homogenous periods of time and the use of the data prior of after the discontinuity. Although in our case the homogeneity tests exhibited several significant change points, most of the data will be used but only up till August 2008 as the change point for (tmax) on that date shows a suspiciously big shift that cannot be ignored.

CHAPTER IV

RESULTS AND DISCUSSION

A. Calculation of the Climate Extreme Indices

The joint World Meteorological Organization Commission for Climatology (CCl) Climate Variability and Predictability (CLIVAR) Expert Team on Climate Change Detection, Monitoring and Indices (ETCCDMI) coordinated an international effort to develop, calculate, and analyze a suite of indices of climate extremes that will enable individuals and organizations to calculate the indices in the same way so that the result of their analyses can be comparable and contribute to building a global climate canvas. Although different researchers may define indices differently based on their particular needs, for the purpose of this thesis, the 27 indices that were defined by the ETCCDI were calculated for the AREC weather data. The indices are based on daily temperature and precipitation amounts and describe particular characteristics of extremes, including frequency, persistence and amplitude. A detailed list is found in the Table 1.7.

Table 1.7 List of 27 ETCCDMI Core Indices

	ID	Indicator Name	Definition	Unit
1.	FD0	Frost days	Annual count of days when TN (daily minimum temperature) < 0^{o}C.	days
2.	SU25	Summer days	Annual count of days when TX (daily maximum temperature) > 25^{o}C.	days
3.	ID0	Ice days	Annual count of days when TX (daily maximum temperature) < 0^{o}C.	days
4.	TR20	Tropical nights	Annual count of days when TN (daily minimum temperature) > 20^{o}C.	days
5.	GSL	Growing season length	Annual (1st Jan to 31st Dec in Northern Hemisphere (NH), 1st July to 30th June in Southern Hemisphere (SH)) count between first span of at least 6 days with daily mean temperature TG>5^{o}C and first span after July 1st (Jan 1st in	days

	ID	Indicator Name	Definition	Unit
			SH) of 6 days with TG<5°C.	
6.	TX_x,	Max Tmax	Monthly maximum value of daily maximum temperature	°C
7.	TN_x,	Max Tmin	Monthly maximum value of daily minimum temperature	°C
8.	TX_n	Min Tmax	Monthly minimum value of daily maximum temperature	°C
9.	TN_n,	Min Tmin	Monthly minimum value of daily minimum temperature	°C
10.	TN10p	Cool nights	Percentage of days when TN < 10th percentile	%
11.	TN90p	Warm nights	Percentage of days when TN > 90th percentile	%
12.	TX10p	Cool days	Percentage of days when TX < 10th percentile	%
13.	TX90p	Warm days	Percentage of days when TX > 90th percentile	%
14.	WSDI	Warm spell duration index	Annual count of days with at least 6 consecutive days when TX > 90th percentile	days
15.	CSDI	Cold spell duration index	Annual count of days with at least 6 consecutive days when TN < 10th percentile	days
16.	DTR	Diurnal temperature range	Monthly mean difference between TX and TN	°C
17.	Rx1day	Max 1-day precipitation amount	Monthly maximum 1-day precipitation	mm
18.	Rx5day	Max 5-day precipitation amount	Monthly maximum consecutive 5-day precipitation	mm
19.	SDII	Simple daily intensity index	Annual total precipitation divided by the number of wet days (defined as PRCP ≥ 1mm) in the year	mm/day
20.	R10mm	Number of heavy precipitation days	Annual count of days when PRCP≥ 10mm	days
21.	R20mm	Number of heavy precipitation days	Annual count of days when PRCP≥ 20mm	days
22.	R25mm	Number of days above 25mm	Annual count of days when PRCP≥ nnmm *For this thesis nn was set at 25mm*	days
23.	CDD	Consecutive dry days	Maximum number of consecutive days with PRCP < 1mm	days
24.	CWD	Consecutive wet days	Maximum number of consecutive days with PRCP ≥ 1mm	days
25.	R95pTOT	Very wet days	Annual total PRCP when PRCP > 95th percentile	mm
26.	R99pTOT	Extremely wet days	Annual total PRCP when PRCP> 99th percentile	mm

	ID	Indicator Name	Definition	Unit
27.	PRCPTOT	Annual total wet day precipitation	Annual total PRCP in wet days (PRCP≥1mm)	mm

Source: www.climdex.org/indices.html

One of the approaches used for the calculation of the indices is based on the calculation of the number of days in a year that exceed specific thresholds. For example, the number of days when rainfall exceeds 20 mm (R20 – number of heavy precipitation days). Many of the indices are based on percentiles where the thresholds are set to assess moderate extremes that usually occur a few times every year rather than high impact rarer weather events that occur once every decade. For precipitation, the percentile thresholds are calculated from the sample of all wet days in the base period. As for temperature, the percentile thresholds are calculated from five-day windows centered on each calendar day to account for the mean annual cycle. Using percentile thresholds rather than fixed thresholds mainly stems from the fact that the number of days exceeding percentile thresholds is more evenly distributed in space and is meaningful in every region (Data, 2009).

Day-count indices based on percentile thresholds relate anomalies to the local climate. Although the values of the thresholds are site-specific, these indices allow for spatial comparisons because they sample the same part of the probability distribution of temperature and precipitation at each location. However, day-count indices based on absolute thresholds are less suitable for spatial comparisons of extremes than those based on percentile thresholds since over large areas they may sample very different parts of the temperature and precipitation distributions. For instance, year-to-year variability in the number of frost days is affected by the variability in the spring and autumn temperatures for the northern part of the Northern Hemisphere and by the variability of the winter temperature for the southern part of the Northern Hemisphere (Data, 2009).

The 27 indices mentioned above were calculated for the AREC data for the period 1960-2008 using the RClimDex software which was developed and maintained by Xuebin Zhang and Feng Yang at the Climate Research Branch of Meteorological Service of Canada[8]. As mentioned in the previous section, weather data after 2008 was disregarded due to the major change point during that year. The period 1971-2000 was selected as a base period as it would allow for comparisons with the results of Zhang et al. (2005) who examined trends for these indices for the period 1950–2003 with data obtained from 52 stations from 15 countries in the Middle East. Some of the indices obtained from the AREC data are graphed in the figures below and the results will be explored in depth in the trend calculation section. Values of all 27 indices are found in Appendix 1.F.

The indices will not always be calculated for the whole period 1960-2008 depending on the amount of missing data. Monthly indices are only calculated if at most 3 days of data are missing per month, while annual indices are calculated if at most 15 days of data are missing per year. Also, no annual value will be calculated if a whole month of data is missing. As for indices that are based on thresholds, a threshold is only calculated if at least 70 percent of the data is available. Finally, regarding spell duration indicators, a spell which starts in a certain year and continues into the next is counted in the year in which it ends.

1. Temperature Indices

Figure 1.4 shows the number of frost days and summer days over the period 1960-2008. Despite the large data gaps, the difference between both indices seems to be increasing to 1960 levels, where the increase in summer days and the decrease in frost days potentially

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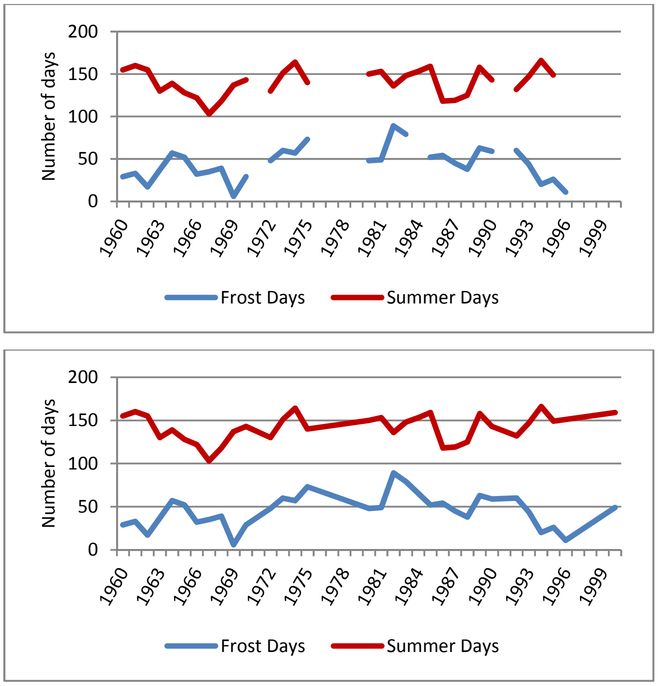
[8] http://etccdi.pacificclimate.org/software.shtml

point to a warming climate. Nevertheless, no conclusions can be drawn before a proper trend analysis is conducted.

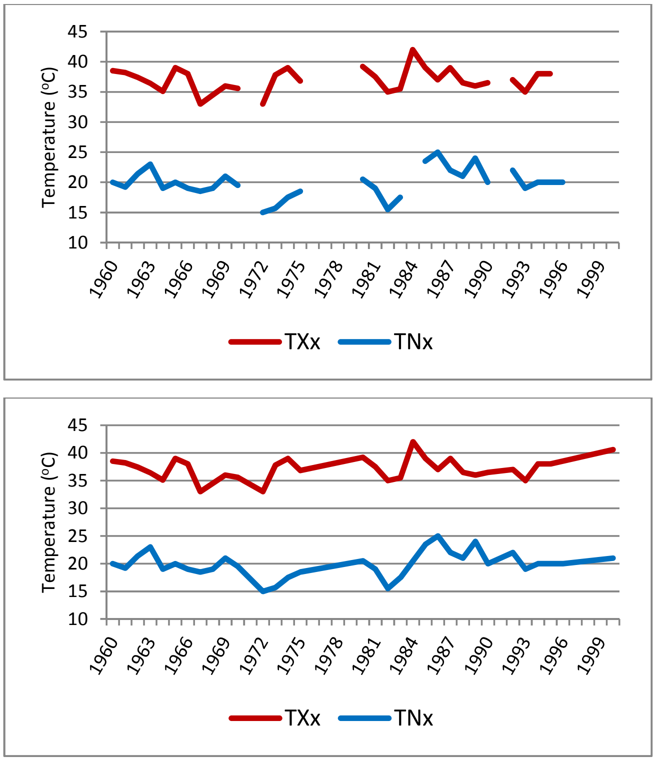
Figure 1.4 Number of frost days and summer days 1960-2000



Note: Lines are discontinuous in upper graph due to the large amount of missing data. The lines were joined in the lower graph to be able to detect any trends.

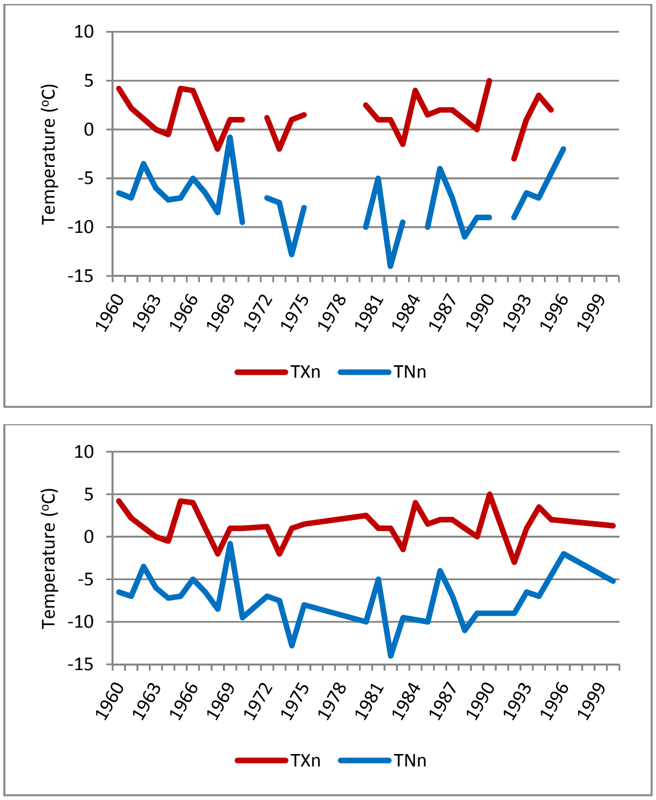
There seems to be no apparent trend in the annual maximum Tmax and the maximum Tmin in Figure 1.5 Since the annual maximum takes on the maximum value reached at any one month throughout the year which is most probably reached in July or August in Lebanon, this may mean that there is no apparent change or trend in the summer temperature. On the other hand, the annual minimum Tmax and Tmin values displayed in Figure 1.6 seem to be diverging from around 1970 to 1984 then converging again from 1985 till the year 2000. However, any trend can be made clearer through the use of percentile based thresholds shown in Figure 1.7.

Figure 1.5 Annual maximum Tmax and Tmin 1960-2000



Note: Lines are discontinuous in upper graph due to the large amount of missing data. The lines were joined in the lower graph to be able to detect any trends.

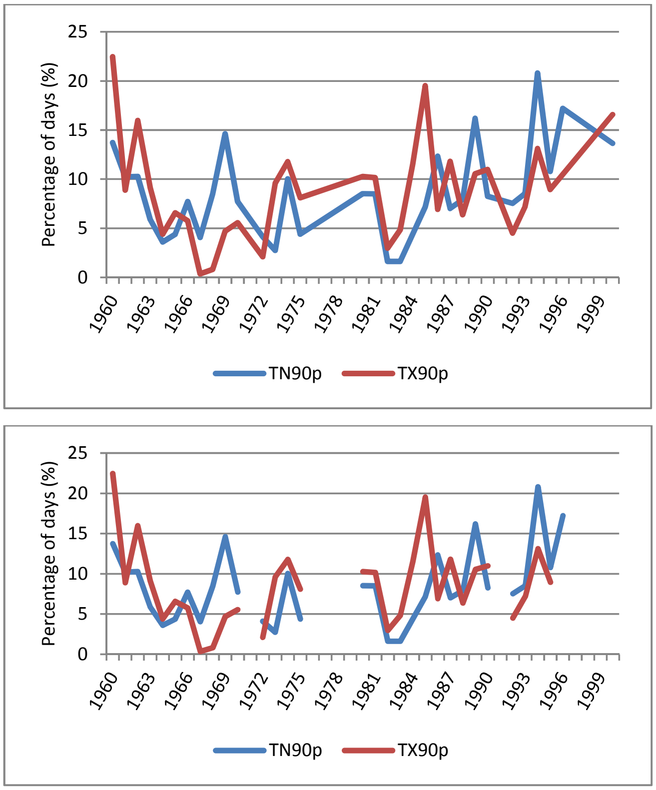
Figure 1.6 Annual minimum Tmax and Tmin 1960-2008



Note: Lines are discontinuous in upper graph due to the large amount of missing data. The lines were joined in the lower graph to be able to detect any trends.

The 90th percentile of Tmax and Tmin clearly show a joint increase in warm days and warm nights starting 1967.

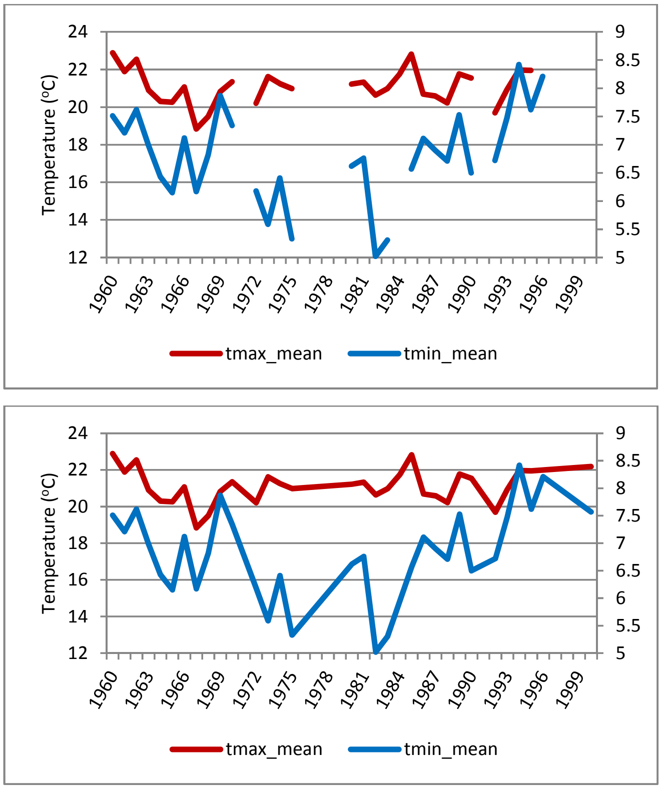
Figure 1.7 Warm night and warm days, 1960-2000



Note: Lines are discontinuous in upper graph due to the large amount of missing data. The lines were joined in the lower graph to be able to detect any trends.

Finally, looking at the mean Tmax and Tmin in Figure 1.8 more clearly depicts the wider variation in Tmin and its clear increase from 1982 onwards compared to a more stable Tmax.

Figure 1.8 Mean Tmax and Tmin, 1960-2000

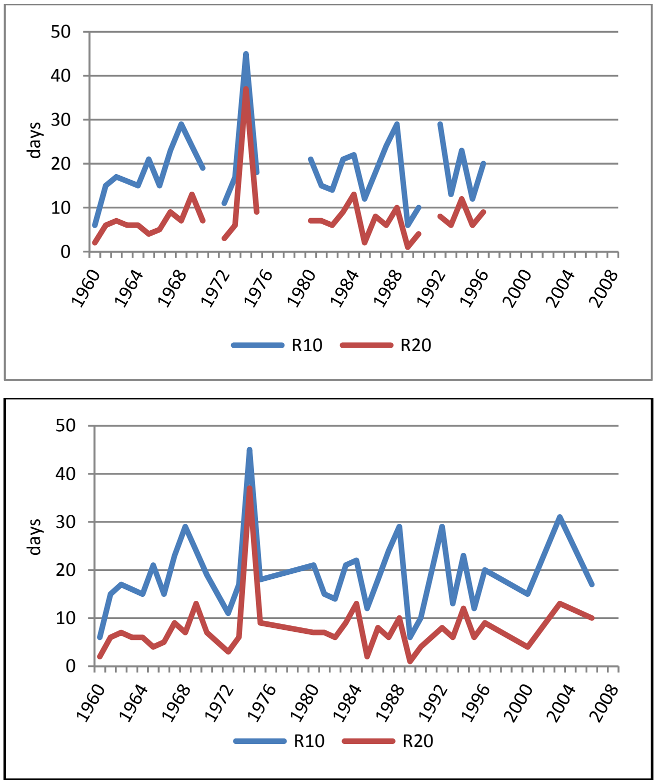


Note: Lines are discontinuous in upper graph due to the large amount of missing data. The lines were joined in the lower graph to be able to detect any trends.

2. Precipitation Indices

Precipitation indices have proven to be harder to analyze by eyeballing with no apparent trends. An example is shown in Figure 1.9 which displays R20mm and R10mm that represent the annual count of days when precipitation is greater or equal to 20mm and 10mm respectively. If for any day precipitation is higher than these two thresholds, this can be considered a heavy precipitation day. The peak obtained in the mid 1970s could not be backed by the literature available.

Figure 1.9 R20mm and R10mm, 1960-2008



Note: Lines are discontinuous in upper graph due to the large amount of missing data. The lines were made continuous despite the missing data in the lower graph for visibility purposes.

Precipitation indices will be further analyzed in the trend calculation section where significant trends would be potentially identified.

B. Trend Calculation

One of the commonly used tools for detecting changes in climatic time series is trend analysis. Yet, scientists who work on climate data do not follow a unified definition for a trend. For instance, in IPCC assessment reports, a trend refers to a change in the level of a variable over longer time scales than the dominant time scales of variability in a time series. But the fact that the climate system exhibits variability at all time scales makes differentiating trend from low-frequency variability a challenging endeavor. On the other hand, the United Nations Framework Convention on Climate Change (UNFCCC) considers that trends and variability have the same time scale but are the result of different causes, whereby the former is related to the portion of climate change that has anthropogenic roots while the latter to the portion of climate change that is caused by natural factors (Data, 2009).

Based on the above, a practical approach would be to calculate trends for any period regardless of whether they are due to natural internal processes within the climate system or due to external forcings such as volcanic aerosols, or anthropogenic, such as greenhouse gases.

Simple trend estimates for the standardized ETCCDMI Core Indices were calculated to provide some insight into changes in extremes due to the non-stationary nature of climate data. The RClimDex software was used to estimate linear trends for the calculated indices using the least squares method. The latter method was adopted in the software because least-squares trends are easy to interpret.

Nonetheless, this method has its disadvantages with a notable one being its sensitivity to individual values (outliers) that lie either near the beginning or the end of the available data. The inclusion or exclusion of these observations can have a great impact on the fitted trend. In addition to the fact that the least squares estimator of a regression coefficient β is vulnerable to these outliers, the associated confidence interval is sensitive to the non-normality of the parent distribution which is mostly the case with climate extreme indices that generally have non-Gaussian distributions. Trends for the 27 indices are shown in Table 1.8 with only 3 indices showing statistically significant trends. Values for trends significant at the 10% level are shown in boldface.

Although lacking statistical significance, the trends depicted in the results are in line with the regional trends obtained by Zhang (2005). A decreasing trend is apparent for both the percentage of days when daily maximum and daily minimum temperature are below the10th percentile (referred to TX10p and TN10p, respectively) suggesting a decrease in the number of cool days and cool nights. The percentage of days when daily maximum or daily minimum temperatures are above the 90th percentile (referred to TX90p and TN90p, respectively) show an increasing trend that is statistically significant at the 10% level for the case of TN90p.

Increasing trends have been found in the annual maximum of daily maximum (TXx) and minimum temperatures (TNx) and the number of summer nights (SU25). However, the annual minimum of daily maximum and minimum temperatures (TXn and TNn) displayed weak decreasing trends in contrast to the positive trends obtained by Zhang (2005). Nevertheless results are not to be interpreted with reservation due to their staggeringly high p-values of 0.966 and 0.73 respectively.

Trends in precipitation indices show an increase (albeit not statistically significant) in the monthly maximum 1-day precipitation amount (RX1day) and the annual total precipitation when precipitation > 95th percentile (very wet days - R95pTOT). This diverges from the weak and spatially incoherent regional precipitation trends obtained by Zhang (2005).

Table 1.8 Linear trends (using OLS) for the 27 indices for the period 1960-2008

Indices	Slope	P-value
SU25	0.293	0.241
ID0	0.012	0.506
TR20	**0.053**	0.076
FD0	0.251	0.39
GSL	**-0.9**	0.022
TXX	0.038	0.232
TXN	-0.001	0.966
TNX	0.045	0.201
TNN	-0.015	0.73
TX10P	-0.006	0.93
TX90P	0.065	0.427
TN10P	-0.031	0.736
TN90P	**0.134**	0.053
WSDI	-0.017	0.911
CSDI	-0.028	0.793
DTR	0	0.979
RX1DAY	0.219	0.2
RX5DAY	-0.118	0.775
SDII	0.005	0.844
R10MM	0.041	0.692
R20MM	0.028	0.725
R25MM	0.037	0.432
CDD	-0.123	0.732
CWD	0.021	0.745
R95P	1.575	0.15
R99P	0.024	0.97
PRCPTOT	1.815	0.496

Though usually both parametric and non-parametric techniques are employed, parametric trend tests are more powerful than nonparametric ones but require data to be independent and normally distributed. On the other hand, non-parametric trend tests require only that the data be independent and can tolerate outliers in the data thereby avoiding any significant changes in the fitted trends based on the inclusion of these observations (Hamed & Rao, 1998). Therefore, to overcome the shortfalls of the least squares method and following Zhang (2005), another linear trend was computed for the indices using a Kendall’s tau based slope estimator due to Sen (1968). This estimator would complement results obtained from the least squares method and would enable us to reach more statistically robust ones given the fact that climate extreme indices generally have non-Gaussian distributions.

The Kendall tau based slope estimator is robust to the effect of outliers in the series and has been widely used to compute trends in climatic and hydro-meteorological series (Wang & Swail, 2001; Zhang, Vincent, Hogg, & Niitsoo, 2000). The estimator which is known as the Theil-Sen estimator or the Kendall robust line-fit method, derives its name from Henri Theil (Theil, 1950) and Pranab K. Sen (Sen, 1968) and is considered to be one of the most popular non-parametric techniques for estimating a linear trend.

While the least squares regression line focuses on how a mean concentration would change linearly with time, the Theil-Sen line would look at how the median (50th percentile) rather than the mean concentration would change. According to Theil (Theil, 1950), the estimator of a set of two-dimensional points (x_i,y_i) is the median of the slopes ($y_j - y_i$)/($x_j - x_i$) of all pairs of sample points. Sen (Sen, 1968) later added the restriction of taking the median of the slopes defined only from pairs of points having distinct x-coordinates. The estimator can be defined as follows:

$$\tilde{\beta}_1 = median\{\tilde{B}\}$$

where

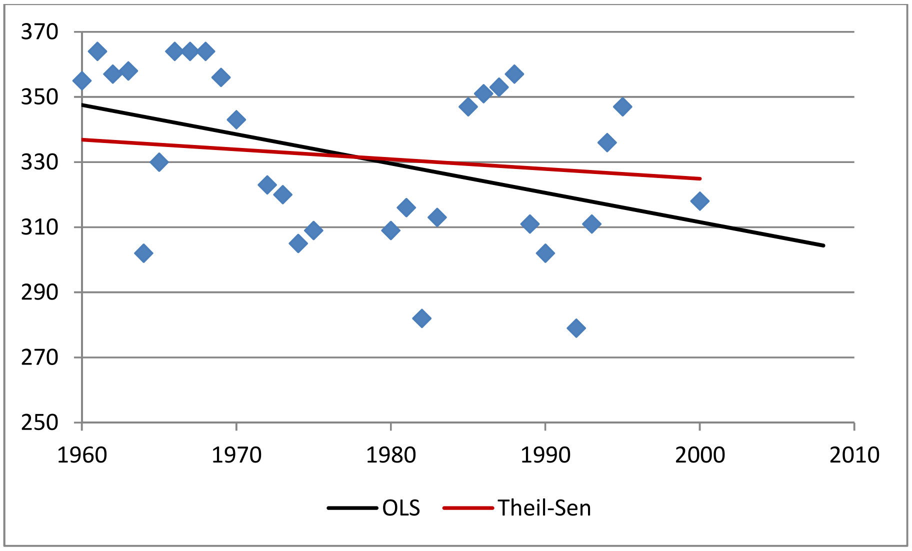
$$\tilde{B} = median\left\{ b_{ij} \middle| b_{ij} = \frac{y_j - y_i}{x_j - x_i}, x_i \neq x_j, 1 \leq i < j < n \right\}$$

And the y-intercept is:

$$\tilde{\beta}_0 = \bar{y} - \tilde{\beta}_1 \bar{x}$$

The Theil-Sen estimator was calculated for the 27 indices for the period 1960-2008 using the somersd package in STATA. As can be seen in Table 1.9, the slopes differ from the ones calculated using OLS and according to the p-values displayed, only the (gsl) index is significant at the 5% level and shows a decreasing trend in the length of the growing season. This decrease is smaller than the one depicted by the least squares method as displayed in Figure 1.10 below.

Figure 1.10 Growing Season Length Index- 1960-2008 with trend lines



Although lacking statistical significance, the trends depicted by the Theil-Sen estimator are both in line with the regional trends obtained by Zhang (2005) and the ones obtained used the least squares method.

A decreasing trend is apparent for both the percentage of days when daily maximum and daily minimum temperatures are below the10th percentile (TX10p and TN10p, respectively).

An increasing trend is observed for the percentage of days when daily maximum or daily minimum temperatures are above the 90th percentile (TX90p and TN90p, respectively) as well as for the annual maximum of daily maximum (TXx) and minimum temperatures (TNx) and the number of summer nights (SU25).

Unlike the negative trend obtained with the least squares method, the annual minimum of the daily maximum temperature (TXn) displayed a positive trend that follows the results of Zhang (2005).

Trends in precipitation indices show an increase (albeit not statistically significant) in the monthly maximum 1-day precipitation amount (RX1day), the annual total precipitation when precipitation > 95th percentile (very wet days or R95pTOT) and the maximum number of consecutive days with PRCP ≥ 1mm (consecutive wet days or CWD). This diverges from the weak and spatially incoherent regional precipitation trends obtained by Zhang (2005).

Table 1.9 Theil-Sen slope estimates for the 27 indices

Indices	Slope	Jackknife SE	P_Value
SU25	0.131183	0.1397703	0.348
ID0	-0.02366	0.0789375	0.764
TR20	0.152688	0.1098978	0.165
FD0	0.135484	0.1450141	0.35
GSL	**-0.29885**	0.1218231	0.014
TXX	0.083871	0.1238191	0.498
TXN	0.015054	0.1429505	0.916
TNX	0.12043	0.0880334	0.171
TNN	-0.06452	0.1293961	0.618
TX10P	-0.0086	0.1637643	0.958
TX90P	0.174194	0.1431247	0.224
TN10P	-0.06237	0.1410019	0.658
TN90P	0.208602	0.1375957	0.13
WSDI	0	0.1428847	1
CSDI	-0.06237	0.0828909	0.452
DTR	-0.01839	0.1273032	0.885
RX1DAY	0.137097	0.1157413	0.236
RX5DAY	0.024194	0.1451424	0.868
SDII	0.062389	0.1235134	0.613
R10MM	0.073084	0.1245289	0.557
R20MM	0.160428	0.1234172	0.194
R25MM	0.187166	0.1212239	0.123
CDD	-0.04991	0.1084422	0.645
CWD	0.181818	0.1387793	0.19
R95P	0.167558	0.1165909	0.151
R99P	0.005348	0.1035679	0.959
PRCPTOT	0.137255	0.133726	0.305

CHAPTER V

CONCLUSION

Climate extreme indices were calculated for the Beqaa Valley using weather data that was collected and digitized from the American University of Beirut Agricultural Research and Education Center. Though several weather variables were collected, only the minimum and maximum temperatures and precipitation variables were used for the calculation of the indices. The data was subjected to quality control through the identification of errors resulting from manual keying and the identification of outliers. The data also underwent homogeneity testing based on a two-phase linear regression test for change point detection. Despite the several significant change points observed, the data was used to calculate the 27 core indices for the period 1960-2008.

The indices, that depicted particular characteristics of extremes, including frequency, persistence and amplitude, were calculated using the RClimDex software which was developed and maintained by Xuebin Zhang and Feng Yang at the Climate Research Branch of Meteorological Service of Canada. Simple trend estimates were also calculated with the RClimDex software using the least squares method to provide some insight into changes in extremes due to the non-stationary nature of climate data. Nonetheless, this method has its disadvantages with a notable one being its sensitivity to outliers.

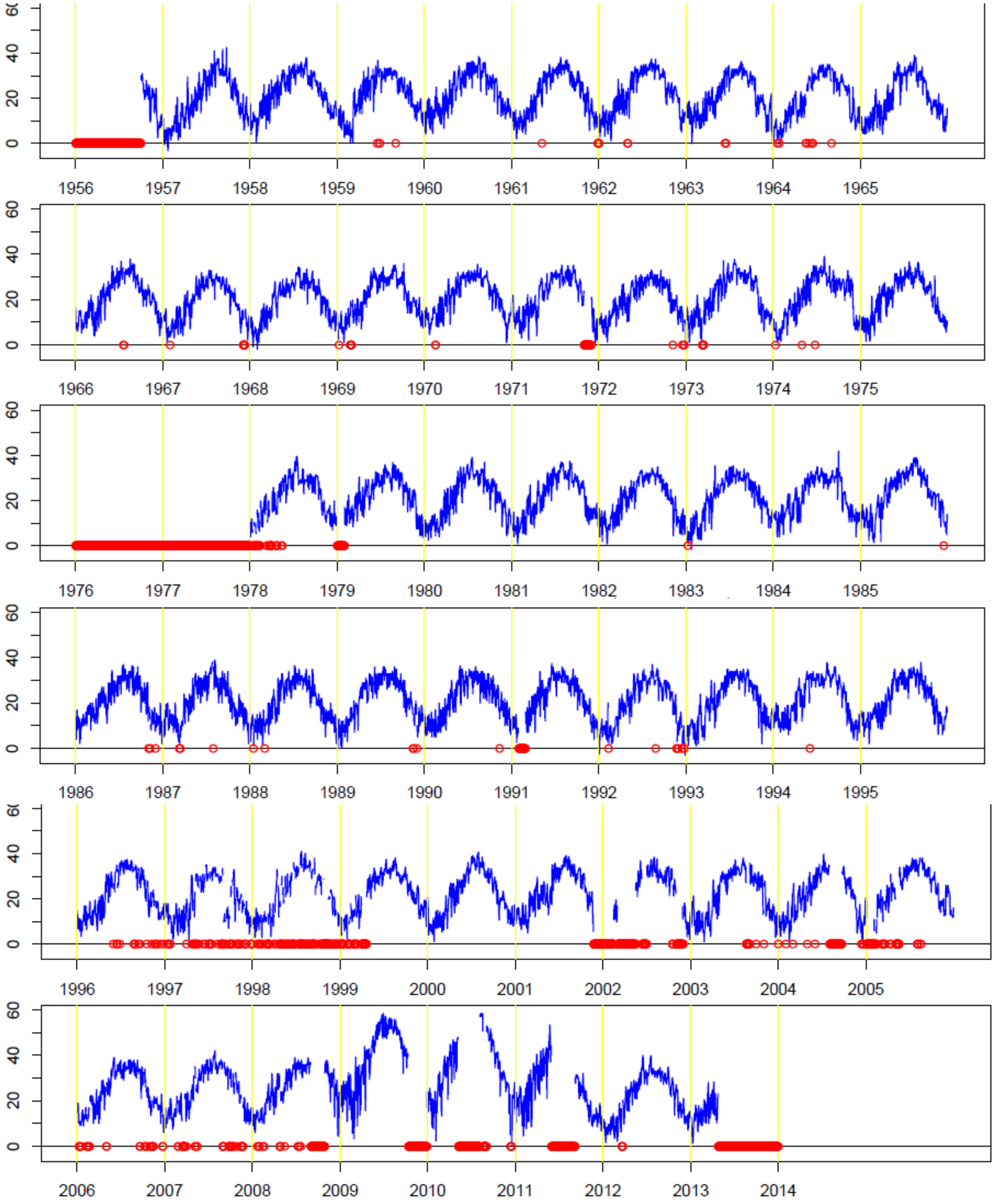
Therefore, to overcome the shortfalls of the least squares method and following Zhang (2005), another linear trend was computed from the indices series using a Kendall's tau based slope estimator due to Sen (1968). The Theil-Sen estimator or the Kendall robust line-fit method is robust to the effect of outliers in the series and has been widely used to compute trends in climatic and hydro-meteorological series.

Although all estimated Theil-Sen estimators for the indices were not statistically significant (except for the GSL index), results were both in line with the regional trends obtained by Zhang (2005) and the ones obtained used the least squares method. Results showed a positive trend in the annual count of summer days and tropical nights. Cool days decreased, warm days increased, cool nights decreased and warm nights increased. The cold spell duration index also followed a decreasing trend. All of the latter highlight the positive temperature trends observed in the Beqaa which are in line with the trends obtained by Zhang (2005).

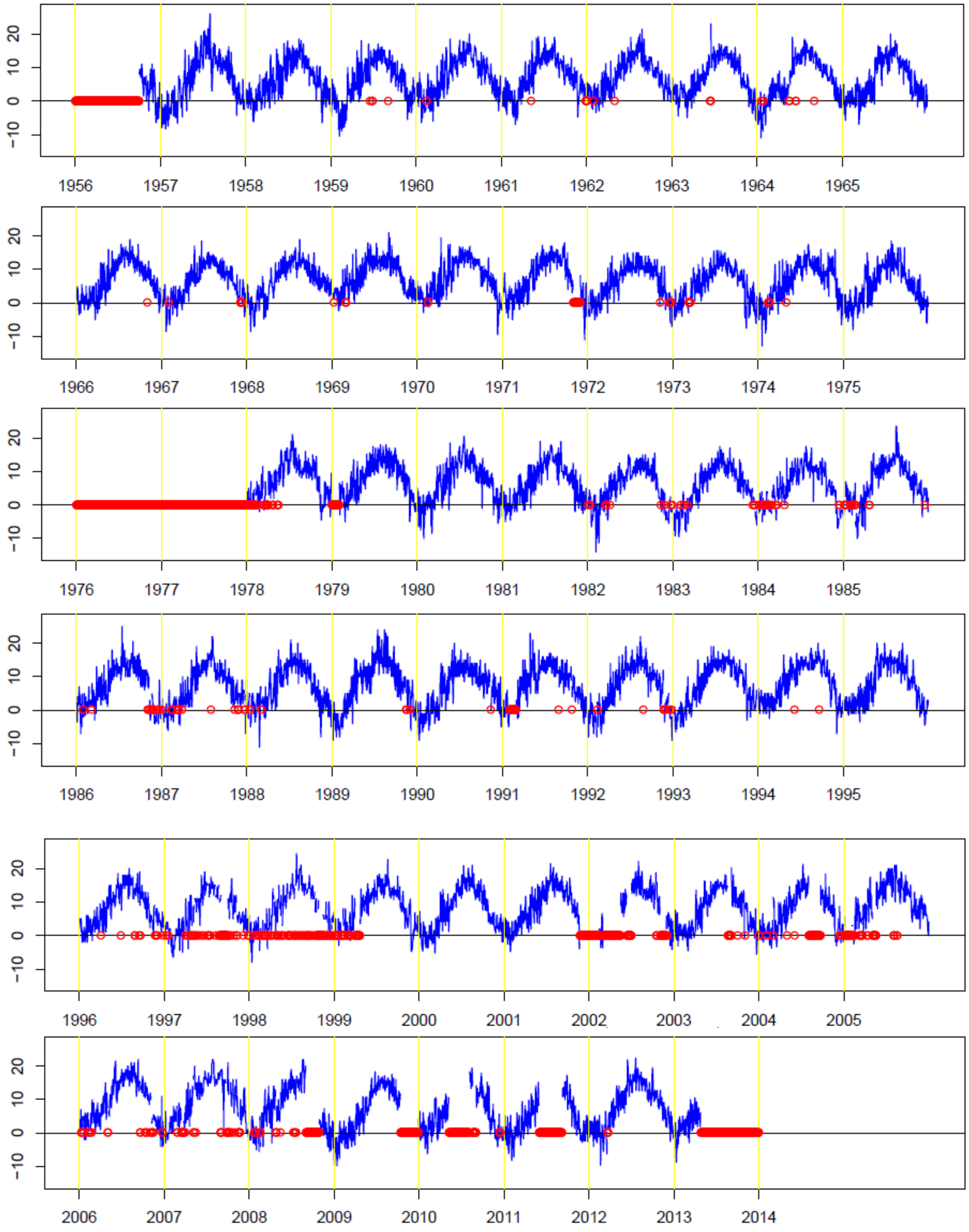
All precipitation indicators displayed a weak positive trend which was confirmed by a decreasing trend for the consecutive dry days indicator. However, these results are not statistically significant and should be interpreted with caution.

APPENDIX

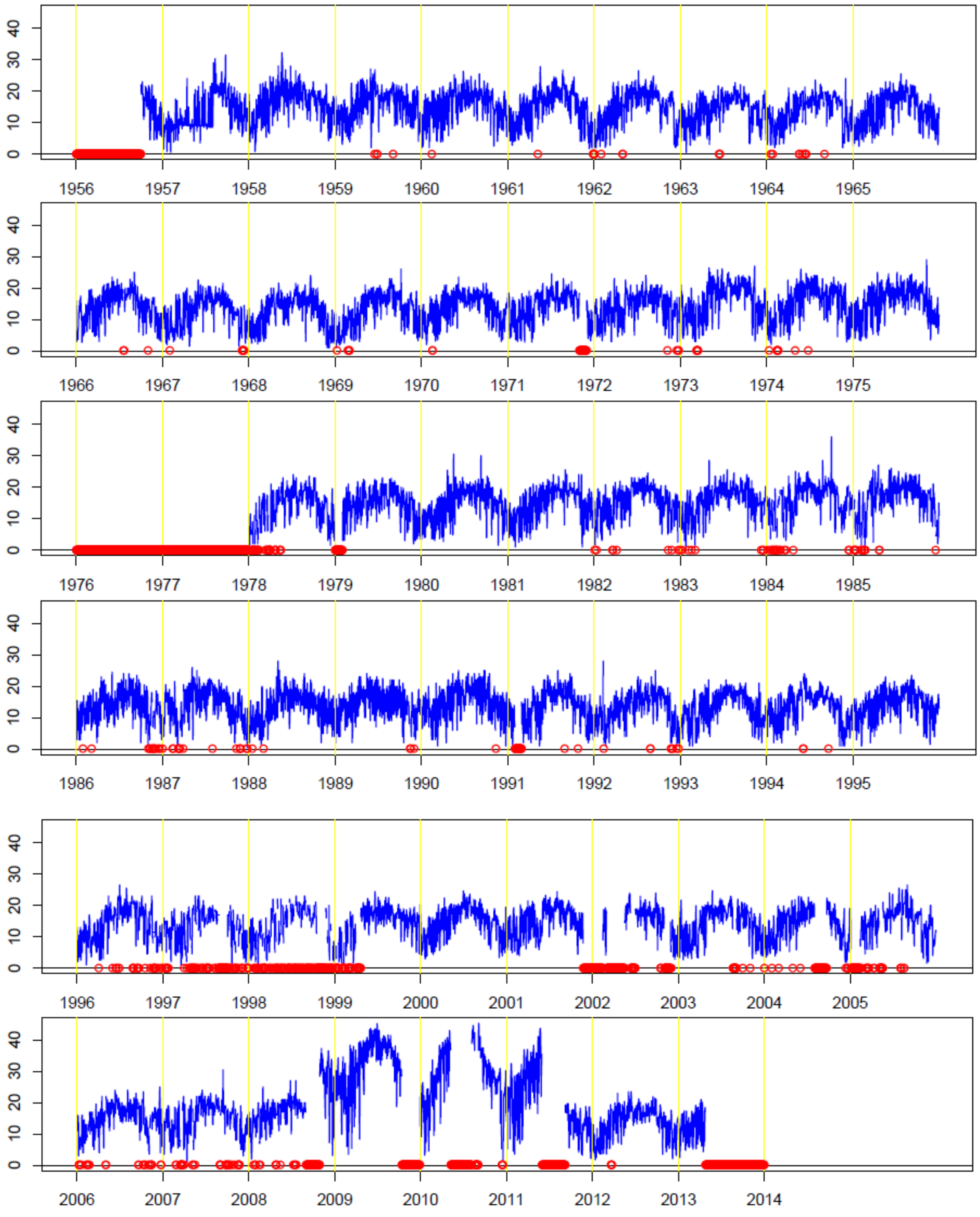
Appendix 1.A Tmax 1956-2013



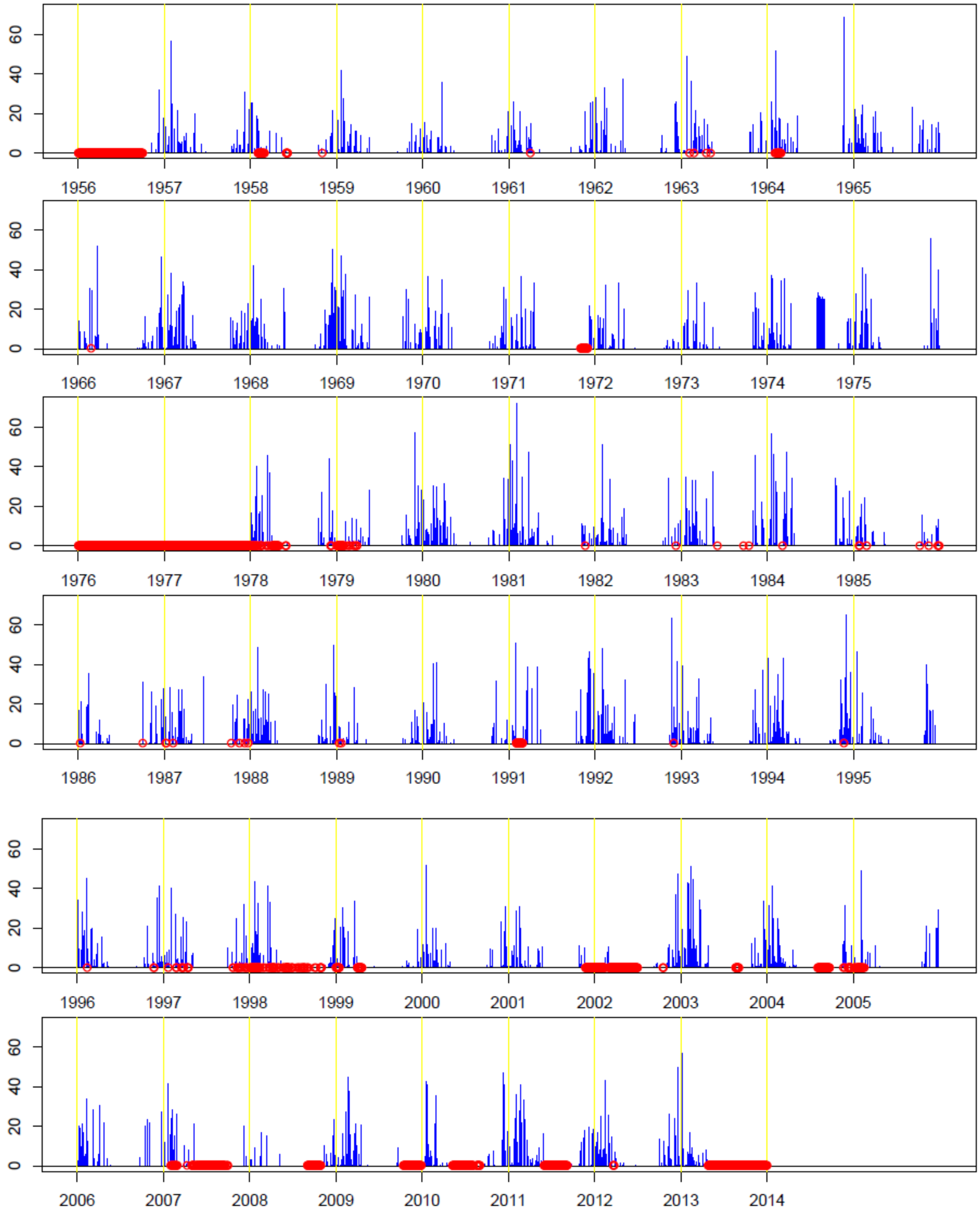
Appendix 1.B Tmin 1956-2013



Appendix 1.C Diurnal Temperature 1956-2013



Appendix 1.D Total Precipitation 1956-2013



Appendix 1.E List of outliers in the data series

year	month	day	tmaxlow	tmax	tmaxup	tminlow	tmin	tminup	dtrlow	dtr	dtrup
1958	1	5	-12.33	35.3	34.55	-14.79	14	16.53	-13.3	21.3	33.72
1958	1	16	-10.33	32.5	30.78	-14.22	10.2	15.51	-10.09	22.3	29.29
1958	1	18	-13.39	35	34.17	-17.31	8.5	16.69	-12.44	26.5	34.1
1958	1	20	-13.11	32.5	34.43	-15.68	16.5	15.27	-13.11	16	34.84
1958	1	24	-11.45	33.7	33.61	-15.57	15.5	15.2	-8.47	18.2	31
1958	1	25	-13.1	33.8	33.93	-14.84	15.2	14.5	-9.36	18.6	30.49
1958	1	27	-12.45	33.5	33.04	-13.98	9.5	13.63	-11.88	24	33.07
1958	1	28	-11.06	33.5	31.42	-15.13	14.3	14.39	-8.63	19.2	29.73
1958	1	29	-11.28	34.8	32.47	-15.55	12.5	14.95	-9.89	22.3	31.58
1958	1	30	-8.3	35	29.36	-12.66	10.2	12.7	-7.11	24.8	28.12
1958	1	31	-11.81	35	33.45	-12.43	11.5	12.77	-10.69	23.5	32.13
1982	2	5	-11.18	1	30.77	-13.59	-14	12.01	-10.81	15	32.28
1994	9	19	9.96	36	49.61	-0.7	26	25	-0.49	10	36.41
2008	11	7	0.83	36.2	39.07	-8.18	0.6	21.02	-8.17	35.6	35.38
2008	12	6	-5.63	34.1	33.02	-9.57	0.1	14.41	-12.9	34	35.03
2008	12	18	-7.11	28.7	31.38	-11.12	-5.1	13.74	-11.63	33.8	33.43
2009	2	4	-10.38	29.9	29.17	-13.8	-1.7	13.79	-12.51	31.6	31.08
2009	2	5	-11.18	32.4	30.77	-13.59	-2.2	12.01	-10.81	34.6	32.28
2009	4	22	-5.37	42.5	46.82	-8.32	3.6	20.61	-7.14	38.9	36.54
2009	5	13	2.83	44.4	46.31	-5.3	4.9	22.76	-7.35	39.5	38.62
2009	5	17	1.47	47	48.76	-4.82	7.3	21.15	-5.49	39.7	39.4
2009	5	18	2.9	48.5	49.28	-5.03	7.7	22.54	-4.94	40.8	39.6
2009	5	19	5.57	48.5	47.9	-4.27	8.6	22.65	-5.28	39.9	40.37
2009	5	27	7.22	46.4	49.19	-1.43	6.5	21.45	-2.78	39.9	39.17
2009	5	28	9.44	44.4	45.9	-1.81	7.7	21.96	-0.25	36.7	35.45
2009	5	29	6.68	50.1	49.1	-1.36	6.9	22.09	-3.43	43.2	38.42
2009	5	30	5.64	50.7	50.38	-3.68	7.7	24.42	-5.43	43	40.71
2009	6	1	5.47	52.4	49.49	-3.03	10.5	23.84	-4.54	41.9	38.69
2009	6	2	3.75	53.5	51.3	-1.16	9.8	22.29	-6.47	43.7	40.4
2009	6	3	6.22	53	50.11	-2.4	12.1	23.42	-2.09	40.9	37.41
2009	6	4	7.06	53	49.04	-1.35	12.5	22.49	-0.99	40.5	35.9
2009	6	5	10.77	47	46.33	-1.92	12.5	22.92	2.34	34.5	33.67
2009	6	6	9.39	47	48.33	-2.01	8.2	23.37	-0.27	38.8	36.64
2009	6	7	6.97	51.2	50.47	-2.54	8.2	23.91	-2.96	43	39.02
2009	6	8	10.28	53.5	48.6	-2.6	13.3	24.63	0.04	40.2	36.81
2009	6	9	6.79	54.7	50.91	-2.33	15.2	24.83	-3.69	39.5	38.89
2009	6	10	10.13	52.4	48.44	0.15	16	22.72	0.1	36.4	35.56
2009	6	11	12.03	51.2	47.4	1.24	16.4	22.42	2.08	34.8	33.69
2009	6	12	11.36	49.1	47.92	2.51	11.7	21.07	-1.18	37.4	36.89
2009	6	13	11.73	49.1	48.56	3.58	12.1	21.61	0.86	37	34.54
2009	6	14	11.53	50.1	48.45	0.19	10.5	24.73	-2.2	39.6	37.26
2009	6	15	9.71	54.7	50.21	0.82	11.7	23.75	-2.26	43	37.72
2009	6	16	8.88	53.5	50.53	0.64	11.7	23.59	-2.99	41.8	38.31

year	month	day	tmaxlow	tmax	tmaxup	tminlow	tmin	tminup	dtrlow	dtr	dtrup
2009	6	18	9.6	51.8	50.34	0.78	11.7	23.21	-3.69	40.1	39.65
2009	6	19	9.78	56	50.65	2.23	12.5	21.79	-0.54	43.5	36.91
2009	6	20	10.55	54.1	50.37	3.08	13.3	21.83	-2.2	40.8	38.07
2009	6	21	10.61	54.1	49.6	1.29	12.9	23.4	-4.79	41.2	40.08
2009	6	22	11.13	54.7	49.82	2.45	12.1	22.46	-3.04	42.6	39.08
2009	6	23	10.06	56	50.68	1.32	12.5	23.85	-3.95	43.5	39.52
2009	6	24	10.53	57.9	51.51	1.68	16.4	23.82	-1.09	41.5	37.62
2009	6	25	12.69	57.2	50.53	2.36	17.5	23.58	1.2	39.7	36.05
2009	6	26	13.29	56.6	49.78	2.43	18.3	22.81	1.99	38.3	35.78
2009	6	27	15.41	47.5	47.2	3.62	14.4	22.64	2.68	33.1	33.77
2009	6	28	14.59	51.2	48.18	3.85	12.1	21.61	1.28	39.1	35.85
2009	6	29	13.54	53.5	49.23	5	11.3	21.52	-0.5	42.2	36.74
2009	6	30	12.27	58.5	50.61	4.16	13.3	22.44	-1.85	45.2	38.13
2009	7	1	10.81	57.2	51.09	3.99	13.7	22.78	-2.27	43.5	37.39
2009	7	2	12.76	55.3	50.06	4.6	13.3	21.81	1.25	42	35.22
2009	7	3	13.98	53	48.48	3.71	12.5	22.41	0.16	40.5	36.18
2009	7	4	13.72	50.7	48.12	3.5	12.5	23	-0.04	38.2	35.3
2009	7	5	14.15	48	48.37	3.36	14.4	23.94	1.99	33.6	33.31
2009	7	6	13.81	52.4	49.57	1.96	15.2	25.13	0.95	37.2	35.35
2009	7	7	14.06	51.8	49.04	3.08	13.3	24.3	1.11	38.5	34.62
2009	7	8	12.33	56	50.94	2.31	12.9	25.58	-1.84	43.1	37.22
2009	7	9	12.88	57.2	51.07	0.61	14.8	26.69	-0.16	42.4	36.86
2009	7	10	12.48	56.6	51.17	2.42	17.1	25.7	-0.18	39.5	35.7
2009	7	11	12.73	56.6	50.87	3.52	16	24.12	-0.12	40.6	36.04
2009	7	12	15.52	54.1	48.94	2.15	14.4	25.1	1.24	39.7	35.97
2009	7	13	17.4	48	47.46	3.98	14.4	23.35	4.77	33.6	32.77
2009	7	14	17.74	47.5	46.32	3.22	14.8	24.01	4.86	32.7	31.98
2009	7	15	17.64	47.5	46.52	3.23	15.6	24.93	4.87	31.9	31.17
2009	7	16	17.22	51.8	48.3	1.87	12.9	26.93	1.19	38.9	35.72
2009	7	17	16.22	53.5	49.56	2.93	14.4	25.11	1.64	39.1	36.01
2009	7	18	17.19	52.4	49.25	3.4	14.8	25.47	2.05	37.6	35.53
2009	7	19	16.88	50.7	48.85	4.47	15.6	25.4	2.37	35.1	33.49
2009	7	20	17.99	49.6	48.02	4	16	25.32	3.79	33.6	32.97
2009	7	21	16.17	50.7	49.58	4.02	16.4	24.94	1.69	34.3	35.09
2009	7	22	14.66	56	51	2.95	15.6	25.73	-0.28	40.4	37.35
2009	7	23	16.04	53	49.54	3.7	16.4	26.13	1.54	36.6	34.58
2009	7	24	15.69	53	49.88	4.83	16.4	23.83	2.93	36.6	33.99
2009	7	25	16.56	51.8	48.9	3.89	14.8	24.43	2.57	37	34.56
2009	7	26	15.23	56	50.61	4.16	16.8	24.68	2.06	39.2	35
2009	7	27	16.47	55.3	49.67	4.94	15.6	24.46	2.23	39.7	34.5
2009	7	28	15.12	56.6	50.9	4.37	15.2	25.36	0.69	41.4	35.6
2009	7	29	14.61	54.1	51.11	3.01	16	26.56	0.27	38.1	35.89
2009	7	30	14.74	53.5	51.3	2.8	13.3	26.5	1.1	40.2	35.73
2009	7	31	16.13	51.8	49.29	2.26	14.4	26.42	2.23	37.4	34.51

year	month	day	tmaxlow	tmax	tmaxup	tminlow	tmin	tminup	dtrlow	dtr	dtrup
2009	8	1	16.99	52.4	48.7	2.84	14.8	26.73	1.95	37.6	34.17
2009	8	2	15.54	54.7	50.05	4.68	13.7	24.75	0.5	41	35.66
2009	8	3	14.85	54.7	50.87	5.54	14.1	23.2	2.18	40.6	34.81
2009	8	4	13.45	56	51.54	6.18	15.6	21.32	0.72	40.4	36.77
2009	8	5	16.71	53	48.44	6.14	17.1	22.09	4.83	35.9	32.32
2009	8	8	11.93	50.7	54.05	1.88	12.5	26.57	-0.59	38.2	38.15
2009	8	16	9.77	56	56.96	2.52	14.4	26.71	-2.3	41.6	39.8
2009	8	19	13.15	54.7	52.99	1.95	15.6	26.33	-1.09	39.1	38.9
2009	8	20	15.42	55.3	50.31	2.35	15.2	25.08	3.29	40.1	35.01
2009	8	21	14.34	55.3	51.43	2.52	16.4	25.96	1.23	38.9	36.07
2009	8	22	15.4	53.5	50.16	2.83	16	25.23	4	37.5	33.53
2009	8	23	12.27	52.4	51.3	3.38	14.1	23.8	-0.29	38.3	36.69
2009	8	24	14.93	51.2	49.46	3.76	13.7	22.55	3.91	37.5	34.26
2009	8	25	15.54	49.1	49.24	0.47	10.9	25.26	3.31	38.2	35.78
2009	8	26	15.97	51.2	49.1	2.9	9.8	24.22	2.17	41.4	35.83
2009	8	27	16.79	52.4	48.42	3.18	13.7	23.92	4.3	38.7	33.7
2009	8	28	16.58	49.6	46.99	4.24	15.6	22.36	3.62	34	33.34
2009	8	30	14.99	49.1	47.06	3.33	11.7	21.81	3.35	37.4	33.81
2009	8	31	14.38	49.1	47.89	2.52	11.7	22.01	2.75	37.4	35.12
2009	9	1	14.52	50.1	48.25	0.87	12.5	24.43	1.92	37.6	35.54
2009	9	2	10.03	51.2	51.62	4.08	13.7	21.85	0.34	37.5	36.14
2009	9	15	9.25	47.5	51.23	1.61	9.4	21.81	0.3	38.1	37.64
2009	9	25	10.09	43	46.91	2.38	8.6	20.68	0.36	34.4	34.18
2009	9	26	9.73	44.4	48.23	1.44	8.6	20.91	1.26	35.8	35.15
2010	3	24	-7.81	39.3	39.16	-9.15	2.3	16.02	-11.11	37	35.59
2010	4	4	-6.96	44.4	43.99	-10.05	5.3	20.02	-12.3	39.1	39.36
2010	8	6	12.51	57.2	53.8	3.92	18.3	24.66	0.6	38.9	37.14
2010	8	7	11.18	57.9	54.73	4.31	17.9	24.42	-2.38	40	39.56
2010	8	8	11.93	57.2	54.05	1.88	16.8	26.57	-0.59	40.4	38.15
2010	8	9	11.29	58.5	54.17	1.12	15.2	26.16	-1.09	43.3	39.34
2010	8	10	11.77	57.9	53.87	2.95	16.4	24.6	0.03	41.5	38.06
2010	8	11	13.06	57.9	53.62	3.35	15.2	25.29	-2.09	42.7	40.13
2010	8	12	12.27	57.9	54.3	4.88	13.3	24.2	-3.5	44.6	40.99
2010	8	13	13.04	57.2	53.55	4.2	14.1	24.41	0.13	43.1	37.87
2010	8	14	10.2	57.9	56.03	2.38	16.8	26.24	-2.57	41.1	40.19
2010	8	15	10.98	58.5	56.23	2.32	19	27.25	-2.04	39.5	39.67
2010	8	16	9.77	57.9	56.96	2.52	19.4	26.71	-2.3	38.5	39.8
2010	8	17	10.68	58.5	55.43	3.09	17.9	26.31	-2.3	40.6	39.01
2010	8	18	10.25	57.9	55.82	3.13	15.6	25.47	-0.69	42.3	38.15
2010	9	4	8.04	52.4	54.5	2.94	9.8	23.79	-2.53	42.6	39.13
2010	9	5	7.91	53	54.04	2.17	7.7	23.71	-3.5	45.3	40.37
2010	9	6	7.84	53	53.74	1.9	9.8	23.6	-2.62	43.2	39.41
2010	9	10	8.15	51.8	52.67	5.27	10.9	18.74	-1.1	40.9	38.7
2010	9	11	6.95	50.1	52.52	1.88	9	22.53	-3.5	41.1	39.32

year	month	day	tmaxlow	tmax	tmaxup	tminlow	tmin	tminup	dtrlow	dtr	dtrup
2010	9	12	11.23	49.6	49.82	2.94	11.3	21.54	-0.62	38.3	37.1
2010	9	16	10.03	48	50.47	2.4	10.9	21.18	0.75	37.1	36.76
2010	9	19	9.96	49.1	49.61	-0.7	11.7	25	-0.49	37.4	36.41
2010	9	20	8.56	50.7	49.57	0.74	13.3	21.3	1.13	37.4	35.75
2010	9	21	8.71	51.8	48.9	1.78	15.2	20.83	1.75	36.6	33.98
2010	9	27	11.83	46.4	45.96	2.75	11.3	19.67	0.98	35.1	34.39
2010	10	6	11.65	41.1	42.29	-0.79	7.7	20.29	1.31	33.4	33.13
2010	10	17	8.91	40.2	40.69	-0.45	6.5	19.02	-2.4	33.7	33.26
2011	5	23	4.91	49.6	50.16	-4.58	6.1	23.27	-6.11	43.5	42.55
2011	5	24	5.81	49.6	48.55	-2.3	9.8	20.34	-1.18	39.8	37.44
2011	5	25	4.08	53.5	51.42	-2.16	9.8	20.92	-5.02	43.7	41.75

Appendix 1.F 27 ETCCDMI Core Indices

Appendix 1.F.1 Frost days, Summer Days, Ice Days, Tropical nights and growing season length (days)

year	FD0	SU25	ID0	TR20	GSL
1960	29	155	0	0	355
1961	33	160	0	0	364
1962	17	155	0	1	357
1963	37	130	0	1	358
1964	57	139	1	0	302
1965	52	128	0	0	330
1966	32	122	0	0	364
1967	35	103	0	0	364
1968	39	118	2	0	364
1969	6	137	0	1	356
1970	29	143	0	0	343
1971					
1972	48	130	0	0	323
1973	60	151	1	0	320
1974	57	164	0	0	305
1975	73	140	0	0	309
1976					
1977					
1978					
1979					
1980	48	150	0	1	309
1981	49	153	0	0	316
1982	89	136	0	0	282
1983	79	148	1	0	313
1984		153	0		
1985	52	159	0	4	347
1986	54	118	0	2	351
1987	45	119	0	3	353
1988	38	125	0	1	357
1989	63	158	0	10	311
1990	59	143	0	0	302
1991					
1992	60	132	6	2	279
1993	44	147	0	0	311
1994	20	166	0	0	336
1995	26	149	0	0	347
1996	11			0	
1997					
1998					
1999					
2000	49	159	0	3	318

Appendix 1.F.2 Maximum and Minimum Tmax and Tmin (ºC)

year	TXx	TNx	TXn	TNn
1960	38.5	20	4.2	-6.5
1961	38.2	19.2	2.2	-7
1962	37.4	21.4	1.1	-3.5
1963	36.4	23	0	-6
1964	35.1	19	-0.5	-7.2
1965	39	20	4.2	-7
1966	38	19	4	-5
1967	33	18.5	1	-6.5
1968	34.5	19	-2	-8.5
1969	36	21	1	-0.8
1970	35.6	19.5	1	-9.5
1971				
1972	33	15	1.2	-7
1973	37.8	15.7	-2	-7.5
1974	39	17.5	1	-12.8
1975	36.8	18.5	1.5	-8
1976				
1977				
1978				
1979				
1980	39.2	20.5	2.5	-10
1981	37.5	19	1	-5
1982	35	15.5	1	-14
1983	35.5	17.5	-1.5	-9.5
1984	42		4	
1985	39	23.5	1.5	-10
1986	37	25	2	-4
1987	39	22	2	-7
1988	36.5	21	1	-11
1989	36	24	0	-9
1990	36.5	20	5	-9
1991				
1992	37	22	-3	-9
1993	35	19	1	-6.5
1994	38	20	3.5	-7
1995	38	20	2	-4.5
1996		20		-2
1997				
1998				
1999				
2000	40.6	21	1.3	-5.2

Appendix 1.F.3 Cool and warm days and nights (percentage of days)

year	TN10p	TX10p	TN90p	TX90p
1960	6.85	4.38	13.73	22.47
1961	6.32	5.3	10.23	8.89
1962	4.12	6.1	10.28	15.98
1963	4.11	10.2	5.88	9.13
1964	9.73	13.05	3.6	4.4
1965	13.7	15.62	4.38	6.58
1966	6.3	9.37	7.72	5.77
1967	11.36	20.51	4.06	0.35
1968	6.58	15.62	8.49	0.82
1969	3.29	9.11	14.61	4.7
1970	5.48	7.67	7.73	5.56
1971				
1972	9.98	14.4	4.12	2.11
1973	17.6	8.36	2.75	9.6
1974	14.75	13.49	10.04	11.79
1975	20.59	5.8	4.4	8.1
1976				
1977				
1978				
1979				
1980	12.58	10.17	8.52	10.27
1981	6.57	9.27	8.5	10.16
1982	26.42	7.89	1.62	2.97
1983	21.51	10.95	1.63	4.84
1984		7.81		11.54
1985	11.71	3.56	7.18	19.52
1986	8.47	15.17	12.34	6.92
1987	9.52	16.6	7.02	11.82
1988	9.8	16.26	7.92	6.37
1989	9.75	8.05	16.2	10.54
1990	14.53	7.82	8.26	10.98
1991				
1992	9.99	18.87	7.54	4.51
1993	3.35	11.87	8.53	7.2
1994	2.21	8.04	20.8	13.12
1995	3.44	7.35	10.78	8.95
1996	2.3		17.21	
1997				
1998				
1999				
2000	2.62	4.48	13.65	16.57

Appendix 1.F.4 warm spell duration index, cold spell duration index, simple daily intensity index and number of heavy precipitation days

year	WSDI	CSDI	SDII	R10mm	R20mm	R25mm
1960	29	0	6.6	6	2	1
1961	0	6	8.2	15	6	3
1962	27	0	10.9	17	7	4
1963	7	0	9.3	16	6	3
1964	6	0	10.7	15	6	6
1965	9	15	9	21	4	0
1966	0	0	10.5	15	5	4
1967	0	0	9	23	9	5
1968	0	0	11.4	29	7	6
1969	0	0	12.2	24	13	9
1970	0	6	10.3	19	7	4
1971						
1972	0	0	8.1	11	3	2
1973	0	14	10.6	17	6	4
1974	26	0	15.6	45	37	19
1975	6	0	11.2	18	9	6
1976						
1977						
1978						
1979						
1980	6	0	8.6	21	7	5
1981	0	0	8.9	15	7	5
1982	0	31	8.4	14	6	6
1983	0	12	10.6	21	9	5
1984	14		12.2	22	13	12
1985	25	9	6.9	12	2	0
1986	0	0	9.3	18	8	5
1987	6	0	8.6	24	6	4
1988	0	0	11.2	29	10	8
1989	7	0	5.5	6	1	1
1990	6	0	8.1	10	4	3
1991						
1992	0	6	11.5	29	8	7
1993	0	0	9	13	6	5
1994	13	0	9.7	23	12	7
1995	6	0	10.1	12	6	5
1996		0	10.3	20	9	7
1997						
1998						
1999						
2000	24	0	8.8	15	4	3
2001						
2002						

Appendix 1.F.4 warm spell duration index, cold spell duration index, simple daily intensity index and number of heavy precipitation days

year	WSDI	CSDI	SDII	R10mm	R20mm	R25mm
2003			11.3	31	13	9
2004						
2005						
2006			12.2	17	10	4
2007						
2008						

Appendix 1.F.5 Consecutive dry days, Consecutive wet days, Very wet days, extremely wet days and annual total wet day precipitation

year	CDD	CWD	R95p	R99p	PRCPTOT
1960	161	4	35.8	0	231.5
1961	132	5	0	0	387.7
1962	148	10	37.3	0	459
1963	161	5	133.4	97	482.2
1964	192	6	154.1	120	522
1965	79	5	0	0	496
1966	151	6	98.2	52	460.1
1967	148	4	71.9	0	678.6
1968	129	7	92.6	50.3	709.4
1969	142	6	157.9	47.2	660.4
1970	160	6	71.3	0	463.5
1971					
1972	176	5	33.5	0	291.8
1973	140	4	0	0	382.4
1974	111	31	175.2	0	1235.3
1975	191	4	173.7	55.6	535.5
1976					
1977					
1978					
1979					
1980	75	9	34.3	0	594.7
1981	123	5	247.8	170.4	596.5
1982	154	6	239.6	51.2	496.8
1983	109	7	117.5	0	584.7
1984	174	6	218	104	669.3
1985	149	7	0	0	349.6
1986	139	6	35.7	0	484.5
1987	116	7	34	0	608.9
1988	175	11	98.3	98.3	683.8
1989	153	5	0	0	193.4
1990	156	5	81.5	0	317.5
1991					
1992	148	12	193	111.5	779
1993	157	8	76.5	0	429.8
1994	126	8	255.5	65	755.2
1995	151	4	120	0	392.9
1996	156	6	200.2	0	639.5
1997					
1998					
1999					
2000	154	8	51.8	51.8	472.8
2001					
2002					

Appendix 1.F.5 Consecutive dry days, Consecutive wet days, Very wet days, extremely wet days and annual total wet day precipitation

year	CDD	CWD	R95p	R99p	PRCPTOT
2003	113	11	248.4	51	850
2004					
2005					
2006	141	3	34	0	426.5
2007					
2008					

Appendix 1.F.6 Diurnal Temperature

year	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	ANNUAL
1960	10.55	13.5	12.63	14.54	18.59	17.99	18.62	18.11	18.1	17.45	11.93	12.75	15.4
1961	9.05	9.09	12.89	15.11	17.39	17.18	19.4	19.92	17.48	17.01	12.67		15.2
1962	8.01	8.67	13.97	14.57	17.08	19.1	19.37	18.9	19.65	14.77	16.42	8.41	14.91
1963	9.68	9.64	12.02	13.47	14.09	16.38	16.68	18.37	17.2	14.33	13.64	11.51	13.92
1964	10.06	8.1	10.76	12.79	16.37	16.13	17.41	17.49	16.78	17.52	12.11	10.99	13.88
1965	7.71	9.9	12.93	12.21	17.15	17.03	18.41	18.72	18.58	12.59	13.55	10.26	14.09
1966	9.31	11.03	11.57	14.11	15.56	18.14	17.76	18.7	16.24	13.96	13.2	8.37	14
1967	9.03	8.3	9.95	12.28	13.36	16.38	17.11	16.43	16.27	13.12	10.27		12.95
1968	6.87	9.32	11.23	15.18	15.08	14.32	16.77	15.96	17.03	13.94	9.95	6.48	12.68
1969	5.34	8.53	8.72	11.73	15.42	15.69	17.07	18.35	16.78	13.02	13.64	9.93	12.85
1970	8.95	11.28	11.37	14.98	15.85	17.76	16.41	17.01	16.52	15.22	11.92	10.6	13.99
1971	12.25	8.76	12.17	11.95	16.46	15.54	17.93	16.45	17.75	15.86		8.77	
1972	10.06	11.22	12.53	12.48	14.37	15.45	16.73	17.48	17.13	15.35	12.62	12.64	14
1973	11.19	12.57		12.15	19.14	19.12	20.34	19.24	21.07	19.33	13.85	13.06	16.46
1974	7.83		11.59	13.04	17.33	19.4	20.14	18.25	16.17	18.45	16.37	9.5	15.28
1975	10.5	10.42	15.61	15.53	17.8	17.59	19.03	18.35	18.95	18.18	14.6	10.83	15.62
1976													
1977													
1978					16.88	15.85	17.63	18.5	16.93	15.37	13.31	8.67	
1979		11.93	13.11	15.42	15.88	16.45	17.48	17.3	18.27	14.13	12.73	9.23	
1980	9.21	9.19	11.91	12.6	16.75	18.3	18.62	17.84	18.22	16.38	14.12	11.85	14.58
1981	8.18	9.65	11.81	13.49	15.04	17.79	18.03	18.54	19.34	18.18	11.42	13.09	14.55
1982	11.8	12.62	12.42	15.7	16.09	19.51	19.65	19.55	18.55	15.73	13.85	13.68	15.76
1983	9.99	10.93	13.15	15.07	17.75	18.76	18.51	19.31	18.63	17.53	14.72	14.65	15.75
1984			14.02	13.49	18.92	20.19	18.73	18.17	19.9	17.96	11.62	15.88	
1985			17.43	18.49	16.92	20.08	19.69	20.07	19.79	16.24	16.18	10.67	17.56
1986	9.61	12.59	12.1	15.17	14.01	14.17	17.84	17.34	15.76	13.23		11.88	13.97
1987	13.71	11.19		14.73	17.34	17.2	17.71	16.06	16.84	12.56		8.29	14.56

Appendix 1.F.6 Diurnal Temperature

year	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	ANNUAL
1988	8.52	9.91	10.55	14	17.47	16.9	17.05	16.94	14.88	13.53	11.55	10.52	13.48
1989	10.71	12.96	13	16.93	16.84	17.02	15.82	15.21	15.55	13.98	11.72	10.97	14.23
1990	13.29	10.71	12.87	14.18	16.5	17.33	18.56	18.76	18.13	15.97	13.24	10.53	15.01
1991	9.87		9.26	12.53	11.48	18.72	16.74	18.37	18.82	14.75	12.1	8.27	
1992	9.59	8.71	10.55	13.53	12.9	15.07	16.27	16.71	15.85	17.13	11.81	6.79	12.91
1993	10.41	9.93	10.89	13.8	12.4	15.72	18.31	17.1	17.69	14.98	10.75	9.25	13.44
1994	10.66	9.32	12	15.29	15.55	18.29	16.26	17.55	16.17	14.23	7.67	8.89	13.49
1995	10.59	11.59	13.05	13.92	15.96	16.63	15.72	18.37	16.77	15.35	11.72	12.13	14.32
1996	8.19	10.21	8.94	11.18	16.52	17.4	19.23	19.37	16.54	14.06	14.12	9.48	
1997		11.57	9.42			16.4							
1998	9.16												
1999					17.82	17.18	17.57	18.66	16.9	15.37	14.59	14.05	
2000	8.05	11.37	12.95	13.97	17.05	18.4	20.22	18.26	16.81	13.32	14.49	10.39	14.61
2001	11.7	10.15	15.07	14.76	10.8	19.34	18.05	18.89	17.48	14.79			
2002							17.7	17.26	17.27	16.14		8.81	
2003	9.85	7.78	9.84	13.53	18.35	17.93	17.65		17.08	16.52	12.95	10.02	
2004	8.31	10.32	14.45	14.98	15.91	17.81	18.72			16.53	11.91		
2005				13.41		16.88	18.29		15.78	16.05	9.97	12.34	
2006			13.08	13.72	18.17	19.15	16.79	18.05	17.73			14.26	
2007	13.23	10.62		12.14	15.09	20.05	18.85	18.87				9.97	
2008	12.04	13.89	15.39	16.67	18.02	18.83		18.13					

Appendix 1.F.7 RX1day Max 1-day precipitation amount

year	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	ANNUAL
1960	15.4	10.9	35.8	3.5	1.3	0	0	0	0	9.02	12	20.9	35.8
1961	26.1	20.8	13.4	15	1.8	0	0	0	3	3.5	21.2	25.7	26.1
1962	28.2	32.8	4.6	37.3	2.4	0	0	0	0	8.9	0	26.1	37.3
1963	48.9	36.4	21.5	17.1	5.5	0	0	0	0	11.6	14.1	20.6	48.9
1964	25.8		15.1	8	18.5	0	0	0	0	0	68.5	7.2	
1965	22	24	18.4	21.1	3	3	0	0	23.2	16.7	14.1	15.6	24
1966	14	30.8	52	0	2.6	0	0	0	0.4	16.3	6.3	46.2	52
1967	38.2	19	33.7	6.5	16.8	0	0	0	0	15.5	19.1	23.1	38.2
1968	42.3	24.9	12.4	2	30.4	0	0	0	0	7.5	19.6	50.3	50.3
1969	47.2	37.8	27.5	12.2	26	0	0	0	0	30	24.8	13.7	47.2
1970	36.3	19	35	17.9	10.7	0	0	0	0	3.9	6.4	31.2	36.3
1971	15.5	36.7	20	33.2	0	0	0	0	0	0		21.9	
1972	17	32.2	7.4	33.5	20	0.4	0	0	0	1.2	4.9	3	33.5
1973	29.3	14.2	33.2	23.4	10.9	1	0	0	0	0	28.4	12.8	33.2
1974	37.1	16	35.2	22.6	0	0	0	28.5	0	2.6	0	15.4	37.1
1975	27.8	40.8	24.9	6.1	0	0	0	0	0	1.5	55.6	39.7	55.6
1976													
1977													
1978					0.5	1	0	0	0	27	4.1	44	
1979		12.2		9	27.8	0	0	0	0	15.5	57	30	
1980	23	30.5	13.8	31.6	5.9	0	1.5	0	0	7.5	5.3	34.3	34.3
1981	51.3	72.1	47	8.4	16.6	2.4	5.1	0	0	0	10.9	9.4	72.1
1982	51.2	43.7	33.8	14.5	19	0	0	0	0	4	34	41.2	51.2
1983	34.5	33.1	33	23.5	37.5	0	0	0	0	17.4	45.5	22	45.5
1984	56.5	32.2	47.5	34	0	0	0	0	0	34	24.3	27.7	56.5
1985	19.5	24	7	0	6.7	0	0	0	0	15.5	5.5	13.2	24
1986	21	35.7	6	11.7	4	0	0	0	0	31	26	28	35.7
1987	28.2	15.5	27.5	5	0	34	0	0	0	19.5	24.3	22.5	34

Appendix 1.F.7 RX1day Max 1-day precipitation amount

year	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	ANNUAL
1988	26	48.8	26	11.5	0	0	0	0	0	11.7	30	49.5	49.5
1989	8.6	10.8	28.5	0	2.2	0	0	0	0	2.8	16.8	13.5	28.5
1990	20.7	40.5	41	3.5	2	0	0	0	0	10.4	31.5	11.8	41
1991	51		39	39	10.4	0	0	0	0	16	27	46.2	
1992	48	27	18.3	3.6	32	14.6	0	0	0	0	63.5	41.5	63.5
1993	39.5	8.3	32.5	5	13	0	0	0	0	17	27	37	39.5
1994	43	35	43	5.7	2.5	0	0	0	1.7	2	33.5	65	65
1995	46.5	25.5	18.5	5.5	1.8	0	0	0	0	4.3	40	17	46.5
1996	34	45.2	20	15.6	3	0	0	0	0.5	20.7	7	41	45.2
1997	9.1	40		23	7.2	0	0	0	10.2	7.6			
1998									0		1.5	24.5	
1999		20.4	33.6		0	0.6	0	0.2	0.2	3.4	2.4	19.2	
2000	51.8	19.8	19.8	12.4	0	0	0	0	1.2	9.4	23.4	30.8	51.8
2001	11	31	10.4	1.2	10.4	0	0	0	0	10.8			
2002							0.2	0.2	2.2	0.2	11.5	47.4	
2003	43	51	34	10.8	0.2	0	0		0.2	12	15	33.4	
2004	41	25	4.2	8.8	1.2	0.2	0			0	31.6		
2005			8	11	0	0	0	0	0	8	21	29	
2006	21	34	28.5	30.5	3.5	0	0	0	4	23.5	21.5	27.5	34
2007	41.5		0	10						0	0	20	
2008	9	17	15	0	6	0	0	1					

Appendix 1.F.8 RX5day Max 5-day precipitation amount

year	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	ANNUAL
1960	26.5	17.8	49.9	4.8	1.3	0	0	0	0	9.02	18.5	33	49.9
1961	38.6	43.8	16.8	25	1.8	0	0	0	3	5.8	39.6	69.2	69.2
1962	56.98	70.1	6.6	37.3	37.3	0	0	0	0	13	2.4	86.9	86.9
1963	119.9	43.5	36.05	29.1	13.9	0	0	0	0	32.3	25.7	34.7	119.9
1964	40.1		19.7	8.3	23.7	0	0	0	0	0	153.2	9.8	
1965	33.3	61	33.1	36.9	10.4	3	0	0	23.2	18.4	16.5	46.2	61
1966	32	34.2	76.1	1.1	2.6	0	0	0	0.4	18.9	11	105.2	105.2
1967	74.8	74.3	77	10.6	25.6	0	0	0	0	22	38.3	42.3	77
1968	90.5	42	22.5	2	50.6	0	0	0	0	9.5	49.4	93.4	93.4
1969	158.1	38.9	93.6	18.1	26	0	0	0	0	35.3	24.8	22	158.1
1970	103.3	53.9	62.4	30.3	10.7	0	0	0	0	3.9	10.2	57	103.3
1971	29	73.9	48.4	107.8	0	0	0	0	0	0		52.6	
1972	31.8	39.3	14.1	51.9	38	0.4	0	0	0	2	11.8	6.1	51.9
1973	71.1	57.5	65	31.2	11.3	1.9	0	0	0	0	52.5	19	71.1
1974	116.7	23.8	64.7	45.6	0	0	0	137.5	96	2.6	2.6	45.8	137.5
1975	33.8	64.5	42.5	11.9	0	0	0	0	0	1.5	63.1	68.7	68.7
1976													
1977													
1978					0.5	1	0	0	0	33.4	28	53.6	
1979		23.5		12.2	31.4	0	0	0	0	31.6	84.5	84.5	
1980	49	74.1	68.9	53.9	16.8	0	1.5	0	0	10.5	11	69.1	74.1
1981	75.7	83.7	55.9	16.1	28.5	3.5	5.1	0	0	0	19.2	19.5	83.7
1982	79.1	147.9	53.3	20.8	23	0	0	0	0	5.8	51	62	147.9
1983	71.8	95.5	62.2	44	53.2	0	0	0	0	17.4	64.4	39.1	95.5
1984	74.4	37.9	78.3	69.3	0	0	0	0	0	64.5	31.3	55.8	78.3
1985	34.7	65.9	18.7	1.7	7.5	0	0	0	0	17.4	8.5	25.6	65.9
1986	40.9	46.2	7.8	16.2	8.6	0	0	0	0	37.1	70	68.2	70
1987	51.3	23.1	67.2	6.5	0	34	0	0	0	23.5	40.8	56.5	67.2

Appendix 1.F.8 RX5day Max 5-day precipitation amount

year	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	ANNUAL
1988	50.3	71.1	71.4	12.7	0	0	0	0	0	11.7	32.5	65.5	71.4
1989	10.8	15.6	34.9	11.7	2.2	0	0	0	0	2.9	25.6	29.5	34.9
1990	28.7	64.2	41.6	12.8	3	0	0	0	0	20.8	50.5	20.3	64.2
1991	64.5		59.9	41.4	49.4	0	0	0	0	29.7	52.8	138.8	
1992	98.9	102.5	28.5	3.6	49.5	27	0	0	0	0	106.1	107.7	107.7
1993	94.4	23.3	61.1	6.5	20.4	0	0	0	0	18	52.2	37	94.4
1994	80	71	57	10.2	4.6	0	0	0	3.4	3.5	77.6	106	106
1995	86.5	47	26.8	11.4	3.7	1.8	0	0	0	4.3	91.6	17	91.6
1996	93	100.6	45.5	26.8	3.5	0	0	0	0.5	43.5	11.5	64.5	100.6
1997	13.9	65.4		55.5	13.5	0	0	0	11	13.5			
1998									0		2.5	53	
1999		52.4	58.5		0	0.6	0	0.2	0.2	3.6	3	22.2	
2000	109	40.4	29.4	13.2	3.4	0	0	0	1.4	19.4	25.8	55.2	109
2001	24.6	56.4	10.4	1.4	11.8	0	0	0	0	15.8			
2002							0.4	0.2	5	0.2	21.5	105.6	
2003	81.6	115.4	71	13.2	12.4	0.2	0		0.2	14	29.8	73	
2004	113.6	78.6	6.8	9.2	1.8	0.2	0.2			0	73.6		
2005			9	26	0	0	0	0	0	9.5	33	51	
2006	56	45.5	34	52.5	3.5	0	0	0	4	27.5	21.5	27.5	56
2007	41.5		26	10						0	0	28	
2008	9	24	15	0	6	0	0	1					

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PART II

HISTORICAL EFFECTS OF TEMPERATURE AND PRECIPITATION ON THE PRODUCTION OF WHEAT IN LEBANON

CHAPTER I

INTRODUCTION

Despite efforts to improve the state of food security through domestic food production, and increased self-sufficiency, Arab countries remain by far net importers of food, and especially cereals, the main staple food and feed for livestock in the region.

The food production capacity of the region is predicted to be further aggravated in the next few decades by climate change through increases in surface temperatures coupled with sharp decreases in precipitation and evaporation. Crop modeling results indicate that climate change will have a negative effect on crop yields in the Middle East and North Africa in 2050.

This vulnerability has major implications for the frail food security status of the region as well as for the livelihoods of the 150 million people in rural areas whose incomes rely predominantly on natural resources (Lee, Ashwill, & Wilby, 2013b). The agriculture sector represents the major income-generating activity in the Beqaa Valley, the main wheat production area in Lebanon, making it a crucial lifeline for farmers and their families.

Lebanon does not fare well in terms of food accessibility as food constitutes 22 percent of the country’s consumer price index (BankMed, 2013). The country is highly vulnerable to international food price fluctuations due to its high reliance on imports to meet its food demand with a specially acute cereals import dependency ratio of around 85 percent (Capone & Bilali, 2013). Therefore, the country currently produces a mere 15 percent of its cereal needs and farmers face several constraining factors such as rent, fertilizer, harvest and irrigation costs that cause their production costs to be relatively high compared to international prices. If the Government wants to continue supporting wheat cultivation as a strategic crop for food security, it will need to take measures beyond the wheat production subsidies it has been providing farmers.

The vulnerability of the agriculture sector in Lebanon will be further intensified with the additional threats of climate change, decreased water availability and land resources, and the pressure exerted by population growth and urbanization. Based on previous findings and forecasted climate change scenarios, the overall agricultural yields of crops and especially rain fed crops are expected to decrease as a result of higher temperatures, reduced precipitation and the consequent decrease in soil moisture and increase in aridity.

Climate extreme indices for the Beqaa Valley, calculated in the first part of this thesis revealed a statistically significant decreasing trend for the growing season length index which can potentially limit the growth of wheat and other crops. Increasing temperature trends were observed through an increase in the annual count of summer days and tropical nights. Cool days decreased, warm days increased, cool nights decreased and warm nights increased. The cold spell duration index also followed a decreasing trend. An increasing but weak and not statistically significant trend was observed for all precipitation indices.

Despite technological advances and the relative prevalence of irrigation in the Beqaa valley, agricultural production remains highly dependent on weather, which can affect both the quantity and quality of harvested crops, and especially rain fed ones such as wheat. This section of the thesis uses digitized AREC data for the first time and aims to study the relationship between wheat production and climate and to evaluate the impact of the latter on observed yield trends.

An improved understanding of the potential effects of climate change on wheat yields, a major staple food, the agriculture sector and the economy as a whole is central to planning appropriate and timely responses. The findings of this thesis can contribute to the formulation of effective policies targeting the agriculture sector and induce policy makers to invest in agricultural and climate change adaptation strategies.

Such strategies could include the support of farmers in adopting sustainable agricultural practices such as conservation agriculture and suitable crop rotations and the efficient use of irrigation in light of the increasing water deficit the country is witnessing coupled with the crop's high reliance on spring irrigation.

CHAPTER II

LITERATURE REVIEW

A. The State of Food Security and Agriculture in the Arab Region

"Food security exists when all people, at all times, have physical and economic access to sufficient, safe and nutritious food to meet their dietary needs and food preferences for an active and healthy life"(FAO, 1996). Despite efforts to improve the state of food security through domestic food production, which falls under the availability pillar of the food security definition, Arab countries remain by far net importers of food, and especially cereals, the main staple food and feed for livestock in the region. This perilous reliance on food imports exposes Arab countries to the vulnerability of food supply chains and volatility of international food prices, as was evidenced by the detrimental effects of the 2007-2008 global food crisis on the region which suffered from the doubling of its food import bill (Sadik, El-Solh, & Saab, 2014).

Food imports stood at USD 51,254.5 million compared to a mere export total of USD 15,624.43 million. The Arab region's self sufficiency ratio for wheat/flour and cereals fell from 44.7 percent and 45.6 percent respectively in 2011 to 40.9 percent and 42.7 percent in 2012 (AOAD, 2013). The latter is a clear indication that the region has not made progress with regards to enhancing food security based on domestically produced food, especially with regards to cereal.

Cereals, which are central to food security, have occupied over the past decades a relatively large part of the total cropland in the world as well as in Arab countries. The percentage of land worldwide under cereal production dropped from 47.3 percent in 1961 to about 45.5 percent in 2010. In contrast, the percentage of land dedicated to cereal production increased from 38 percent in 1961 to 47.5 percent in 2011 in the Arab region. Nevertheless, average cereal productivity in Arab Countries lags considerably behind the world average. While global cereal production growth was mainly driven by an increase in yields, the region increased its production through the expansion of the area under cereal cultivation (Sadik et al., 2014).

The region's net food importer status and lagging agricultural productivity can be attributed to its less than perfect agricultural conditions characterized by hyper-arid, semi-arid and arid land conditions, limited agricultural land and water resources and erratic cropping patterns (Tolba & Saab, 2009b). The average agricultural land share per capita is decreasing annually to due rapid population growth rates and urbanization and lags below the world average. Rain fed agriculture is the dominant agricultural system in the region where irrigated areas constitute a mere 14.25 million ha or less than 30 percent of total agricultural areas (Sadik et al., 2014).

The food production capacity of the region is predicted to be further aggravated in the next few decades by climate change through increases in surface temperatures coupled with sharp decreases in precipitation and evaporation. The region will be home to shorter winters, drier and hotter summers, more frequent heat waves and other short-term extreme weather events such as severe storms, droughts, frost, and floods (IPCC, 2014) which can lead to potentially lower crop yields or a total crop failure.

Crop modeling results indicate that climate change will have a negative effect on crop yields in the Middle East and North Africa in 2050. The region will face yield declines of up to 30 percent for rice and 20 percent for wheat. Projections suggest that Egypt, Which is the only Arab country among the top-ten wheat stock holding countries

(Lampietti, Larson, & Battat, 2011), can expect to lose 15 to 36 percent of its wheat crops if temperatures rise by 2 to 4°C (Sadik et al., 2014).

B. The State of Food Security and Agriculture in Lebanon

Lebanon produces half of its population's consumption needs and relies on exported commodities such as fruits and vegetables to partially cover its import bill mostly constituted of cereals, meat and dairy products, sugar and vegetable oils. The gap between increasing imports and local production is widening due to demographic pressures, the weakening of the agriculture system and climate change. Relying on an increase in exports to close this gap is a failing strategy the country should avoid due to its limited agricultural capacities and the predicted impact of climate change (Ministry of Environment, 2011).

Lebanon does not fare well in terms of food accessibility as food constitutes 22 percent of the country's consumer price index. In fact, the food price index has been increasing faster than the consumer price index indicating mounting food prices. This increase is in line with trends in international food prices highlighting the vulnerability of the country to international food price fluctuations due to its high reliance on imports to meet its food demand (BankMed, 2013).

While Lebanon is somehow self-sufficient in some products like poultry meat, fruits and vegetables, it produces 45 and 10 percent of its legumes and sugar needs and relies heavily on milk, red meat and vegetable oil imports (Lee et al., 2013b). Although the country has witnessed an increase in self-sufficiency in wheat/flour and cereals from 16.7 percent and 11 percent in 2011 to 22.2 percent and 15.5 percent in 2012 respectively (AOAD, 2013), it is still considered a net importer of wheat with a high cereals import dependency ratio of around 85 percent. Therefore, cereals and wheat prices specifically can have dramatic impacts on Lebanese and other southern and eastern Mediterranean consumers as cereals form a significant portion of the populations' daily diet (Capone & Bilali, 2013).

The agriculture sector's contribution to the economy is quite modest and constitutes 5 percent of Lebanon's GDP. In fact, land dedicated to agriculture has been plummeting over the last two decades reaching a low of 11 per cent in 2011 (Haddad, Farajalla, & Camargo, 2014) and agricultural production has decreased by 12 percent between 1970-2008. Although one of the Ministry of Agriculture's objectives is to increase the contribution of the sector to at least 8 percent of GDP, the country's economic policies mostly favor the services sector over the primary and secondary sectors (Asmar, 2011). A mere 1-3 percent of the annual public budget is allocated to agricultural services. A notable issue which is influencing the decrease in the land dedicated to agriculture is the decrease in the already low average plot size due to inheritance laws, making agricultural exploitation less profitable and attractive to investors and the young work force (Ministry of Environment, 2011).

According to the country's latest agriculture survey (Ministère de l'Agriculture, 2010), a total of 2.3 million dunums of land were cultivated and owned by 169,512 landholders. Almost half of the land plots (49 percent) are less than 5 dunums and represent 8 percent of the cultivated land. Land plots larger than 100 dunums constitute 2 percent of land plots and constitute 35 percent of total cultivated land. The average size of holdings cultivated in Lebanon is small and reaches 13.6 dunums; 29 dunums in the Beqaa, 7 dunums in Mount Lebanon and 10-12 dunums in other governorates.

Agriculture is the most water demanding sector taking up about 65-70 percent of water resources. Irrigated land amounts to 1.13 million dunums or 49 percent of total cultivated areas. It increased by 8 percent over the 1998-2010 period. Notably, 65 percent of landholders rely on full irrigation and 35 percent on supplemental irrigation for rain fed crops such as wheat (Ministère de l'Agriculture, 2010).

In addition to limited water resources, and land degradation, farmers in Lebanon face additional challenges that are specific to smallholder farmers. They suffer from fragmentation which limits their accessibility to improvements and are most vulnerable to rises in input prices such as fuel and fertilizer and climate change. They are locked in a cycle of low productivity, high production costs, a lack of assets and services and weak market and bargaining power.

C. Winter Wheat Production in Beqaa, Lebanon

1. Beqaa Climate and Agriculture Profile

The Beqaa Valley is characterized by a semi-arid to continental climate with unpredictable rainfall and recurrent droughts. The peak of the rainy season is between January and April, where 75 percent of rainfall occurs. Average temperatures range from 9°C in the winter to 27°C in the summer. Potential evapotranspiration exceeds 70 percent of precipitation leaving the valley with an acute water deficit problem (Bou-Zeid & El-Fadel, 2002). Yet, the region is highly reliant on irrigation to grow crops, as 72 percent of its cultivated area is irrigated, the highest rate amongst all governorates. It is estimated that the Valley consumes 1.5 times the annual ground and surface water replenishment, leading to declining groundwater tables (FAO, 1997).

It is the most important agricultural region of the country and includes 46 percent of the total cultivated area (Lee et al., 2013b). However, agriculture is severely constrained by the physical nature of the land The mountain ranges that border, high population density, traditional land tenure patterns, and rapidly increasing urbanization are jointly responsible for the small landholdings which constrain agricultural productivity, limit the introduction of improvements and leave its owners vulnerable to increasing input prices and climate change. Key agricultural products in grown include grains, sugar beets, grapes, and livestock (Lee et al., 2013b).

2. Winter Wheat Production

In 2010, cereals constituted 20 percent of cultivated land, of which 70 percent was covered with wheat. 85 percent of wheat was grown on land plots averaging 40 dunums or more and 43 percent grown on plots of 200 dunums and above. The Beqaa is home to 65 percent of cereal production (35 percent in the Beqaa district and 30 percent in the Baalbek-Hermel district) and 58 percent of wheat (44 percent in the Beqaa district and 14 percent in the Baalbek-Hermel district). Most wheat bought by the General Directorate of Cereals and Sugar Beets is from the Beqaa as the rest of the wheat grown in the South and Nabatieh governorates are used for borghul and other products by families for self-sufficiency purposes. In Lebanon, 50 percent of wheat grown undergoes supplemental irrigation. This proportion is equivalent in the Beqaa district but is surpassed by far in the Baalbek-Hermel district (80 percent) (Ministère de l’Agriculture, 2010).

The main varieties of wheat cultivated include both soft (23 percent) and hard/Durum wheat (77 percent). Although Durum wheat is mostly used for local food products such as borghul, freek, kishek, pasta etc. and is not suitable for bread production, millers use a blend of 65 percent hard/Durum wheat and 35 percent soft wheat (AHDB-HGCA, 2013).

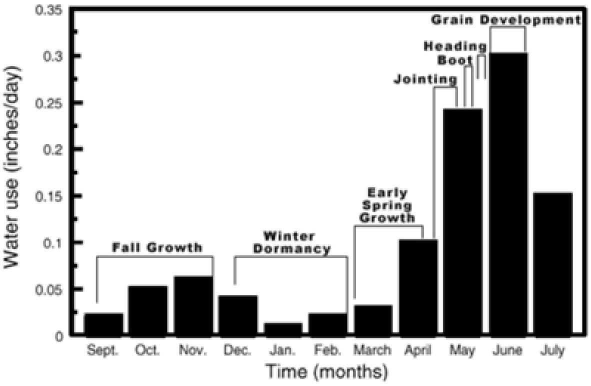
Wheat plantings occur between October and December and harvest takes place in June and July. Crop size varies from year to year depending on the amount of rainfall during February to April. Wheat production increased from 143,700 tonnes on 49,500 ha of land in 2005 to 150,000 tonnes on 38,000 ha in 2012 and went back down to 140,000 tonnes over 37,000 ha in 2013 (Ministry of Environment, 2011). The clear decrease in land area but relative constant production indicates an increase in wheat yields. Though wheat is largely a rain fed crop, this increase in yield can be attributed to the introduction of supplemental irrigation usually in April-May when rainfall is not sufficient.

Lebanon provides a conducive growing environment for wheat. Its temperature range and mild humid winters are favorable for wheat growth. Yield is mostly affected by Tmax in November and Tmin in March (Ministry of Environment, 2011). The limit of wheat production in Lebanon is in areas where annual rainfall is above 400 mm. The most vulnerable areas are in the Beqaa where extreme conditions such as reduced precipitation and frost are more frequent.

Wheat yields are often lower than in other similar climatic regions due to the lack of spring rain especially in April. Wheat is quite sensitive to water stress which affects many plant processes. Organ development is slowed and growth is decreased resulting in fewer leaves, spikelets and grains, which adversely affects grain yield (Abou Rached, 2004).

The most critical growth stages for irrigations are during fall when the soil profile should be filled to a depth of 4 to 6 feet (September - November) and during the boot to heading stage (May) as shown in Figure 2.1. According to Li et al. (2001), 47 percent of the wheat yield is dependent on stored soil-water at the planting stage. Plants, with a soil profile at field capacity during germination, are equipped with good vegetative cover and resistance to low winter temperatures. The rate of water use starts to accelerate at the elongation stage. The highest plan water demand occurs during peak vegetative development in the Spring time (Abou Rached, 2004).

Figure 2.11 Winter weat water use at different growth stages



Source: Al-Kaisi, M.M. & Shanahan, J.F., 2004. *Irrigation of Winter Wheat*, Available at: http://www.extension.umn.edu/agriculture/small-grains/soil-water/docs/irrigation-of-winter-wheat.pdf.

D. Impact of Climate Change on Agriculture and Wheat Production in Lebanon

According to the UNDP Climate Change Profile for Lebanon, temperature increases of 0.15°C and 0.26°C per decade in MAM (March, April, May) and JJA (June, July, August) were found to be statistically significant. As for precipitation patterns, although not statistically significant, the biggest percentage decrease in precipitation per decade (1960-2006) amounts to 4.3 percent during the months of MAM, when precipitation can play a crucial role in the growth of wheat crops. The biggest percentage increase of 3.5 percent occurs in September, October and November (McSweeney et al., 2010). A study by Bou-Zeid and El-Fadel (2002) hints to a possible increase in irrigation demand in the Beqaa Valley of up to 6 percent by the 2020s.

Results obtained by the PRECIS model in Lebanon's second communication to the UNFCCC show that by 2040, temperatures in Lebanon will increase by 1°C on the coast and 2°C in the mainland, and in 2090 by 3.5°C to 5°C on the coast and in the mainland respectively. Compared to current precipitation levels, rainfall is projected to decrease by 10-20 percent by 2040, and by 25-45 percent by the year 2090.

The decrease in precipitation and increase in temperature will lead to an extended hot and dry climate with intensified extremes. The drought periods, over the whole country, will become 9 days longer by 2040 and 18 days longer by 2090 (Ministry of Environment, 2011). The resulting higher temperature, reduced precipitation and high evapotranspiration will decrease soil moisture and increase aridity, which will affect the overall agricultural yield of crops and especially rain fed crops, such as wheat, if rain or complementing irrigation does not occur in the Spring.

Predicting specific crop responses to changes in temperature can be tricky namely due to the fact that plant processes, such as photosynthesis, occur at different times and many of these processes are not linearly related to temperature (Gregory & Johnson, 2009). Also, plants often depend on certain levels of temperature to trigger key developmental stages, such as germination or fruit ripening (Fuhrer, 2003). Increased temperatures during the colder winter months in Lebanon can accelerate a crop's development, which in turn can reduce the amount of time that crops like wheat or barley spend during the grain-filling stage leading to smaller harvests. In combination with evapotranspiration decreasing soil moisture, this is expected to lead to lower wheat yields after 2050 (Lee et al., 2013a).

Water stress can have varying effects on plants depending on the timing, intensity, and duration of the stress. If water stress spells are mild and develop slowly, plants may be able to speed up their life cycle and reach maturity before the drought gets too severe. But if the drought occurs rapidly, the plan can undergo substantial damages. Wheat yields are strongly affected by rainfall and the crop should be ideally grown in areas where minimum annual rainfall surpasses 400 millimeters. The Beqaa Valley is endowed with frequent periods of low rainfall rendering its wheat yields particularly susceptible to climate change. In 2010, a combination of heat, drought, and fires caused a 45.75 percent drop in wheat production compared to 2009 (Lee et al., 2013b).

Changes in temperature and precipitation could also have indirect effects on yields by affecting the types and numbers of pests and diseases. Increases in temperatures may increase the number of insect generations possible each year. Extreme events, such as the predicted increases in droughts and floods from climate change, can act as triggers for insect outbreaks (Fuhrer 2003). Impacts have been observed in wheat crops in the Beqaa Valley which have experienced general yellowing, root rot, stem blackening, Fusarium sp. infections, rust, and an unusual prevalence of insect pests such as aphids and thrips.

In this second part of the thesis, temperature and precipitation data for the Beqaa will be modeled to assess their impact on wheat yields and obtained results will be compared to the abovementioned findings.

E. The State of Regional and Local Wheat Imports

1. Regional Import and Storage

World wheat production for 2014 was forecasted to reach a record of 718.5 million tonnes. Global wheat inventories are also expected to reach 192.4 million tonnes by the end of seasons in 2015, their highest levels since 2003. The large supply of wheat has exerted major downward pressure on prices that have fallen in September 2014 to their lowest levels in four years (FAO, 2014).

Nevertheless, the food price shocks of 2007–2008 and 2010–2011 have scarred the world economies and are a reminder to remain cautious of such positive outlooks.

They suggest that international wheat prices may be entering a period of increased price volatility which mainly stems from population and income growth, bio-fuels and volatile fuel prices. Climate change and low global stock-to-use ratios exacerbate the crop's price volatility and the number of reported droughts, floods, and extreme temperatures appears to be on the rise. An increase in severe weather events can increase variability in agricultural yields, while relatively low stock levels make the international wheat market more vulnerable to supply disruptions (Lampietti et al., 2011).

Arab countries are particularly vulnerable to increased volatility in international wheat markets due to their heavily reliance on wheat imports and their relatively inelastic short-term demand for wheat which constitutes a significant portion of the population's daily diet. Arab countries import about 56 percent of the cereal calories they consume, the largest share of which comes from wheat. As net wheat importers, Arab countries are exposed to both supply risks, which can occur due to military conflict or civil unrest, and price risks which are mainly caused by high and volatile international prices that affect domestic food. Also, given the limited water resources and arable land, the ratio of food imports to total exports is above the current international average, and projections of the region's food balance indicate that wheat imports will increase by almost 75 percent over the next 30 years (Lampietti et al., 2011).

To shield citizens and particularly the poor from food inflation, Arab governments use safety nets in the form of direct transfers and food consumption subsidies which insulate the population from the pass-through of international prices.

2. Wheat and Bread Subsidies in Lebanon

Bread is a staple food in the Lebanese diet and the country requires around 400,000 to 450,000 tonnes of wheat per year to meet its consumption needs. Bread is produced by using a blend of 65 percent hard (Durum) wheat and 35 percent soft wheat. About 50,000 tonnes are used as crushed whole wheat for local recipes whereas the rest goes to mills flour and bran production (Ministry of Environment, 2011).

Despite the fact that the price of imported wheat is much lower than the farm gate price of locally-grown wheat, the Government supports wheat cultivation as a strategic crop for food security and subsidizes both the production of domestic wheat as well as the consumption of Arabic bread.

Based on the current government policy, the General Directorate of Cereals and Sugar Beets under the Ministry of Economy and Trade, purchases wheat produced by local farmers at a guaranteed price and sells it at international market prices to the 11 operating mills in the country. However, not all farmers sell their wheat to the Directorate despite the guaranteed prices and opt to sell them in the market instead to avoid the lengthy and bureaucratic procedures. The purchase of wheat usually results in a net loss to the Directorate which is covered by the subsidies allocated in the National Budget for this purpose.

The Directorate is also responsible for the storage of wheat and seeks to maintain a two months reserve at the Beirut port silos that have a 120,000 tonne capacity. Millers also have private storage space with an estimated capacity of 100,000 tonnes (AHDB-HGCA, 2013).

Since wheat production is not sufficient to meet consumption needs, both traders and milling companies import wheat and other cereals and face no quotas. The

Directorate intervenes in certain cases to subsidize bread by importing wheat at international prices and selling it to the mills at subsidized prices incurring a loss that is covered by budget transfers (Ministry of Finance, 2012).

Bread and wheat subsidies form a significant public finance burden and have summed up to LBP 129 billion between 2007 and 2011; although, the wheat subsidy for farmers form a negligible percentage of the total and stand at less than 0.01 percent of GDP (Ministry of Finance, 2012).

CHAPTER III

DATA AND METHODOLOGY

A. Data Source and Compilation

Weather data, namely daily minimum (tmin) and maximum temperature (tmax) and precipitation (prcpt) was collected from the American University of Beirut Agricultural Research and Education Center covering the period 1956-2013. The data, initially found in hard copy, was digitized and cleaned with the help of a group of AUB students.

Data quality control and homogeneity testing was conducted using the RClimDex software which was developed and maintained by Xuebin Zhang and Feng Yang at the Climate Research Branch of Meteorological Service of Canada[9]. Obviously wrong values and outliers falling outside a pre-defined threshold were turned to missing values. Using the RHtestsV4 data homogenization software package of Xiaolan L. Wang and Yang Feng[10], the weather data, namely maximum/minimum temperatures, was subjected to a two-phase linear regression test for change point detection (Wang, 2003).

The data shows several significant shifts with a maximum temperature (tmax) change point in 2008 being the most notable one. Nevertheless, the data for series will be used from 1961-2012 for precipitation and 1961-2008 for tmax and tmin as the

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[9] http://etccdi.pacificclimate.org/software.shtml

[10] http://etccdi.pacificclimate.org/software.shtml

change point for (tmax) in 2008 reflects a suspiciously big jump in observations that cannot be ignored. For a more thorough explanation of the data collection, quality control and homogenization process, please refer to the data section in part 1of the thesis.

For the purpose of this section, monthly averages for daily tmin and tmax were calculated. Since daily precipitation series are typically non-Gaussian, a log-transformed monthly total precipitation series was calculated.

Country-level data for Lebanon for crop area, production and yield for the period 1961-2012 was obtained from the Food and Agriculture Organization statistics website. Data was available for 2013 but was omitted as my weather data is only available up to 2012. Wheat yield is obtained by dividing total production in tonnes by the harvested area in hectares. Although, the thesis focuses on wheat production in the Beqaa only, no wheat data is available by sub-regional level. Nevertheless, the Beqaa is home to 58 percent of wheat production in the country. The rest of the wheat grown in the South and Nabatieh governorates are used for borghul and other products by families for self-sufficiency purposes. Against this backdrop, the national wheat data was used to better understand the relationship between wheat production and climate in the Beqaa Valley.

Table 2.10 Compiled Variables

Variable	**Source**	**Transformation**	**unit**	**Year**
daily tmax	AREC	monthly mean of tmax	ºC	1961-2008
daily tmin	AREC	monthly mean of tmin	ºC	1961-2008
daily prcpt	AREC	monthly sum of log-prcpt	mm	1961-2012
wheat yield	FAO		Tonnes/Hectare	1961-2012

B. Methodology

Changes in yield over time stem not only from changes in climate, but from management practices and technology trends. Figure 2.2 below shows a time plot of the wheat data obtained from FAO for the years 1961-2013. The figure shows a clear positive increasing trend in wheat yields as is predicted in the literature based on the use of new technology, fertilizer etc...

Figure 2.12 Annual Wheat Yields in Lebanon 1961-2013

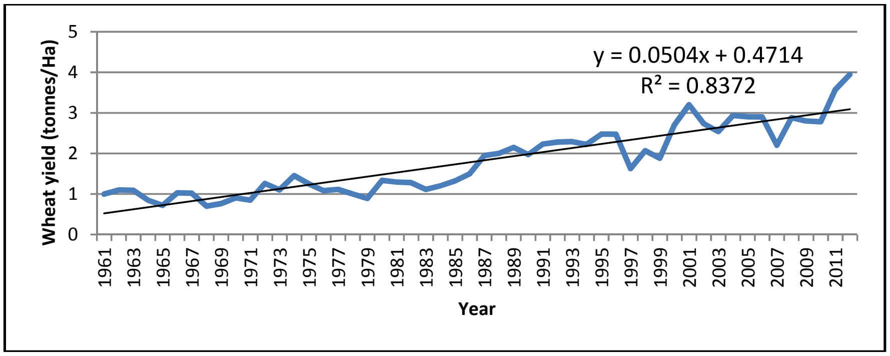
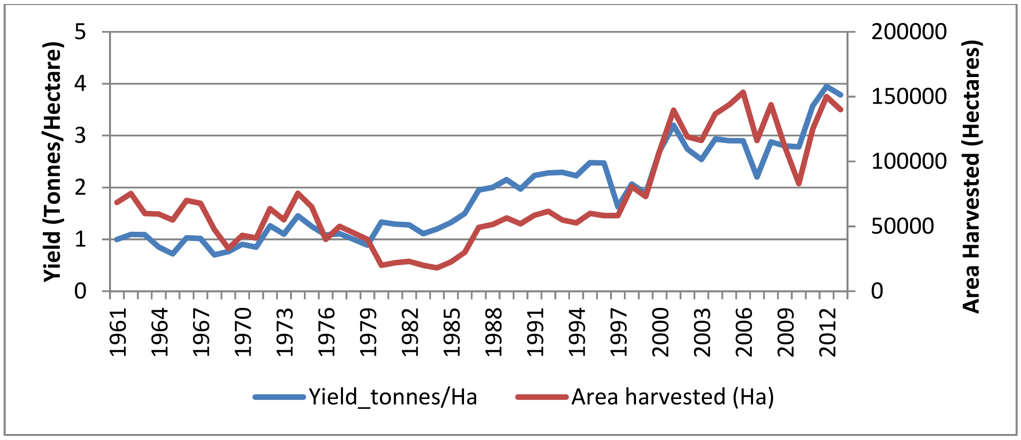


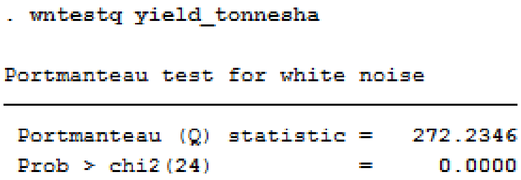
Figure 2.3 shows the wheat yield (blue line) and harvested area (red line) for the years 1961-2013. Both show a clear positive increase throughout the years except for the sharp drop in harvested area in 2010 due to a combination of heat, drought, and fires (Lee et al., 2013b).

Figure 2.13 Wheat yield and harvested area 1961-2013



Also, the data suffers from serial correlation, which is not unusual in time series. The Portmanteau test for white noise in Stata checks for autocorrelation where the null assumes that there is no serial correlation. Since we reject the null, as shown in Table 2.2 below, our wheat data in fact suffers from autocorrelation.

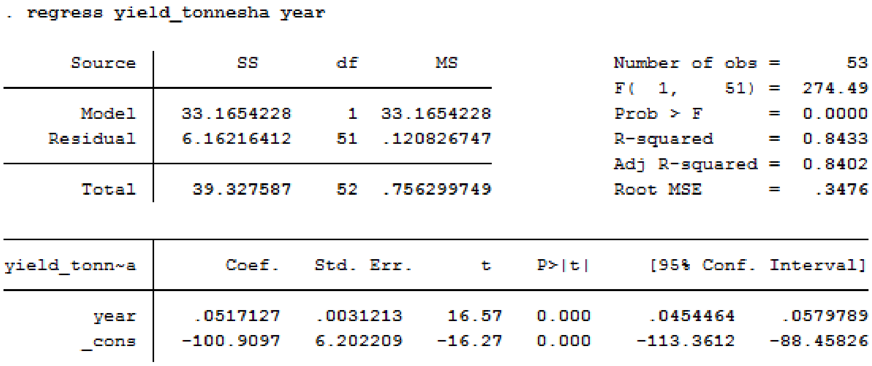
Table 2.11 Portmanteau test for white noise



```
. wntestq yield_tonnesha

Portmanteau test for white noise
---------------------------------------------------

 Portmanteau (Q) statistic =    272.2346
 Prob > chi2(24)           =      0.0000
```

Given the lack of data on crop-specific technology and cost information for wheat production in Lebanon, technological advances such as the adoption of new seed varieties, application of fertilizers, irrigation and other factors were identified through the use of a time variable (Haddad et al., 2014). More specifically the approach consisted of fitting a linear trend to the wheat yield time series and using the resulting residuals as the technology-adjusted yield values. The following section is based on the approach used by Lobell et al. (2007) who studied the relationship between crop yield and three climatic variables (tmin, tmax and prcpt) for 12 major Californian crops over the period 1980-2003.

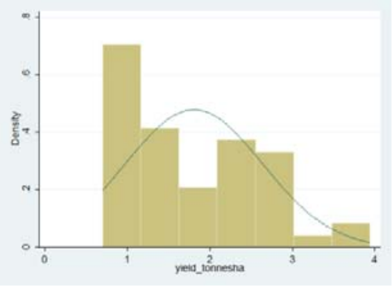
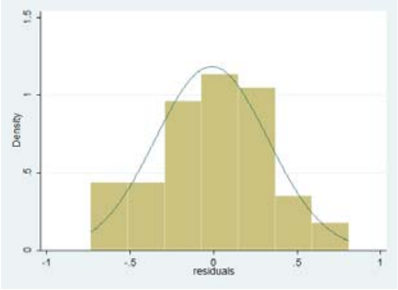
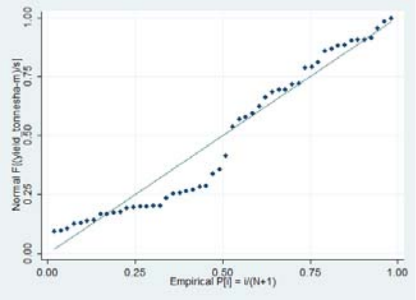
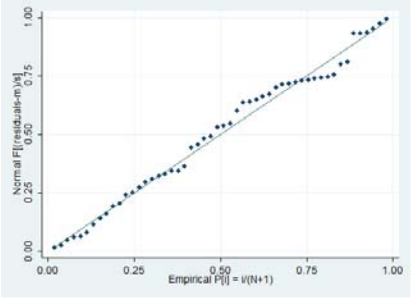
Table 2.12 Fitting a linear trend to wheat yield time series



```
. regress yield_tonnesha year

      Source |       SS       df       MS              Number of obs =      53
-------------+------------------------------           F(  1,    51) =  274.49
       Model |  33.1654228     1  33.1654228           Prob > F      =  0.0000
    Residual |  6.16216412    51  .120826747           R-squared     =  0.8433
-------------+------------------------------           Adj R-squared =  0.8402
       Total |   39.327587    52  .756299749           Root MSE      =   .3476

------------------------------------------------------------------------------
yield_tonn~a |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        year |   .0517127   .0031213    16.57   0.000     .0454464    .0579789
       _cons |  -100.9097   6.202209   -16.27   0.000    -113.3612   -88.45826
```

Our technology-adjusted yield values fare better in the normality tests than their raw yield counterparts as shown in Figure 2.4. The histogram of the yield residuals is more in line with the normal distribution curve, and the normal probability plot shows little deviations from the straight line.

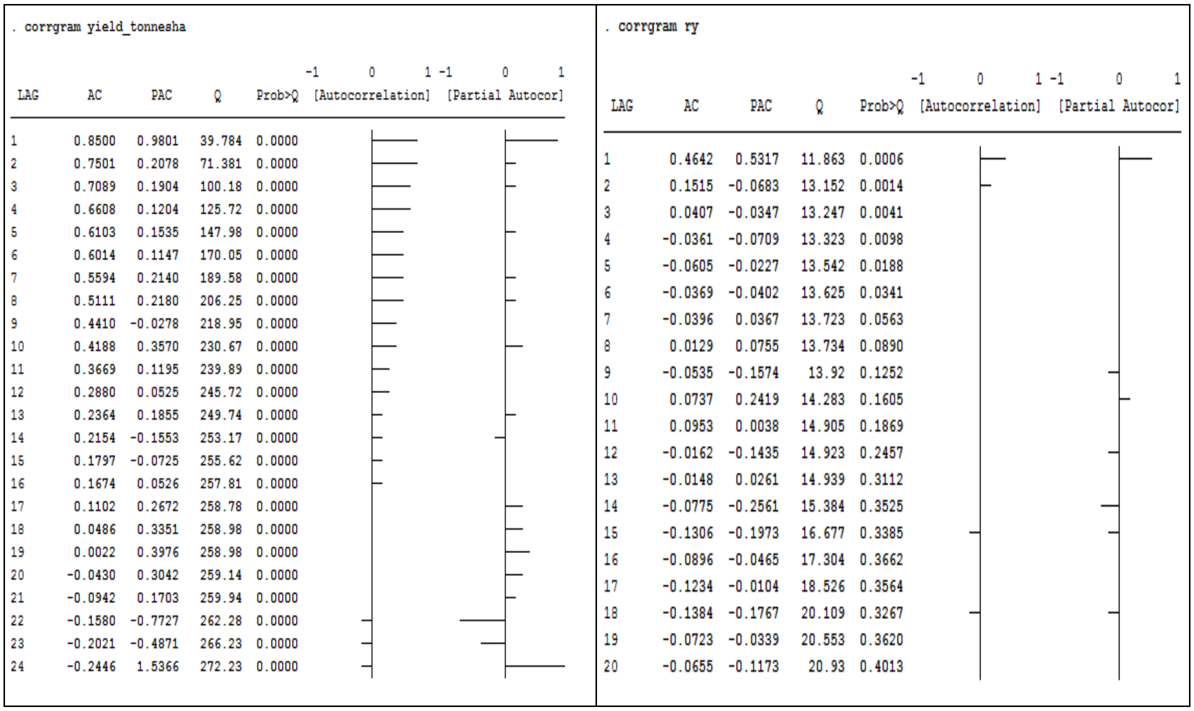
Figure 2.14 Yield Normality Tests

Raw Yield Data	Technology-adjusted Yield Data
Histogram	
	
Normal Probability Plot	
	

Since our data has already exhibited signs of autocorrelation, the latter needs to be remedied and accounted for. Many crops exhibit alternate bearing, with alternating years of high yields followed by high vegetative growth or low yields. While others might simply be affected positively by the previous year's yield.

The correlation between the yield variable and its previous values is explored in the correlogram of the yield (left) and the technology-adjusted yield (right) in Table 2.4. The correlation between the current and previous yield values is high (above 0.1) for yield and technology-adjusted yield for 17 years and 2 years respectively. The latter is an indication that fitting a linear trend to yield values accounts for several factors that affect the serial correlation of the data. It also shows that previous year yields affect current yields positively and thus wheat does not exhibit alternate bearing.

Table 2.13 Correlogram



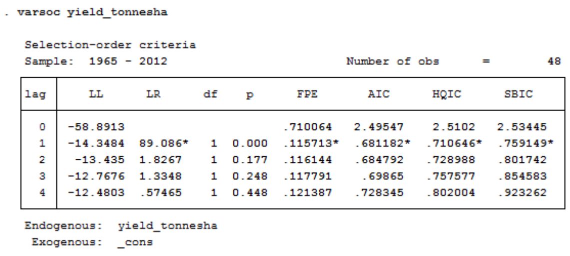
```
. corrgram yield_tonnesha

                                          -1       0       1 -1       0       1
LAG       AC       PAC      Q     Prob>Q  [Autocorrelation]  [Partial Autocor]

1       0.8500   0.9801   39.784  0.0000
2       0.7501   0.2078   71.381  0.0000
3       0.7089   0.1904   100.18  0.0000
4       0.6608   0.1204   125.72  0.0000
5       0.6103   0.1535   147.98  0.0000
6       0.6014   0.1147   170.05  0.0000
7       0.5594   0.2140   189.58  0.0000
8       0.5111   0.2180   206.25  0.0000
9       0.4410  -0.0278   218.95  0.0000
10      0.4188   0.3570   230.67  0.0000
11      0.3669   0.1195   239.89  0.0000
12      0.2880   0.0525   245.72  0.0000
13      0.2364   0.1855   249.74  0.0000
14      0.2154  -0.1553   253.17  0.0000
15      0.1797  -0.0725   255.62  0.0000
16      0.1674   0.0526   257.81  0.0000
17      0.1102   0.2672   258.78  0.0000
18      0.0486   0.3351   258.98  0.0000
19      0.0022   0.3976   258.98  0.0000
20     -0.0430   0.3042   259.14  0.0000
21     -0.0942   0.1703   259.94  0.0000
22     -0.1580  -0.7727   262.28  0.0000
23     -0.2021  -0.4871   266.23  0.0000
24     -0.2446   1.5366   272.23  0.0000
```

```
. corrgram ry

                                          -1       0       1 -1       0       1
LAG       AC       PAC      Q     Prob>Q  [Autocorrelation]  [Partial Autocor]

1       0.4642   0.5317   11.863  0.0006
2       0.1515  -0.0683   13.152  0.0014
3       0.0407  -0.0347   13.247  0.0041
4      -0.0361  -0.0709   13.323  0.0098
5      -0.0605  -0.0227   13.542  0.0188
6      -0.0369  -0.0402   13.625  0.0341
7      -0.0396   0.0367   13.723  0.0563
8       0.0129   0.0755   13.734  0.0890
9      -0.0535  -0.1574    13.92  0.1252
10      0.0737   0.2419   14.283  0.1605
11      0.0953   0.0038   14.905  0.1869
12     -0.0162  -0.1435   14.923  0.2457
13     -0.0148   0.0261   14.939  0.3112
14     -0.0775  -0.2561   15.384  0.3525
15     -0.1306  -0.1973   16.677  0.3385
16     -0.0896  -0.0465   17.304  0.3662
17     -0.1234  -0.0104   18.526  0.3564
18     -0.1384  -0.1767   20.109  0.3267
19     -0.0723  -0.0339   20.553  0.3620
20     -0.0655  -0.1173    20.93  0.4013
```

Too many lags could increase the error in the forecasts whereas too few could leave out relevant information. Therefore, to determine the number of year of previous yields to include in the autoregressive model and find the model with the best balance between yield prediction and simplicity, the Schwarz's Bayesian information criterion (SBIC), the Akaike's information criterion (AIC), and the Hannan and Quinn information criterion (HQIC) were used. All three criteria suggest the inclusion of 1 lag as shown in Table 2.5.

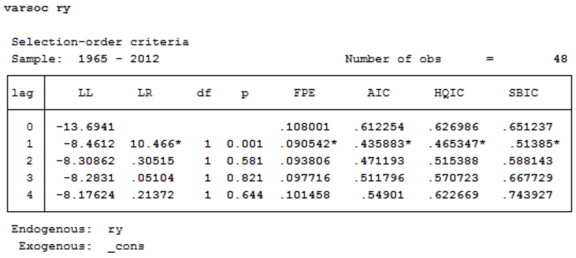
Table 2.14 BIC, HIC and HQIC

Yield



```
. varsoc yield_tonnesha

   Selection-order criteria
   Sample:  1965 - 2012                         Number of obs      =        48
  +---------------------------------------------------------------------------+
  |lag |    LL      LR      df    p      FPE       AIC       HQIC      SBIC    |
  |----+----------------------------------------------------------------------|
  |  0 | -58.8913                     .710064   2.49547    2.5102   2.53445   |
  |  1 | -14.3484  89.086*   1  0.000  .115713*  .681182*  .710646*  .759149*  |
  |  2 |  -13.435  1.8267    1  0.177  .116144   .684792   .728988   .801742   |
  |  3 | -12.7676  1.3348    1  0.248  .117791    .69865   .757577   .854583   |
  |  4 | -12.4803  .57465    1  0.448  .121387   .728345   .802004   .923262   |
  +---------------------------------------------------------------------------+
   Endogenous:  yield_tonnesha
    Exogenous:  _cons
```

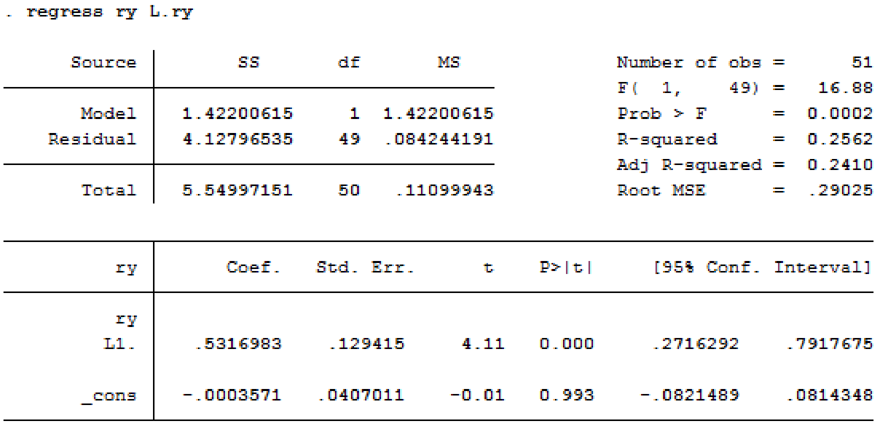
Technology-adjusted yield



```
varsoc ry

 Selection-order criteria
 Sample:  1965 - 2012                         Number of obs      =        48
+---------------------------------------------------------------------------+
|lag |    LL      LR      df    p      FPE       AIC       HQIC      SBIC    |
|----+----------------------------------------------------------------------|
|  0 | -13.6941                     .108001   .612254   .626986   .651237   |
|  1 |  -8.4612  10.466*   1  0.001  .090542*  .435883*  .465347*   .51385*  |
|  2 | -8.30862  .30515    1  0.581  .093806   .471193   .515388   .588143   |
|  3 |  -8.2831  .05104    1  0.821  .097716   .511796   .570723   .667729   |
|  4 | -8.17624  .21372    1  0.644  .101458    .54901   .622669   .743927   |
+---------------------------------------------------------------------------+
 Endogenous:  ry
  Exogenous:  _cons
```

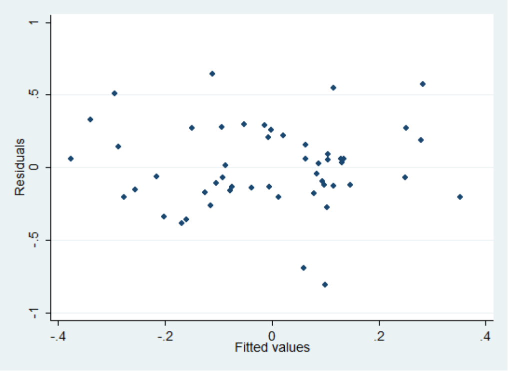
The residuals from the autoregressive model (shown in Table 2.6 below) were used in subsequent analyses, so that all resulting time series (YR) reflect yield changes with the effects of technology trends and previous years' yields removed. The model residuals (YR) are plotted against fitted values in Figure 2.5 below appear to be homoscedastic and independent and show no apparent patterns, an indication that the problematic aspects of the time series have been accounted for and dealt with.

Table 2.15 Autoregressive model of technology-adjusted



```
. regress ry L.ry

      Source |       SS       df       MS              Number of obs =      51
-------------+------------------------------           F(  1,    49) =   16.88
       Model |  1.42200615     1  1.42200615           Prob > F      =  0.0002
    Residual |  4.12796535    49  .084244191           R-squared     =  0.2562
-------------+------------------------------           Adj R-squared =  0.2410
       Total |  5.54997151    50   .11099943           Root MSE      =  .29025

------------------------------------------------------------------------------
          ry |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          ry |
         L1. |   .5316983    .129415     4.11   0.000     .2716292    .7917675
             |
       _cons |  -.0003571   .0407011    -0.01   0.993    -.0821489    .0814348
------------------------------------------------------------------------------
```

Figure 2.15 Autoregressive model residuals (YR)



In order to identify the most relevant climatic variables, independent regressions were performed between yield residuals (YR) and monthly climatic variables for each of the three climate variables for the months included in the wheat growth cycle namely September through December of the pre-harvest year and January through July for the harvest year (11 months). Although initially, all 24 months of the pre-harvest and harvest year were included, none of the months falling outside the wheat growth cycle showed statistically significant results and as such were removed from the results and discussion. Since temperature and precipitation usually have a non-monotonic effect on yields, a second order polynomial regression was used:

$YR = \alpha_0 X + \alpha_1 X^2$

Where YR is the wheat yield residual and X is the selected climate variable. The maximum temperature for March and May, the minimum temperature for May and the log precipitation for November were found to have statistically significant effects. The effect of the latter months on the growth and yield of wheat are in agreement to what is mentioned in the literature. The month of November is a sowing month and adequate water access during this month is critical for wheat. The most critical growth stages for irrigations are during fall when the soil profile should be filled to a depth of 4 to 6 feet (September - November) and during the boot to heading stage (May). According to Li et al. (2001), 47 percent of the wheat yield is dependent on stored soil-water at the planting stage. The months of March and May also have a major impact on the growth of wheat as it passes through early Spring growth and reaches the grain development stage. Surprisingly, precipitation during the months of March and April was not found to have statistically significant results on our wheat yields in the independent regression. This can be explained by the high reliance on supplemental irrigation by farmers during these critical months which is not accounted for in the regressions. Therefore wheat yields do not move hand in hand with variations in precipitation levels as a key factor, supplemental irrigation, was omitted from the analysis due to the lack of data. Regression results are found in Appendix 2.A.

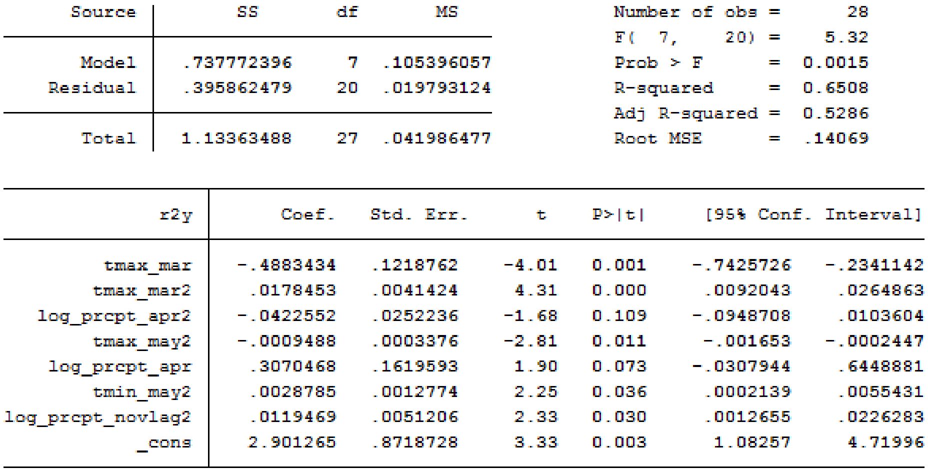
Based on previous findings and forecasted climate change scenarios, the overall agricultural yields of crops and especially rain fed crops such as wheat are expected to decrease as a result of higher temperatures, reduced precipitation and the consequent decrease in soil moisture and increase in aridity. Supplemental irrigation might have been mitigating such changes in the climate so far as might be deduced from the regression results, but with the increasing water deficit the country is facing and the already relatively high and uncompetitive local wheat production costs, this might not be sustainable.

CHAPTER IV

RESULTS AND DISCUSSION

Variables were selected based on the results of the exploratory analysis described above and knowledge of the wheat growth cycle. A multiple regression was then performed using these variables as predictors, with a linear and quadratic term included for each variable using an automated step-wise regression procedure. The regression results are shown in Table 2.7 below. The regression shows a relatively high adjusted R^2 of 0.5286.

Table 2.16 YR Regression Results

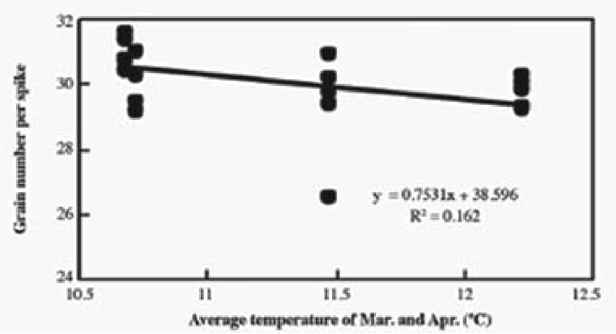


```
      Source |       SS       df       MS              Number of obs =      28
-------------+------------------------------           F(  7,    20) =    5.32
       Model |  .737772396     7  .105396057           Prob > F      =  0.0015
    Residual |  .395862479    20  .019793124           R-squared     =  0.6508
-------------+------------------------------           Adj R-squared =  0.5286
       Total |  1.13363488    27  .041986477           Root MSE      =  .14069

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    tmax_mar |  -.4883434   .1218762    -4.01   0.001    -.7425726   -.2341142
   tmax_mar2 |   .0178453   .0041424     4.31   0.000     .0092043    .0264863
log_prcpt_apr2 |  -.0422552   .0252236    -1.68   0.109    -.0948708    .0103604
   tmax_may2 |  -.0009488   .0003376    -2.81   0.011     -.001653   -.0002447
log_prcpt_apr |   .3070468   .1619593     1.90   0.073    -.0307944    .6448881
   tmin_may2 |   .0028785   .0012774     2.25   0.036     .0002139    .0055431
log_prcpt_novlag2 |   .0119469   .0051206     2.33   0.030     .0012655    .0226283
       _cons |   2.901265   .8718728     3.33   0.003      1.08257     4.71996
------------------------------------------------------------------------------
```

The maximum temperature in March (tmax_mar) has a high statistically significant negative effect on YR (-0.48). This is backed by results obtained by Lv et al. (Lv, Yao, Zhang, & Dong, 2013) who found that grain number per spike was negatively correlated with average temperature in March and April (r = -0.514*, n = 19) during the spike differentiation period (Figure 2.6). A low average temperature in

March and April tends to delay spike differentiation and promotes grain number per spike.

Figure 2.16 Relationship between grain number per spike and average temperature in March -April (2005-2009)



Source: Lv, L. et al., 2013. Winter wheat grain yield and its components in the North China Plain: irrigation management, cultivation, and climate. *Chilean Journal of Agricultural Research*. Available at: http://www.scielo.cl/scielo.php?pid=S0718-58392013000300005&script=sci_arttext&tlng=en [Accessed January 28, 2015].

The logged precipitation for April and logged precipitation squared for November show a significant positive correlation with a coefficient of 0.3 and 0.01. This goes in line with the high water requirements of wheat during the months of November (planting/germination stage – Fall growth) and April and May (early spring growth, boot and heading stages) (Al-Kaisi & Shanahan, 2004).

To assess the contribution of climate to yield trends, the original yield data was used (without removing the time trend) and selected climatic variables using automated step-wise regression procedure. A smaller pool of variables were included in the regression to increase the precision of the predictions. Results are displayed in Table 2.8.

Table 2.17 Regression results of yield on selected climatic variables

```
      Source |       SS       df       MS              Number of obs =      28
-------------+------------------------------           F(  4,    23) =   66.13
       Model |  14.2675829     4  3.56689573           Prob > F      =  0.0000
    Residual |   1.2405091    23  .053935178           R-squared     =  0.9200
-------------+------------------------------           Adj R-squared =  0.9061
       Total |   15.508092    27  .574373779           Root MSE      =  .23224

--------------------------------------------------------------------------------
yield_tonnesha |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
          year |   .0488972    .003686    13.27   0.000      .0412722    .0565222
     tmax_mar  |  -.4008092   .1953048    -2.05   0.052     -.8048279    .0032095
    tmax_mar2  |   .0148761   .0066025     2.25   0.034      .0012177    .0285345
log_prcpt_apr2 |  -.0111043   .0078966    -1.41   0.173     -.0274397    .0052311
         _cons |  -92.57883    7.75303   -11.94   0.000     -108.6172   -76.54047
--------------------------------------------------------------------------------
```

The coefficient of the time variable (year) represents the yield trend after the effects of the selected climatic variables are accounted for. The deviation of this value (0.049) from the trend in the raw time series reported in Table 2.3 (0.05) can be used to indicate a substantial effect of recent climate changes on wheat yield trends.

The ratio of the time trends from both the regression including the climatic variables and the raw yield time series was calculated: 0.049/0.05=0.98. This value signals the degree to which the climate has affected yield trends. While values above one indicate that climate has pushed down growth, values below one indicate that climate has aided yield growth. As the ratio turned out to be almost 1, 0.98, no climate effect was depicted.

Results should be interpreted with caution though due to the caveats faced. Climate variables are highly correlated (tmin, tmax, prcpt) and can affect the significance and direction of the relationships obtained. Also, variables that have important effects on yields have been omitted from the model due to the lack of available data. Most notably supplemental irrigation which is highly used in wheat production in the Beqaa during Spring time to compensate for the insufficient precipitation levels in March and April. In fact, as much as 50-80% of wheat grown in the Beqaa Baalbek-Hermel districts is irrigated. Other variables include solar radiation, management changes, soil quality, fertilizer use, crop variety amongst others.

Nevertheless, the model clearly shows the negative impact of rising temperatures, notably in March, on the grain development and production of wheat.

What does this mean to wheat farmers? Rising temperatures and projected decreases in precipitation for the months of MAM will create additional pressures on farmers who already face factors that cause their production costs to be relatively high.

Table 2.9 below shows that irrigation, the main factor that can directly be affected by climate, accounts for 9 percent of wheat production costs. It comes in fourth place after rent (45 percent) harvest cost (12 percent) and fertilizer costs (11 percent).

Table 2.18 Cost structure of wheat production

	LL per Donum Unless Specified Otherwise	Percent
Seeds	7,500	4%
Tilling and Plantation	7,000	4%
Fertilizers	18,000	11%
Irrigation	15,000	9%
Medicaments	2,500	1%
Harvest	20,000	12%
Bags	12,000	7%
Transportation	10,000	6%
Rent	75,000	45%
Total Gross Cost	**167,000**	**100%**
Exc. Revenues from Chaff Sales	60,000	
Net Cost	107,000	
Net Cost (LL Per Ton)	**214,000**	

Source**:** Ministry of Economy and Trade, General Directorate of Cereals and Beetroot

The cost of producing wheat locally has surpassed international prices over the years and if the Government wants to continue supporting wheat cultivation as a strategic crop for food security it need to take measures beyond the wheat production subsidies it has been providing farmers. The Directorate has been purchasing wheat from farmers at a subsidized price of LBP 375,000-400,000 (USD 250-267[11]) when international prices ranged between USD130 and USD150 in 2002-2006 (Ministry of Finance, 2012). Nevertheless, many farmers prefer not to sell wheat to the Government due to the lengthy bureaucratic procedures it entails.

The main problem is the high costs paid by farmers in the production process which will keep on increasing due to the climatic changes affecting the Beqaa and Lebanon as a whole. The gap between local and international prices will widen rending the wheat production sector more and more unproductive.

---

[11] 1 USD=1500 LBP

CHAPTER V

CONCLUSION AND RECOMMENDATIONS

The relationship between wheat yields and three monthly climatic variables (maximum temperature, minimum temperature and precipitation) was evaluated for Lebanon for the period 1961-2008. The climatic data was collected from the American University of Beirut Agricultural Research and Education Center covering the period 1956-2013. The data, initially found in hard copy, was digitized and cleaned with the help of a group of AUB students. Country-level data for Lebanon for crop area, production and yield for the period 1961-2012 was obtained from the Food and Agriculture Organization statistics website.

A series of independent regressions was performed between technology-adjusted residuals and monthly climatic variables for each of the three climate variables for the months of September through December of the pre-harvest year and the months of January through July for the harvest year (11 months). A multiple regression was then performed with a select group of variables based on the results of the exploratory analysis described above and knowledge of the wheat growth cycle.

Results showed that the maximum temperature for March turned out to have a high statistically significant negative effect, a finding backed by Lv et al. (Lv et al., 2013) who found that grain number per spike was negatively correlated with average temperature in March and April. A low average temperature in March and April tends to delay spike differentiation and promotes grain number per spike. The logged precipitation for April and logged precipitation squared for November also showed a significant positive correlation with a coefficient of 0.3 and 0.01. This goes in line with the high water requirements of wheat during the months of November (planting/germination stage – Fall growth) and April and May (early spring growth, boot and heading stages) (Al-Kaisi & Shanahan, 2004).

Finally, the ratio of the time trends from both the regression including the climatic variables and the raw yield time series indicate no clear climate effect.

Results should be interpreted with caution though due to the caveats faced. Climate variables are highly correlated (tmin, tmax, prcpt) and can affect the significance and direction of the relationships obtained. Also, an important variable, supplemental irrigation, has been omitted from the model due to the lack of available data.

Wheat production in the Beqaa is highly dependent on supplemental irrigation especially during Spring time to compensate for the insufficient precipitation levels in March and April. In fact, as much as 50-80% of wheat grown in the Beqaa Baalbek-Hermel districts is irrigated. Irrigation also forms a significant portion of the farmers' production costs.

Rising temperatures and projected decreases in precipitation for the months of MAM will create additional pressures on farmers who already face factors that cause their production costs to be relatively high.

Investing in better irrigation data is crucial for a better understanding of climate-yield relationships and the effect of additional climate-induced impediments the wheat production sector in Lebanon.

APPENDIX

Appendix 2.G Regression Results

Tmax (Jan-July of harvest year)

```
.   regress r2y tmax_jan tmax_jan2, noc;

      Source |       SS       df       MS              Number of obs =      38
-------------+------------------------------           F(  2,    36) =    1.07
       Model |  .126984277     2  .063492139           Prob > F      =  0.3541
    Residual |  2.13867426    36  .059407618           R-squared     =  0.0560
-------------+------------------------------           Adj R-squared =  0.0036
       Total |  2.26565854    38  .059622593           Root MSE      =  .24374

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    tmax_jan |   .0278212   .0203038     1.37   0.179    -.0133569    .0689993
   tmax_jan2 |  -.0022926   .0018399    -1.25   0.221    -.0060242     .001439
------------------------------------------------------------------------------
```

```
.  regress r2y tmax_feb tmax_feb2, noc;

      Source |       SS       df       MS              Number of obs =      39
-------------+------------------------------           F(  2,    37) =    0.04
       Model |  .007253606     2  .003626803           Prob > F      =  0.9561
    Residual |  2.98438478    37  .080659048           R-squared     =  0.0024
-------------+------------------------------           Adj R-squared = -0.0515
       Total |  2.99163838    39  .076708676           Root MSE      =  .28401

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    tmax_feb |   .0071538   .0243203     0.29   0.770    -.0421238    .0564315
   tmax_feb2 |  -.0006195   .0020665    -0.30   0.766    -.0048066    .0035676
------------------------------------------------------------------------------
```

```
.  regress r2y tmax_mar tmax_mar2, noc;

      Source |       SS       df       MS              Number of obs =      38
-------------+------------------------------           F(  2,    36) =    2.95
       Model |  .356007526     2  .178003763           Prob > F      =  0.0652
    Residual |  2.17345873    36  .060373854           R-squared     =  0.1407
-------------+------------------------------           Adj R-squared =  0.0930
       Total |  2.52946626    38  .066564901           Root MSE      =  .24571

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    tmax_mar |  -.0310975   .0154354    -2.01   0.051     -.062402    .0002069
   tmax_mar2 |   .0021652   .0009757     2.22   0.033     .0001864    .0041439
------------------------------------------------------------------------------
```

```
.  regress r2y tmax_apr tmax_apr2, noc;

      Source |       SS       df       MS              Number of obs =      41
-------------+------------------------------           F(  2,    39) =    1.04
       Model |  .153565605     2  .076782802           Prob > F      =  0.3629
    Residual |  2.87799519    39  .073794748           R-squared     =  0.0507
-------------+------------------------------           Adj R-squared =  0.0020
       Total |  3.03156079    41  .073940507           Root MSE      =  .27165

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    tmax_apr |  -.0263567   .0190772    -1.38   0.175    -.0649441    .0122306
   tmax_apr2 |   .0013332   .0009392     1.42   0.164    -.0005666     .003233
------------------------------------------------------------------------------
```

```
.  regress r2y tmax_may tmax_may2, noc;

      Source |       SS       df       MS              Number of obs =      41
-------------+------------------------------           F(  2,    39) =    2.57
       Model |  .301716717     2  .150858358           Prob > F      =  0.0897
    Residual |  2.29209173    39  .058771583           R-squared     =  0.1163
-------------+------------------------------           Adj R-squared =  0.0710
       Total |  2.59380845    41  .063263621           Root MSE      =  .24243
```

```
------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    tmax_may |   .0394802   .0175012     2.26   0.030     .0040806    .0748798
   tmax_may2 |   -.001574   .0006947    -2.27   0.029    -.0029792   -.0001688
------------------------------------------------------------------------------

.  regress r2y tmax_jun tmax_jun2, noc;

      Source |       SS       df       MS              Number of obs =      43
-------------+------------------------------           F(  2,    41) =    0.19
       Model |  .030096698     2  .015048349           Prob > F      =  0.8263
    Residual |  3.21814096    41  .078491243           R-squared     =  0.0093
-------------+------------------------------           Adj R-squared = -0.0391
       Total |  3.24823766    43  .075540411           Root MSE      =  .28016

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    tmax_jun |  -.0138862   .0235343    -0.59   0.558    -.0614146    .0336422
   tmax_jun2 |   .0004584   .0007939     0.58   0.567     -.001145    .0020617
------------------------------------------------------------------------------

.  regress r2y tmax_jul tmax_jul2, noc;

      Source |       SS       df       MS              Number of obs =      43
-------------+------------------------------           F(  2,    41) =    0.27
       Model |  .033915831     2  .016957916           Prob > F      =  0.7669
    Residual |  2.60241288    41  .063473485           R-squared     =  0.0129
-------------+------------------------------           Adj R-squared = -0.0353
       Total |  2.63632872    43   .06130997           Root MSE      =  .25194

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    tmax_jul |  -.0145703   .0203803    -0.71   0.479    -.0557292    .0265886
   tmax_jul2 |   .0004574    .000633     0.72   0.474    -.0008209    .0017358
------------------------------------------------------------------------------
```

Tmax (Sept-Dec of pre-harvest year)

```
.  regress r2y L.tmax_sep L.tmax_sep2, noc;

      Source |       SS       df       MS              Number of obs =      41
-------------+------------------------------           F(  2,    39) =    0.12
       Model |  .018293791     2  .009146895           Prob > F      =  0.8878
    Residual |  2.98761093    39  .076605409           R-squared     =  0.0061
-------------+------------------------------           Adj R-squared = -0.0449
       Total |  3.00590472    41  .073314749           Root MSE      =  .27678

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    tmax_sep |
         L1. |   .0098484    .031288     0.31   0.755    -.0534375    .0731343
             |
   tmax_sep2 |
         L1. |  -.0003521   .0010607    -0.33   0.742    -.0024976    .0017933
------------------------------------------------------------------------------

.  regress r2y L.tmax_oct L.tmax_oct2, noc;

      Source |       SS       df       MS              Number of obs =      41
-------------+------------------------------           F(  2,    39) =    0.00
       Model |  .000308848     2  .000154424           Prob > F      =  0.9976
    Residual |  2.52129351    39  .064648552           R-squared     =  0.0001
-------------+------------------------------           Adj R-squared = -0.0512
       Total |  2.52160236    41  .061502497           Root MSE      =  .25426

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    tmax_oct |
         L1. |  -.0003773   .0221959    -0.02   0.987    -.0452727    .0445181
             |
   tmax_oct2 |
         L1. |   .0000196   .0008982     0.02   0.983    -.0017971    .0018364
------------------------------------------------------------------------------

.  regress r2y L.tmax_nov L.tmax_nov2, noc;

      Source |       SS       df       MS              Number of obs =      38
```

```
-------------+------------------------------           F(  2,    36) =    0.02
       Model |  .003106146     2  .001553073           Prob > F      =  0.9767
    Residual |  2.36756159    36    .0657656           R-squared     =  0.0013
-------------+------------------------------           Adj R-squared = -0.0542
       Total |  2.37066773    38  .062385993           Root MSE      =  .25645

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    tmax_nov |
         L1. |   .0028486   .0143601     0.20   0.844    -.0262751    .0319723
             |
   tmax_nov2 |
         L1. |  -.0001391    .000767    -0.18   0.857    -.0016947    .0014166
------------------------------------------------------------------------------

.  regress r2y L.tmax_dec L.tmax_dec2, noc;

      Source |       SS       df       MS              Number of obs =      39
-------------+------------------------------           F(  2,    37) =    0.15
       Model |  .023806938     2  .011903469           Prob > F      =  0.8596
    Residual |  2.89918936    37  .078356469           R-squared     =  0.0081
-------------+------------------------------           Adj R-squared = -0.0455
       Total |   2.9229963    39  .074948623           Root MSE      =  .27992

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    tmax_dec |
         L1. |   .0107692   .0217373     0.50   0.623    -.0332748    .0548133
             |
   tmax_dec2 |
         L1. |  -.0008862   .0016753    -0.53   0.600    -.0042807    .0025082
------------------------------------------------------------------------------
```

Tmin (Jan-July of harvest year)

```
      Source |       SS       df       MS              Number of obs =      37
-------------+------------------------------           F(  2,    35) =    0.21
       Model |  .033385037     2  .016692519           Prob > F      =  0.8139
    Residual |    2.821011    35  .080600314           R-squared     =  0.0117
-------------+------------------------------           Adj R-squared = -0.0448
       Total |  2.85439604    37  .077145839           Root MSE      =   .2839

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    tmin_jan |  -.0029932   .0285953    -0.10   0.917    -.0610447    .0550583
   tmin_jan2 |  -.0054683    .008958    -0.61   0.546    -.0236539    .0127173
------------------------------------------------------------------------------

.  regress r2y tmin_feb tmin_feb2, noc;

      Source |       SS       df       MS              Number of obs =      35
-------------+------------------------------           F(  2,    33) =    3.33
       Model |  .477280591     2  .238640296           Prob > F      =  0.0480
    Residual |  2.36192846    33    .07157359          R-squared     =  0.1681
-------------+------------------------------           Adj R-squared =  0.1177
       Total |  2.83920905    35  .081120259           Root MSE      =  .26753

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    tmin_feb |   .0374335   .0302752     1.24   0.225    -.0241618    .0990288
   tmin_feb2 |  -.0284581   .0110385    -2.58   0.015     -.050916   -.0060002
------------------------------------------------------------------------------

.  regress r2y tmin_mar tmin_mar2, noc;

      Source |       SS       df       MS              Number of obs =      37
-------------+------------------------------           F(  2,    35) =    1.44
       Model |  .186592613     2  .093296306           Prob > F      =  0.2511
    Residual |  2.27079826    35    .06487995          R-squared     =  0.0759
-------------+------------------------------           Adj R-squared =  0.0231
       Total |  2.45739087    37    .06641597          Root MSE      =  .25472

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    tmin_mar |   -.009604   .0385203    -0.25   0.805    -.0878044    .0685965
   tmin_mar2 |   .0066452   .0082277     0.81   0.425     -.010058    .0233484
------------------------------------------------------------------------------
```

```
.  regress r2y tmin_apr tmin_apr2, noc;

      Source |       SS       df       MS              Number of obs =      40
-------------+------------------------------           F(  2,    38) =    0.54
       Model |  .066061786     2  .033030893           Prob > F      =  0.5855
    Residual |  2.31224683    38  .060848601           R-squared     =  0.0278
-------------+------------------------------           Adj R-squared = -0.0234
       Total |  2.37830861    40  .059457715           Root MSE      =  .24668

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    tmin_apr |  -.0122663   .0285497    -0.43   0.670    -.0700621    .0455294
   tmin_apr2 |   .0026943   .0042412     0.64   0.529    -.0058916    .0112801
------------------------------------------------------------------------------

.  regress r2y tmin_may tmin_may2, noc;

      Source |       SS       df       MS              Number of obs =      41
-------------+------------------------------           F(  2,    39) =    1.46
       Model |  .180373061     2  .090186531           Prob > F      =  0.2452
    Residual |  2.41343538    39  .061882959           R-squared     =  0.0695
-------------+------------------------------           Adj R-squared =  0.0218
       Total |  2.59380845    41  .063263621           Root MSE      =  .24876

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    tmin_may |   .0400939   .0239114     1.68   0.102    -.0082715    .0884592
   tmin_may2 |  -.0043018   .0025197    -1.71   0.096    -.0093985    .0007948
------------------------------------------------------------------------------

.  regress r2y tmin_jun tmin_jun2, noc;

      Source |       SS       df       MS              Number of obs =      43
-------------+------------------------------           F(  2,    41) =    0.06
       Model |  .008868004     2  .004434002           Prob > F      =  0.9455
    Residual |  3.23936965    41  .079009016           R-squared     =  0.0027
-------------+------------------------------           Adj R-squared = -0.0459
       Total |  3.24823766    43  .075540411           Root MSE      =  .28109

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    tmin_jun |  -.0092559   .0345537    -0.27   0.790    -.0790384    .0605267
   tmin_jun2 |   .0006937   .0028248     0.25   0.807    -.0050112    .0063985
------------------------------------------------------------------------------

.  regress r2y tmin_jul tmin_jul2, noc;

      Source |       SS       df       MS              Number of obs =      42
-------------+------------------------------           F(  2,    40) =    0.17
       Model |  .021480525     2  .010740263           Prob > F      =  0.8431
    Residual |  2.50572716    40  .062643179           R-squared     =  0.0085
-------------+------------------------------           Adj R-squared = -0.0411
       Total |  2.52720769    42  .060171612           Root MSE      =  .25029

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    tmin_jul |  -.0142881   .0244029    -0.59   0.561    -.0636082     .035032
   tmin_jul2 |   .0009869   .0016934     0.58   0.563    -.0024355    .0044093
------------------------------------------------------------------------------
```

Tmin (Sept-Dec of pre-harvest year)

```
.  regress r2y L.tmin_sep L.tmin_sep2, noc;

      Source |       SS       df       MS              Number of obs =      41
-------------+------------------------------           F(  2,    39) =    0.08
       Model |  .012216877     2  .006108439           Prob > F      =  0.9237
    Residual |  2.99368785    39  .076761227           R-squared     =  0.0041
-------------+------------------------------           Adj R-squared = -0.0470
       Total |  3.00590472    41  .073314749           Root MSE      =  .27706

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    tmin_sep |
         L1. |   .0043091   .0320866     0.13   0.894     -.060592    .0692103
             |
   tmin_sep2 |
         L1. |  -.0004603   .0026178    -0.18   0.861    -.0057553    .0048347
```

```
------------------------------------------------------------------------------

.  regress r2y L.tmin_oct L.tmin_oct2, noc;

      Source |       SS       df       MS              Number of obs =      42
-------------+------------------------------           F(  2,    40) =    0.41
       Model |  .051081823     2  .025540912           Prob > F      =  0.6645
    Residual |  2.47394766    40  .061848691           R-squared     =  0.0202
-------------+------------------------------           Adj R-squared = -0.0288
       Total |  2.52502948    42   .06011975           Root MSE      =  .24869

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    tmin_oct |
         L1. |  -.0259775   .0311118    -0.83   0.409    -.0888567    .0369017
             |
   tmin_oct2 |
         L1. |   .0028911   .0033001     0.88   0.386    -.0037786    .0095608
------------------------------------------------------------------------------

.  regress r2y L.tmin_nov L.tmin_nov2, noc;

      Source |       SS       df       MS              Number of obs =      37
-------------+------------------------------           F(  2,    35) =    0.01
       Model |  .001012256     2  .000506128           Prob > F      =  0.9923
    Residual |  2.29789598    35  .065654171           R-squared     =  0.0004
-------------+------------------------------           Adj R-squared = -0.0567
       Total |  2.29890823    37  .062132655           Root MSE      =  .25623

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    tmin_nov |
         L1. |   .0032968   .0265836     0.12   0.902    -.0506708    .0572643
             |
   tmin_nov2 |
         L1. |    -.00047   .0040297    -0.12   0.908    -.0086507    .0077106
------------------------------------------------------------------------------

.  regress r2y L.tmin_dec L.tmin_dec2, noc;

      Source |       SS       df       MS              Number of obs =      40
-------------+------------------------------           F(  2,    38) =    0.99
       Model |  .144729087     2  .072364543           Prob > F      =  0.3815
    Residual |  2.78169433    38  .073202482           R-squared     =  0.0495
-------------+------------------------------           Adj R-squared = -0.0006
       Total |  2.92642342    40  .073160585           Root MSE      =  .27056

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    tmin_dec |
         L1. |   .0436559   .0322415     1.35   0.184    -.0216136    .1089254
             |
   tmin_dec2 |
         L1. |  -.0106306   .0078857    -1.35   0.186    -.0265943     .005333
------------------------------------------------------------------------------
```

PRCPT (Jan-July of harvest year)

```
>  regress r2y prcpt_jan prcpt_jan2, noc;

      Source |       SS       df       MS              Number of obs =      43
-------------+------------------------------           F(  2,    41) =    0.36
       Model |  .063590499     2   .03179525           Prob > F      =  0.7006
    Residual |  3.63163068    41  .088576358           R-squared     =  0.0172
-------------+------------------------------           Adj R-squared = -0.0307
       Total |  3.69522118    43  .085935376           Root MSE      =  .29762

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   prcpt_jan |   .0002717   .0010684     0.25   0.801    -.0018859    .0024293
  prcpt_jan2 |   1.47e-07   6.04e-06     0.02   0.981     -.000012    .0000123
------------------------------------------------------------------------------

.  regress r2y prcpt_feb prcpt_feb2, noc;

      Source |       SS       df       MS              Number of obs =      42
-------------+------------------------------           F(  2,    40) =    0.60
       Model |  .095668281     2  .047834141           Prob > F      =  0.5533
    Residual |   3.1851094    40  .079627735           R-squared     =  0.0292
```

```
-------------+------------------------------           Adj R-squared = -0.0194
       Total |  3.28077768    42  .078113754           Root MSE      =  .28218

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   prcpt_feb |    .000854     .00078     1.09   0.280    -.0007224    .0024304
  prcpt_feb2 |  -3.52e-06   3.68e-06    -0.96   0.345     -.000011    3.92e-06
------------------------------------------------------------------------------

.  regress r2y prcpt_mar prcpt_mar2, noc;

      Source |       SS       df       MS              Number of obs =      43
-------------+------------------------------           F(  2,    41) =    0.69
       Model |  .088820382     2  .044410191           Prob > F      =  0.5058
    Residual |  2.62733619    41  .064081371           R-squared     =  0.0327
-------------+------------------------------           Adj R-squared = -0.0145
       Total |  2.71615657    43  .063166432           Root MSE      =  .25314

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   prcpt_mar |   .0012987   .0013162     0.99   0.330    -.0013595    .0039569
  prcpt_mar2 |  -6.91e-06   9.65e-06    -0.72   0.478    -.0000264    .0000126
------------------------------------------------------------------------------

.  regress r2y prcpt_apr prcpt_apr2, noc;

      Source |       SS       df       MS              Number of obs =      45
-------------+------------------------------           F(  2,    43) =    0.16
       Model |   .02787164     2   .01393582           Prob > F      =  0.8540
    Residual |  3.78284301    43  .087973093           R-squared     =  0.0073
-------------+------------------------------           Adj R-squared = -0.0389
       Total |  3.81071465    45  .084682548           Root MSE      =   .2966

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   prcpt_apr |   .0002918   .0022454     0.13   0.897    -.0042364      .00482
  prcpt_apr2 |  -8.21e-06   .0000228    -0.36   0.720    -.0000542    .0000377
------------------------------------------------------------------------------

.  regress r2y prcpt_may prcpt_may2, noc;

      Source |       SS       df       MS              Number of obs =      45
-------------+------------------------------           F(  2,    43) =    1.01
       Model |  .151138265     2  .075569133           Prob > F      =  0.3740
    Residual |  3.22868684    43  .075085741           R-squared     =  0.0447
-------------+------------------------------           Adj R-squared =  0.0003
       Total |  3.37982511    45  .075107225           Root MSE      =  .27402

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   prcpt_may |   .0068573    .005666     1.21   0.233    -.0045692    .0182838
  prcpt_may2 |  -.0001773   .0001274    -1.39   0.171    -.0004343    .0000796
------------------------------------------------------------------------------

.  regress r2y prcpt_jun prcpt_jun2, noc;

      Source |       SS       df       MS              Number of obs =      44
-------------+------------------------------           F(  2,    42) =    0.82
       Model |   .11199093     2  .055995465           Prob > F      =  0.4458
    Residual |  2.85506808    42  .067977811           R-squared     =  0.0377
-------------+------------------------------           Adj R-squared = -0.0081
       Total |  2.96705901    44  .067433159           Root MSE      =  .26073

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   prcpt_jun |  -.0288697   .0392552    -0.74   0.466    -.1080898    .0503504
  prcpt_jun2 |   .0011135   .0012558     0.89   0.380    -.0014208    .0036478
------------------------------------------------------------------------------

.  regress r2y prcpt_jul prcpt_jul2, noc;

      Source |       SS       df       MS              Number of obs =      45
-------------+------------------------------           F(  2,    43) =    0.20
       Model |  .027555587     2  .013777794           Prob > F      =  0.8205
    Residual |  2.98084666    43  .069322015           R-squared     =  0.0092
-------------+------------------------------           Adj R-squared = -0.0369
       Total |  3.00840225    45  .066853383           Root MSE      =  .26329

------------------------------------------------------------------------------
```

```
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   prcpt_jul |   .0711724   .2356595     0.30   0.764    -.4040802     .546425
  prcpt_jul2 |  -.0197916   .0481204    -0.41   0.683    -.1168357    .0772525
------------------------------------------------------------------------------
```

PRCPT (Sept-Dec of pre-harvest year)

```
.  regress r2y L.prcpt_sep L.prcpt_sep2, noc;

      Source |       SS       df       MS              Number of obs =      44
-------------+------------------------------           F(  2,    42) =    0.40
       Model |  .062713709     2  .031356854           Prob > F      =  0.6705
    Residual |  3.26322238    42  .077695771           R-squared     =  0.0189
-------------+------------------------------           Adj R-squared = -0.0279
       Total |  3.32593609    44  .075589457           Root MSE      =  .27874

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   prcpt_sep |
         L1. |  -.0176158   .0274045    -0.64   0.524    -.0729204    .0376888
             |
  prcpt_sep2 |
         L1. |   .0011628   .0014316     0.81   0.421    -.0017263    .0040518
------------------------------------------------------------------------------

.  regress r2y L.prcpt_oct L.prcpt_oct2, noc;

      Source |       SS       df       MS              Number of obs =      46
-------------+------------------------------           F(  2,    44) =    2.14
       Model |  .332023308     2  .166011654           Prob > F      =  0.1300
    Residual |   3.4168905    44  .077656602           R-squared     =  0.0886
-------------+------------------------------           Adj R-squared =  0.0471
       Total |  3.74891381    46  .081498126           Root MSE      =  .27867

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   prcpt_oct |
         L1. |   .0066918   .0048292     1.39   0.173    -.0030407    .0164244
             |
  prcpt_oct2 |
         L1. |  -.0001802   .0001006    -1.79   0.080     -.000383    .0000227
------------------------------------------------------------------------------

.  regress r2y L.prcpt_nov L.prcpt_nov2, noc;

      Source |       SS       df       MS              Number of obs =      44
-------------+------------------------------           F(  2,    42) =    0.31
       Model |  .052409973     2  .026204987           Prob > F      =  0.7377
    Residual |  3.59171456    42  .085517013           R-squared     =  0.0144
-------------+------------------------------           Adj R-squared = -0.0326
       Total |  3.64412453    44  .082821012           Root MSE      =  .29243

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   prcpt_nov |
         L1. |  -.0006417   .0017597    -0.36   0.717    -.0041929    .0029096
             |
  prcpt_nov2 |
         L1. |   8.39e-06   .0000143     0.59   0.562    -.0000205    .0000373
------------------------------------------------------------------------------

.  regress r2y L.prcpt_dec L.prcpt_dec2, noc;

      Source |       SS       df       MS              Number of obs =      44
-------------+------------------------------           F(  2,    42) =    0.20
       Model |  .034535691     2  .017267846           Prob > F      =  0.8222
    Residual |  3.68666499    42  .087777738           R-squared     =  0.0093
-------------+------------------------------           Adj R-squared = -0.0379
       Total |  3.72120068    44  .084572743           Root MSE      =  .29627

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   prcpt_dec |
         L1. |   .0000733   .0009193     0.08   0.937    -.0017819    .0019286
             |
```

```
  prcpt_dec2 |
         L1. |   8.03e-07   4.61e-06     0.17   0.863    -8.49e-06    .0000101
------------------------------------------------------------------------------
```

PRCPT log (Jan-July of harvest year)

```
>  regress r2y lprcpt_jan lprcpt_jan2, noc;

      Source |       SS       df       MS              Number of obs =      43
-------------+------------------------------           F(  2,    41) =    0.33
       Model |  .058902583     2  .029451291           Prob > F      =  0.7194
    Residual |  3.63631859    41  .088690697           R-squared     =  0.0159
-------------+------------------------------           Adj R-squared = -0.0321
       Total |  3.69522118    43  .085935376           Root MSE      =  .29781

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  lprcpt_jan |  -.0227992   .0917691    -0.25   0.805    -.2081306    .1625321
 lprcpt_jan2 |   .0063283   .0191992     0.33   0.743    -.0324454     .045102
------------------------------------------------------------------------------

.  regress r2y lprcpt_feb lprcpt_feb2, noc;

      Source |       SS       df       MS              Number of obs =      42
-------------+------------------------------           F(  2,    40) =    0.52
       Model |   .08340476     2   .04170238           Prob > F      =  0.5975
    Residual |  3.19737292    40  .079934323           R-squared     =  0.0254
-------------+------------------------------           Adj R-squared = -0.0233
       Total |  3.28077768    42  .078113754           Root MSE      =  .28273

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  lprcpt_feb |   .0497203   .0764404     0.65   0.519    -.1047715     .204212
 lprcpt_feb2 |  -.0088931   .0162889    -0.55   0.588    -.0418143    .0240281
------------------------------------------------------------------------------

.  regress r2y lprcpt_mar lprcpt_mar2, noc;

      Source |       SS       df       MS              Number of obs =      42
-------------+------------------------------           F(  2,    40) =    1.62
       Model |  .167440299     2  .083720149           Prob > F      =  0.2100
    Residual |  2.06323688    40  .051580922           R-squared     =  0.0751
-------------+------------------------------           Adj R-squared =  0.0288
       Total |  2.23067718    42  .053111361           Root MSE      =  .22711

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  lprcpt_mar |   .0704593   .0556941     1.27   0.213    -.0421027    .1830214
 lprcpt_mar2 |  -.0133645   .0126798    -1.05   0.298    -.0389912    .0122623
------------------------------------------------------------------------------

.  regress r2y lprcpt_apr lprcpt_apr2, noc;

      Source |       SS       df       MS              Number of obs =      41
-------------+------------------------------           F(  2,    39) =    0.56
       Model |  .100381795     2  .050190897           Prob > F      =  0.5751
    Residual |  3.48830089    39  .089443612           R-squared     =  0.0280
-------------+------------------------------           Adj R-squared = -0.0219
       Total |  3.58868268    41  .087528846           Root MSE      =  .29907

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  lprcpt_apr |   .0709904    .069273     1.02   0.312    -.0691274    .2111081
 lprcpt_apr2 |  -.0196451    .018567    -1.06   0.297    -.0572004    .0179102
------------------------------------------------------------------------------

.  regress r2y lprcpt_may lprcpt_may2, noc;

      Source |       SS       df       MS              Number of obs =      36
-------------+------------------------------           F(  2,    34) =    1.22
       Model |  .192068972     2  .096034486           Prob > F      =  0.3090
    Residual |  2.68562029    34  .078988832           R-squared     =  0.0667
-------------+------------------------------           Adj R-squared =  0.0118
       Total |  2.87768926    36  .079935813           Root MSE      =  .28105

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  lprcpt_may |   .0932703   .0602565     1.55   0.131    -.0291855    .2157262
```

```
 lprcpt_may2 |  -.0284672   .0185945    -1.53   0.135    -.0662557    .0093213
------------------------------------------------------------------------------

.  regress r2y lprcpt_jun lprcpt_jun2, noc;

      Source |       SS       df       MS              Number of obs =      10
-------------+------------------------------           F(  2,     8) =   23.39
       Model |  .598689659     2   .29934483           Prob > F      =  0.0005
    Residual |  .102381804     8  .012797726           R-squared     =  0.8540
-------------+------------------------------           Adj R-squared =  0.8175
       Total |  .701071464    10  .070107146           Root MSE      =  .11313

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  lprcpt_jun |  -.1360038   .0245145    -5.55   0.001    -.1925343   -.0794732
 lprcpt_jun2 |   .0543793   .0082388     6.60   0.000     .0353807     .073378
------------------------------------------------------------------------------

.  regress r2y lprcpt_jul lprcpt_jul2, noc;

      Source |       SS       df       MS              Number of obs =       3
-------------+------------------------------           F(  2,     1) =    2.74
       Model |  .072883326     2  .036441663           Prob > F      =  0.3930
    Residual |  .013311031     1  .013311031           R-squared     =  0.8456
-------------+------------------------------           Adj R-squared =  0.5367
       Total |  .086194358     3  .028731453           Root MSE      =  .11537

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  lprcpt_jul |    .127113    .082165     1.55   0.365    -.9168929    1.171119
 lprcpt_jul2 |   -.131821   .0563511    -2.34   0.257    -.8478293    .5841873
------------------------------------------------------------------------------
```

PRCPT log (Sept-Dec of pre-harvest year)

```
.  regress r2y L.lprcpt_sep L.lprcpt_sep2, noc;

      Source |       SS       df       MS              Number of obs =      13
-------------+------------------------------           F(  2,    11) =    0.05
       Model |   .02005244     2   .01002622           Prob > F      =  0.9537
    Residual |   2.3147438    11  .210431254           R-squared     =  0.0086
-------------+------------------------------           Adj R-squared = -0.1717
       Total |  2.33479624    13   .17959971           Root MSE      =  .45873

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  lprcpt_sep |
         L1. |   .0355987   .1160579     0.31   0.765     -.219843    .2910405
             |
 lprcpt_sep2 |
         L1. |  -.0102093   .0480228    -0.21   0.836    -.1159067     .095488
------------------------------------------------------------------------------

.  regress r2y L.lprcpt_oct L.lprcpt_oct2, noc;

      Source |       SS       df       MS              Number of obs =      39
-------------+------------------------------           F(  2,    37) =    0.58
       Model |   .10369596     2   .05184798           Prob > F      =  0.5669
    Residual |  3.32877728    37  .089966953           R-squared     =  0.0302
-------------+------------------------------           Adj R-squared = -0.0222
       Total |  3.43247324    39  .088012134           Root MSE      =  .29994

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  lprcpt_oct |
         L1. |   .0599809   .0716448     0.84   0.408    -.0851853    .2051472
             |
 lprcpt_oct2 |
         L1. |  -.0202331   .0209031    -0.97   0.339    -.0625868    .0221207
------------------------------------------------------------------------------

.  regress r2y L.lprcpt_nov L.lprcpt_nov2, noc;

      Source |       SS       df       MS              Number of obs =      41
-------------+------------------------------           F(  2,    39) =    3.86
       Model |  .575065301     2  .287532651           Prob > F      =  0.0297
    Residual |  2.90857106    39  .074578745           R-squared     =  0.1651
-------------+------------------------------           Adj R-squared =  0.1223
       Total |  3.48363636    41   .08496674           Root MSE      =  .27309
```

```
------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  lprcpt_nov |
         L1. |  -.1698998   .0615274    -2.76   0.009    -.2943507    -.045449
             |
 lprcpt_nov2 |
         L1. |   .0404949   .0146255     2.77   0.009     .0109119    .0700778
------------------------------------------------------------------------------

.  regress r2y L.lprcpt_dec L.lprcpt_dec2, noc;

      Source |       SS       df       MS              Number of obs =      44
-------------+------------------------------           F(  2,    42) =    0.65
       Model |  .111040054     2  .055520027           Prob > F      =  0.5293
    Residual |  3.61016063    42  .085956205           R-squared     =  0.0298
-------------+------------------------------           Adj R-squared = -0.0164
       Total |  3.72120068    44  .084572743           Root MSE      =  .29318

------------------------------------------------------------------------------
         r2y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  lprcpt_dec |
         L1. |  -.0782211   .0738145    -1.06   0.295    -.2271848    .0707426
             |
 lprcpt_dec2 |
         L1. |   .0174344   .0157731     1.11   0.275     -.014397    .0492657
------------------------------------------------------------------------------
```

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