THE IMPACT OF CLIMATE CHANGE ON AGRICULTURAL PRODUCTION IN MEDITERRANEAN COUNTRIES

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ABSTRACT

THE IMPACT OF CLIMATE CHANGE ON AGRICULTURAL PRODUCTION IN MEDITERRANEAN COUNTRIES

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The aim of the study is to determine the impact of climate change on agriculture for Mediterranean countries by employing vulnerability and econometric analysis. At first step, a composite agricultural vulnerability index is created by principal component analysis (PCA) for Mediterranean counties and world's top 35 cereal producer countries. Then, based on index scores, countries are grouped by cluster analysis. Several indicators are selected from different international databases according to three components of vulnerability which are exposure, sensitivity and adaptive capacity by assessing the related previous studies, examining the relevancy of indicators with food security and data availability from the international sources. As a second step, econometric analysis is conducted for clustered country groups obtained from the vulnerability index development part of the study. Panel ARDL method for pooled mean group (PMG), mean group (MG) and dynamic fixed effect (DFE) estimators is applied to clusters for three mostly harvested crop in Mediterranean region which are wheat, maize and potato. The novelty of this study is based on the methodology applied to determine the impact of climate change on crops. As a result, it is suggested that North African countries are more vulnerable to climate change in agriculture than South European countries due to their low adaptive capacity level. Another finding is that selected crops are more influenced from temperature in the long run when compared to impact of precipitation. An increase in temperature by 1% for cluster-1 and cluster-2 countries leads to decline in 0.3% and increase in 1.1% in wheat yield; 0.36% and 0.67% decline in maize yield, rise in about 2.0% and 2.8% in potato yield, respectively. Further, output of this study helps policy makers to measure and understand better the degree of risk to climate change and implement appropriate regulations for the agricultural sector.

Keywords: Climate Change, Agriculture, Vulnerability, Principle Component Analysis, Panel ARDL Method

ÖZ

İKLİM DEĞİŞİKLİĞİNİN AKDENİZ ÜLKELERİNDEKİ TARIMSAL ÜRETİM ÜZERİNDEKİ ETKİSİ

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Bu çalışmanın amacı, iklim değişikliğin tarım üzerine olan etkisinin Akdeniz ülkeleri için kırılganlık ve ekonometrik analizler yapılarak incelenmesidir. İlk adımda, kompozit tarımsal kırılganlık indeksi, temel birleşenler analizi uygulanarak, Akdeniz ülkeleri ve dünyanın en fazla tahıl üreten 35 ülkesi için oluşturulmaktadır. Sonrasında, indeks skorlarına göre ülkeler gruplandırılmıştır. Değişik göstergeler; farklı uluslararası veri tabanlarından, kırılganlığın üç bileşeni olan maruz kalma, hassaslık ve uyum kapasitesine göre, geçmiş çalışmalar değerlendirilerek, göstergelerin gıda güvencesi ile ilgisi, uluslararası kaynakların veri uygunluğu incelenerek seçilmiştir. İkinci adım olarak, çalışmanın kırılganlık indeksi geliştirme kısmından elde edilen ülke gruplarına ekonometrik analiz uygulanmıştır. Kümelere, Akdeniz Bölgesi'nde çok yetişen üç ürün olan buğday, mısır ve patates için, Panel Otoregresif Dağıtılmış Gecikmeli Model için Havuzlanmış Ortalama Grup Tahmincisi (PMG), Ortalama Grup Tahmincisi (MG) ve Dinamik Sabit Etkiler Tahmincisi (DFE) uygulanmıştır. Bu çalışmanın orijinalliği iklim değişikliğinin ürünler üzerine olan etkisini belirlemede uygulanan yöntemlere dayalıdır. Sonuçlar gösterir ki, Kuzey Afrika ülkeleri, tarım alanında iklim değişikliğine uyum kapasitelerinin düşük seviyede olmasından dolayı, Güney Avrupa ülkelerinden daha fazla kırılgandır. Diğer bir bulgu ise, seçilen ürünler uzun dönemde yağışın etkisiyle kıyaslandığında sıcaklıktan daha fazla etkilenmektedirler. Sıcaklıktaki %1'lik artış buğday verimliliğinde, sırasıyla Küme-1 ve Küme-2 ülkelerinde, % 0,3'lük düşüşe ve %1'lik artışa, mısır üretiminde %0,36 ve % 0,67'lik düşüşe ve %2 ve %2,8'lik artışa neden olacaktır. Bu çalışmanın çıktıları iklim değişikliği riskinin ölçülmesi ve anlaşılmasına, ayrıca, uygun düzenlemelerin tarım sektöründe yürürlüğe girmesine yardımcı olacaktır.

Anahtar Kelimeler: İklim Değişikliği, Tarım, Kırılganlık, Temel Bileşenler Analizi, Panel Otoregresif Dağıtılmış Gecikmeli Model

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LIST OF ABBREVIATIONS

ADH	Away to District
AHP	Analytic Hierarchy Process
AIC	Akaike Information Criterion
ARDL	Autoregressive Distributed Lag
ASME	Agricultural Sector Model of Egypt
CAVI	Composite Agricultural Vulnerability Index
CCCma	Canadian Centre for Climate Modeling and Analysis
CD	Cross-sectional Dependence
CH_4	Methane
CGE	Computable General Equilibrium
CO_2	Carbon Dioxide
CRU	Climate Research Unit
CSIRO	Commonwealth Scientific and Industrial Research Organisation
CVIW	Climate Vulnerability Index for Water
DDC	Data Distribution Center
DEA	Data Envelopment Analysis
DFE	Dynamic Fixed Effect Estimator
DOE	Department of Energy
EM-DAT	The International Disaster Database
FAO	The Food and Agriculture Organization
GCM	General Circulation Model

GDP	Gross Domestic Product
GMM	Generalized Method of Moments
HadCM3	Hadley Centre for Climate Prediction and Research
HI	Hunger Importance
HIR	Hunger Importance Ranking
HQ	Hannan-Quinn
IAVI	Intermediate Agricultural Vulnerability Indicators
IPCC	The Intergovernmental Panel on Climate Change
KMO	Kaiser-Meyer-Olkin
KMSA	Kaiser-Meyer-Olkin Measure of Sampling Adequacy
MG	Mean Group Estimator
MIROC	Model for Interdisciplinary Research on Climate
NCAR	National Center for Atmospheric Research
NDH	Near to District
N2O	Nitrous Oxide
OLS	Ordinary Least Square
PCA	Principle Component Analysis
PMG	Pooled Mean Group Estimator
ppm	part per million
SBC	Schwarz Bayesian Criterion Criterion
SRES	Special Report on Emissions Scenarios
TARSEM	Turkish Agricultural Sector Model
TFP	Total Factor Productivity

UNFCCC	United Nation Framework Convention on Climate Change
VAR	Vector Autoregressive
VEP	Vulnerability Expected Poverty

CHAPTER 1

INTRODUCTION

Industrial revolution and growing global population have increased the demand for food and energy sources, which eventually led to increase in fossil fuel use, land use change, deforestation, and fertilizer consumption. The consequence of these phenomena in the long run has changed the atmospheric concentration of the greenhouse gases such as carbon dioxide (CO_2), nitrous oxide (N_2O), methane (CH_4), and water vapor. Due to the change in atmospheric concentration, mankind have encountered with a man-made global threat, called “climate change” which is likely to result in lack of sustainable livelihoods and reliable water resources and food security problem. In addition, change in the distribution of species and in the ecosystem is expected to occur in the near future and it also endangers the achievement of Millennium Development Goals aimed at poverty and hunger reduction, health improvement and environmental sustainability (UNDP, 2010).

CO_2 is the major greenhouse gas that contributes to over 40% of the total emission of the greenhouse gases (Odingo, 2008). According to measurements of Mauna Loa Observatory, atmospheric research center that has been continuously monitoring and collecting data related to emissions since the 1950's, the emission levels has increased from 310 ppm to above 400 ppm levels in almost last 50 years as indicated in the Figure 1-1 and such large amounts have never been seen by mankind history (Tans and Keeling, 2013). What is more, in line with increase in emission levels, climate change due to anthropogenic factors has revealed that the earth is warming. As also seen from the Figure 1-2, global temperature has risen by almost by 0.7 °C after industrial revolution and studies have indicated that the trend is increasing, so that average temperature will likely to increase by 0.2 °C in every following decade (IPCC, 2007a).

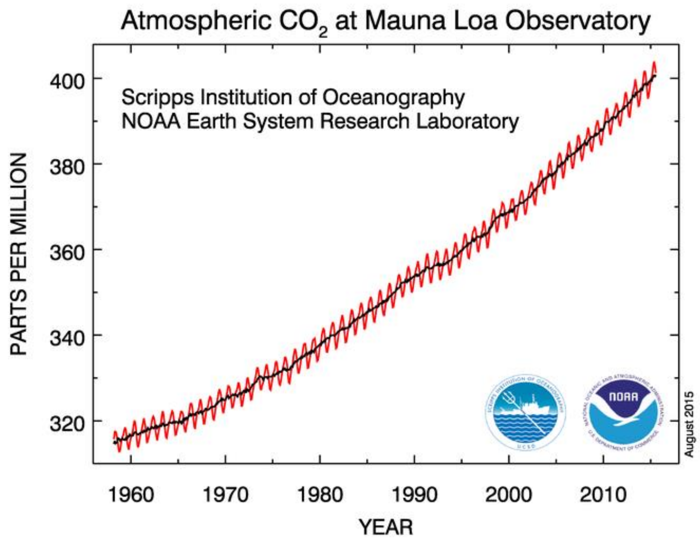

Figure 1-1: Atmospheric CO2 Global Emission Level Measure at Mauna Loa Observatory

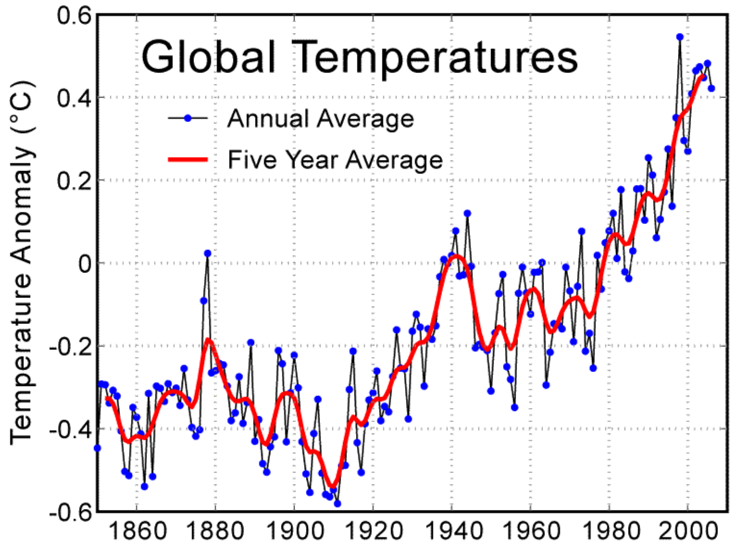

Figure 1-2: Temperature Anomaly after Industrial Revolution

Agriculture is a human activity that highly depends on weather patterns variations (Rosenzweig et al. 1994). Climate change can lead to rise in magnitude, frequency and duration of extreme weather events such as floods, droughts, heat waves and storms and thus, reduces agricultural production and raises food prices (Lobell et al., 2011; IPCC, 2014). Changes in climate variability, particularly changes in intensity and/or frequency of floods, drought and storms, evapotranspiration, sowing and harvesting dates are also expected to influence agricultural production significantly (IPCC, 2007b). Most of the developing countries with a rainfed based agricultural activities are directly influenced by climatic conditions (Mertz et al., 2009). Therefore, it is highly likely that possible exacerbation of climate change in future may lead to influence food supply and food security.

One of the zones in the world susceptible to climate change is the Mediterranean Basin which is mostly warm and rainy in winter, dry and hot during summer. The region is situated in a transition part between the arid and hot climate of North Africa and the temperate and wet climate of central part of Europe. Higher rate of evapotranspiration in Mediterranean basin (Moriondo et al., 2010), past evidences of sudden climate change in this region (Giorgi, 2006), the region's heterogeneity about the development level and also the population of the countries are the main reasons for the selection of countries lying on the Mediterranean region for this dissertation. In fact, it is between the developed countries of Southern European Region and Northern African countries with some of the East Mediterranean countries which have low development level when compared to related European countries. Therefore, existence of countries in different structures in the same region, having almost same or common climatic conditions in general, motivate us to measure the impact of climate change in terms of food security and agriculture.

This dissertation aims to make a comprehensive assessment of the effect of climate change on agriculture in Mediterranean countries. Based on detailed searching of the literature on climate change and agriculture, this study is mainly composed of two major parts which are vulnerability index development and detailed econometric analysis. In the first part of the study, agricultural vulnerability index is created for Mediterranean countries and world's top 35 cereal producer countries by employing principal component analysis (PCA) in order to identify the position of the Mediterranean countries in terms of their response to climate change among the selected countries. Then, based on the index results, a cluster analysis is conducted to group the countries having the similar characteristics related to climate change. In the second part of the study, econometric analysis is employed in order to determine the impact of climate change on three mostly cultivated crops in Mediterranean region: wheat, maize and potato. Panel Autoregressive Distributed Lag (ARDL) method is applied to clustered country groups generated in the first part of the study for each crop with three different estimators that are "pooled mean group estimator (PMG)", "mean group estimator (MG)" and "dynamic fixed effect estimator (DFE)".

It is aimed to contribute the climate change literature in a number of ways. There are many studies related to agriculture and climate change for different regions of the world. However, as presented in Literature Review part, only few climate change effect studies focus on crops cultivated in Mediterranean region. Therefore, the region studied provides remarkable contribution to literature. There are many studies related to vulnerability analysis done in a national and regional scale by developing index based on equal weight approach (i.e., Sullivan, 2002) or expert opinion. This study differs from others in that it has a global scale since it includes 50 countries and PCA is used to weight the indicators based on objective selection of the indicators. For this reason, these aspects can be considered as the unique features of the dissertation. Furthermore, for the second part of the dissertation, the applied methodology, Panel ARDL method with PMG, MG and DFE estimators, is most commonly used for different study areas such as energy economics, economic growth and energy consumption. However, this is most likely to be the first study that combines concepts related to impact of climate change on agriculture and the methodology selected; dynamic panel data analysis.

The dissertation is organized in six chapters. Chapter 2 reports brief information about climate change and its main impacts, vulnerability concept and gives detailed information about the effect of climate change on agriculture. Comprehensive literature review is presented regarding the studies on vulnerability approach and crop models. In Chapter 3, the details of data used and methodology applied in the dissertation are introduced. The PCA with cluster analysis and panel ARDL methods are also explained in detail in this chapter. Chapter 4 reports the results of the vulnerability and econometric analysis. In the first part of this chapter, the PCA and cluster analysis outputs are presented. Panel ARDL outputs with PMG, MG and DFE estimators as well as the other preliminary analyses such as unit root test results are given in the other section of this chapter. Besides, Chapter 5 is devoted to discussion of the results obtained in the previous chapter. The outputs are compared with the results from other similar studies in literature and they are discussed in detail. In Chapter 6 which is the conclusion part; the directions for future researches and policy recommendations are presented. Finally, some additional tables are presented in Appendices.

CHAPTER 2

LITERATURE REVIEW

In the literature review, first of all, the historical evolution of vulnerability concept is given and the most related literature is reviewed. Then, we proceed with reviewing the relationship between climate change and agriculture and lastly, focused on the literature about crop models that were used for the impact of climate change.

2.1. Vulnerability Approach

Vulnerability assessments render complex and real world knowledge into a simpler form by identifying relevant indicators that employs practical and effective evaluations. It is a strong analytical tool to identify susceptibility to damage and weakness of physical and social systems so as to develop well-being by decreasing risk (Adger, 2006). It is useful for measuring the impact of climate change and identifying the effectiveness and adaptive degrees for a variety of related indicators to obtain reliable way for examining climate change (Dong et al., 2015). It can be used for different scientific research areas such as food security and agriculture, water supply and management, disaster risk management, health, and climate change (Füssel & Klein, 2006). The vulnerability concept has been studied by many research communities for more than 30 years and many definitions have been made. It is firstly taken into account as a broad concept which considered to be useless and naturally uncertain, and only used for rhetorical areas of concern (Timmermann, 1981). Then, it is linked to related concepts such as resilience, marginality, susceptibility, adaptability, fragility, and risk (Liverman, 1990). In late 1990's, social aspects and human dimension, that are disregarded in the early studies of vulnerability and adaptation, are incorporated to concept. In fact, social vulnerability is defined as the ability of people or societies to react withstand or recover from the stress or shock coming from exogenous risks such as climatic stimuli that influence their livelihood and welfare (Adger and Kelly, 1999). It is used as the magnitude or frequency of damage, that a system is affected negatively, when encountered with a natural hazard or disaster (Turner et al., 2003). In addition, within the last decade, attention has been drawn on evaluating the vulnerability of natural systems such as environment, ecosystem and habitats to climate change (Zhao, et al. 2007). Furthermore, IPCC defines vulnerability as “the degree to which a system is susceptible to, and unable to cope with, adverse effects of climate change, including climate variability and extremes. It is a function of the character, magnitude, and rate of climate change and variation to which a system is exposed, its sensitivity, and its adaptive capacity” (IPCC, 2007a). It is more clearly defined as the interaction among these three components. *Exposure* is the magnitude and duration of the climate-related stimuli such as flood, change in temperature or more generally, extreme meteorological events. *Sensitivity* is the degree to which system is influenced by serious climatic variable. *Adaptive capacity* is related to the ability of a system to recover from or cope with the adverse impacts of climate-related stimuli (IPCC, 2007c).

2.1.1 Literature Review about Climate Vulnerability Analysis

There is a variety of studies done related to vulnerability analysis by employing different weighting methods at regional, national and global scales. Weighting of the indicators is an important issue when they are compiled into a single index. A number of weighting techniques exist. The mostly used method is an equal weighting approach. Based on this approach, each component contributes equally to the index ignoring the number of indicators under each component (Sullivan, 2002). Thus, the component score is divided by the number of indicators. Another weighting method is Data Envelopment Analysis (DEA) which uses linear programming tools to estimate an efficiency frontier that would be used as a benchmark to determine the relative performance of countries. This entails construction of a benchmark and the measurement of the distance between countries in a multi-dimensional framework (OECD, 2008). Furthermore, Analytic Hierarchy Process (AHP) is another widely used method for multi-attribute decision making. It makes the decomposition of a problem into a hierarchical structure easier and enables the inclusion of both qualitative and quantitative aspects of a problem into the evaluation process. In this regard, opinions are systematically measured by means of pairwise comparisons. Besides, expert opinion can also be used to determine the weight of the indicators.

In the last decade, Füssel H. M. (2010) take into account the inequity by analyzing asymmetries between responsibility of countries for climate change with their capability to cope with it and their vulnerability to climate change. A group of disaggregated vulnerability indicators are considered. They constituted four climate affected sectors, namely water supply, food security, human health, and coastal populations. They relied on IPCC's definition of vulnerability components which are chosen as biophysical sensitivity and impacts, socio-economic exposure, and socio-economic coping capacity. Inequity is evaluated by using Spearman's rank correlation coefficient with equal weighting of the selected indicators. For instance, one of the results they found is that two indicators for social and economic capability (Human Development Index and Gross Domestic Product (GDP) per capita) and the CO_2 emissions are strongly linked to each other. Moreover, their correlation with any vulnerability is almost the same.

Simelton et al. (2012) generated quantitative harvest vulnerability index by using annual soil moisture and grain production data as the dependent variable in a linear mixed effects model. They concluded that the socio-economic factors that rise or reduce the vulnerability of cereal production to drought change depending on the type of cereal and the type of region. They found out that rice, wheat and maize production were particularly vulnerable to droughts in middle income countries. They also found that countries having small population and stronger economies have lower vulnerability.

Krishnamurthy, et al. (2014) developed hunger and climate vulnerability index to determine the vulnerability to climate change associated with food security issues at a country level. They have measured vulnerability by taking into account the correlations between the hunger and climate risk for each country. For each component of vulnerability, related indicators are selected and their correlation with hunger index is examined. To obtain vulnerability index, highly correlated indicators are aggregated according to equal weight approach, assuming that each indicator equally contributes to exposure, sensitivity, and adaptive capacity components. They reported that hunger and climate vulnerability index for Bangladesh and Afghanistan from South Asia and Sub-Saharan countries is higher than the one for other countries.

There are some studies done at national level by using equal weighting approach and data envelopment analysis (Monterroso et al. 2014; Cervantes et al. 2015; Huang et al., 2012 and Yuan et al., 2015). Monterroso et al. (2014) determined vulnerability to climate change in the agricultural sector at the national level using municipal data in Mexico. They chose social, economic and environmental indicators related to agricultural production. They assumed that each indicator contributes equally to the index. The results revealed that 16% of the total population is living in high-exposure areas. Besides, 41% of population lives in municipalities identified as highly-sensitive and 20 % lives in 1273 municipalities with low-adaptive capacity.

Cervantes et al. (2015) assessed local agricultural vulnerability to climate change by using social, economic, and environmental factors that are involved in the agricultural production of five municipalities in Mexico where agricultural production has a high share. They assigned equal weights to each variable and they calculated the arithmetic mean of variables obtained from opinion of experts. Among the 20 rural districts, eight of them were categorized as having very low vulnerability and two of them had very high vulnerability due to climate factors such as high frequency of days with temperatures below 5 °C.

In another study, Huang et al. (2012) developed four models of flood vulnerability assessment according to theoretical framework of the flood disaster system by using data envelopment analysis (DEA) for 31 provinces of China. They used flood damage data and socioeconomic statistical data for 2001–2010 periods. Finally, the impact of flood vulnerability on population, death, agriculture and economy is determined for each province of China and some policies have been suggested.

Yuan et al. (2015) developed a vulnerability index in order to assess regional vulnerability to drought of China by applying data envelopment analysis (DEA) and analytic hierarchy process (AHP) as weighting methods. These indices revealed the causes of drought vulnerability. The data are gathered from the statistical yearbooks of China based on expert judgement. They found that the inland regions of China have more drought vulnerable cities than coastal areas. Moreover, the cities located in the south are less vulnerable to drought than those in the central and north regions of China. Furthermore, they also have some policy implications about drought management and preparedness.

There are also many studies at regional scale to measure the impact of climate change by conducting household surveys by employing different weighting techniques (Makondo et al., 2014; Skjeflo, S., 2013; Hahn et al., 2009; Pandey et al.; 2014; Pandey and Jha, 2012; Murthy et al.,2015; Bogale, A., 2012; Notenbaert et al., 2013; Amos et al., 2013; Kienberger, S., 2012; Dong et al., 2015; Ahsan and Warner, 2014 and Shah et al., 2013).

Makondo et al., (2014) developed a livelihood vulnerability index to determine the vulnerability of rain dependent small farms on food security in three agro-ecological zones of Zambia. They preferred to use balanced mean approach, that is to say, each sub-component contribute equally to the final index. In the study, it is found that rain dependent small-holder farmers are more vulnerable to sudden weather stimuli which extremely influence their agricultural production and vulnerability levels change depending on gender and agro-ecological zone.

Skjeflo, S. (2013) investigated the indirect impacts of climate change such as prices on households dealing with maize production in Malawi by computing computable general equilibrium (CGE) model to estimate household vulnerability to climate change by 2030. The results revealed that rural households living in large land may improve their livelihoods from the adverse effect of climate change on maize yields as a result of rise in maize prices.

Hahn et al. (2009) have calculated a livelihood vulnerability index to examine the climate change vulnerability in two regions of Mozambique by conducting household surveys in selected areas determined by socio-demographics, livelihoods, food and water security. They used equal weight approach for the calculation of index. They asserted that, using primary household data can avoid the disadvantages of using secondary data. In this regard, they provide policy makers a realistic method to comprehend the socioeconomic factors that influence climate vulnerability. However, they also stated that subjectivity included in choosing the indicators and determining the direction of relationship between indicators and vulnerability are among some restrictions of their approach. The results of the study revealed that Moma district is more vulnerable when water resources are taken into account and Mabote is more vulnerable with socio-demographic structure is taken into account.

Pandey et al. (2014) formed climate vulnerability index for water (CVIW) for assessing the climate related water vulnerability of households in mountainous region of Uttrakhand, India. An indicator-based approach was applied to constitute the components of the index. They used equal weighting approach for all components. The study area was arranged under rural and urban areas. Results revealed that index value for urban areas are higher than the rural areas which indicate that urban households have less water vulnerability. Low standard of health facilities, the existing water problems and agricultural issues contribute to water vulnerability of rural households, as well.

Pandey and Jha (2012) conducted a study that evaluates climate change vulnerability of communities in Himalayan region of India by developing vulnerability index. Eight major components; namely socio-demographic profile, livelihood strategies, social network, health, food, water, natural disaster and climate variability, were taken into account. Household questionnaire survey was done for two districts which are near to district (NDH) and away to district (ADH). They concluded that high vulnerability was obtained for livelihood strategies, food and natural disaster for ADH households and health and water for NDH households.

Murthy et al. (2015) created crop-generic agricultural drought vulnerability index based on exposure, sensitivity and adaptive capacity indices by using a set of indicators at disaggregated level. Study is performed on 120 sub-district administrative units. They assigned variance-based weightages to the input indicators selected. They found that 51 sub-districts located in the southern and western parts of the state are highly vulnerable to climate change. In this region, groundwater quality is saline and water holding capacity of soils is restricted. Moreover, they discovered that crop condition variability, groundwater quality and soil factors are related to index.

Bogale, A. (2012) investigated factors related to household level vulnerability to food security by applying vulnerability expected poverty (VEP) approach. They gathered household survey data from the eastern highlands of Ethiopia. The results indicate that 32.5% of households suffered from chronic food insecurity since their food consumption expenditure was below the threshold levels and were highly vulnerable to food security. However, 4.7% of households have low vulnerability to food security and they have chance to recover from the food insecurity in the future.

Notenbaert et al. (2013) focused on the adaptive capacity of households in Mozambique and examined the coping strategies and vulnerability to climatic shocks that people dealing with agriculture and livestock breeding. They developed household-level vulnerability index by using survey data and examined the validity of commonly used vulnerability indicators. The results of the study revealed that 9 out of 26 indicators revealed statistically significant relationship with vulnerability of households.

Amos et al. (2013) investigated the perception of households about the climate change in Coastal area of Akwa Ibom State, Nigeria by generating a livelihood vulnerability index to assess susceptibility of those to climatic shocks. They used balance approach to weight the indicators before developing the index. Moreover, the index mainly measures the level of exposure of livelihoods to climate change, sensitivity of households to climate variability based on health, food, and shelter and finally socioeconomic features of households which affect their ability to cope with climate change. They concluded that timing and duration of the average rainy season have varied over the period which was also confirmed by the data attained from Nigerian Meteorological Agency. Finally, the authors asserted that study will help policy makers for figuring out the difficulties that coastal communities encounter about acquiring the sustainable climate change adaptation strategies.

Kienberger, S. (2012) examined the vulnerability of Central Mozambique in district level by more focusing on the susceptibility and adaptive capacity side of the vulnerability concept. They determined homogenous vulnerability regions by taking into account application of integrated modelling approaches based on combination of expert and community knowledge and weightings. Finally, they determined proper measures and weights for representing vulnerability according to different perceptions of experts, decision makers, district managers, and community members and portrayed the results through the maps at district level.

Dong, et al. (2015) developed an approach for quantitative evaluation of agricultural vulnerability to climate change and used this approach as a case study for Wuchuan County in Inner Mongolia. They based calculations on objective and quantitative assessment techniques. They proposed the unit vulnerability and regional vulnerability concepts and they find correlation between climatic yield per year and climatic factors. They claimed that the approach developed in that study provides researchers with evaluating the vulnerability of a specific crop through objective indicators. Moreover, it is asserted that vulnerability of the same crop in different districts can be measured and compared to each other by the approach they developed. As a result of the case study, they concluded that unit vulnerability between the period of 1991 and 2009 reveals an increasing trend and there is a reduction in regional vulnerability due to planted area and degree of exposure.

In another study, Ahsan and Warner (2014) developed a socioeconomic vulnerability index to measure the impact of climate change on the coastal communities in the district of south-western coast of Bangladesh. They gathered the data by conducting household surveys and assigned weights to indicators based on opinions of local experts. Finally, relative magnitudes of the indictors were assessed by taking into account the vulnerability concept. They concluded that people living in the southern and south-eastern communities are relatively more vulnerable to climate change since they are suffering from natural hazards. Moreover, authors of the study asserted that the developed socioeconomic vulnerability index is simple and useful for the future vulnerability studies related to coastal communities having spatial variation.

Shah et al. (2013) generated a livelihood vulnerability index to measure the impacts of climate change on agricultural and natural resource-dependent two wetland communities in Trinidad and Tobago. They selected the indicators related to eight areas such as health, food and water by taking into account the critical focus group discussions that local community representatives, government officials and researchers were involved. Data were obtained by conducting household surveys. Equal weighting approach was used when creating the livelihood vulnerability index. They concluded that Caroni community was less vulnerable than the other community Nariva in terms of socio-demographics, health and water security, natural disaster and climate variability assets.

Moreover, authors stated that livelihood vulnerability index could be commonly used for comparing the communities in small island countries having different socio-ecological settings.

In Mwakalila, S. (2011)’s study, the sustainable livelihood framework approach was focused to measure vulnerability for livelihood of the community related to water resources in semi-arid rural area of Tanzania. The equal weight approach was used with primary and secondary data by making interviews and found that alterations in intensity and duration of precipitation leads to water stress and making the region more vulnerable.

The review of literature about climate vulnerability models are reported in details in Table 2-1.

Table 2-1: Previous Studies Related to Climate Vulnerability based on Different Weighting Methods and Scales

Index name	Reference	Weighting (Method)	Sector/Area	Region	Data Gathering Method (Data Type)	Main Result
Vulnerability Index (No specific name)	Füssel H. M. (2010)	Equal Weight Approach	Water resources, food, health and coasts	Global scale (World)	Secondary data	Two indicators for social and economic capability (human development index and GDP per capita) and the CO_2 emissions are strongly correlated with each other.
Drought Vulnerability Index	Simelton et al. (2012)	Linear Mixed Effects Model	Agriculture (rice, wheat and maize)	Global scale (World)	Secondary data (Climate and weather data)	Socio-economic factors that increase or reduce the vulnerability of cereal production to drought change according to the type of cereal and region. Rice, wheat and maize production were particularly vulnerable to droughts in middle income countries.
Hunger and Climate Vulnerability Index	Krishnamurthy et al. (2014)	Equal Weight Approach	Agriculture	Global scale (World)	Secondary data (Climate and socioeconomic structure)	Hunger and climate vulnerability index for Bangladesh and Afghanistan is higher than the one for other countries.
Vulnerability Index (No specific name)	Monterroso et al. (2014)	Equal Weight Approach	Agriculture	National scale (Municipal scale in Mexico)	Secondary data (Indicators related to social, financial, human and agriculture)	16 % of the total population is living in high-exposure areas. 41 % people live in municipalities identified as highly-sensitive 20 % of the population lives with low-adaptive capacity.
Vulnerability Index (No specific name)	Cervantes et al. (2015)	Equal Weight Approach	Agriculture	National scale (Municipal scale in Mexico)	Secondary data	Among the 20 rural districts, eight of them categorized as having very low vulnerability and two of them have very high vulnerability due to climate factors.
Flood vulnerability index	Huang et al. (2012)	Data Envelopment Analysis	Population, agriculture and economy	National scale (China)	Secondary data (Flood Damage Data and Socioeconomic Statistics)	Impact of flood vulnerability on population, death, agriculture and economy is determined for each province of China.

Table 2-1: Previous Studies Related to Climate Vulnerability based on Different Weighting Methods and Scales (continued)

Index name	Reference	Weighting (Method)	Sector/Area	Region	Data Gathering Method (Data Type)	Main Result
Vulnerability Index (No specific name)	Yuan et al. (2015)	Data Envelopment Analysis (DEA) and Analytic Hierarchy Process (AHP)	Agriculture and water resources	National scale (65 provinces of China)	Mixed Data from National Sources	Inland regions of China have more drought vulnerable cities than coastal areas. The cities located in the south are less vulnerable to drought than those in the central and north regions of China.
Livelihood Vulnerability Index	Makondo et al. (2014)	Equal Weight Approach	Food production	Regional scale (Selected districts of Zambia)	Primary data (Household survey)	Rain dependent small-holder farmers are more vulnerable to sudden weather stimuli. Vulnerability levels change according to gender and agro-ecological zone.
Vulnerability Index (No specific name)	Skjeflo, S. (2013)	Computable General Equilibrium (CGE)	Crop yields (maize)	Regional scale (rural regions of Malawi)	Primary data (Interview, Household survey)	Rural households living in large land may improve their livelihoods from the adverse effect of climate change on maize yields as a result of rise in maize prices.
Livelihood Vulnerability Index	Hahn et al. (2009)	Equal Weight Approach	Socio-demographic profile, livelihood strategies, social networks, health, food, water	Regional scale (Districts of Mozambique)	Primary data (Household surveys, 200 households)	Moma district may be more vulnerable in terms of water resources while Mabote district may be more vulnerable in terms of socio-demographic structure.
Climate Vulnerability Index for Water	Pandey et al. (2014)	Equal Weight Approach	Water resources	Regional scale (Uttrakhand, India)	Primary data (Household survey)	Vulnerability index of urban areas was higher than the one of rural areas which indicates that urban households have less water vulnerability.

Table 2-1: Previous Studies Related to Climate Vulnerability based on Different Weighting Methods and Scales (continued)

Index name	Reference	Weighting (Method)	Sector/Area	Region	Data Gathering Method (Data Type)	Main Result
Climate Vulnerability Index	Pandey and Jha (2012)	Equal Weight Approach	Socio-demographic profile, livelihood strategies, social network, health, food, water, natural disaster and climate variability	Regional scale (Communities in Himalayan region of India)	Primary data (Household surveys, 50 households)	Index value of urban areas was higher than the one of rural areas which indicates that urban households have less water vulnerability.
Agricultural Drought Vulnerability Index	Murthy et al (2015)	Variance Based Weighting Method given in Lyengar and Sudarshan (1982)	Agriculture	Regional scale (12 districts in Haryana state, India),	Rainfall and crop condition data	51 sub-districts located in the southern and western parts of the state are highly vulnerable to climate change.
Vulnerability Index (No specific name)	Bogale, A. (2012)	Emprical Models Vulnerability as Expected Poverty (VEP) Method	Food security	Regional scale (eastern highlands of Ethiopia)	Primary data (Household surveys, 277 households)	32.5 % of households suffered from chronic food insecurity since their food consumption expenditure was below the threshold levels and were highly vulnerable to food security.

Table 2-1: Previous Studies Related to Climate Vulnerability based on Different Weighting Methods and Scales (continued)

Index name	Reference	Weighting (Method)	Sector/Area	Region	Data Gathering Method (Data Type)	Main Result
Vulnerability Index (No specific name)	Notenbaert et al. (2013)	Correlation Coefficient Matrix	Areas related to adaptive capacity (income, health, food consumption)	Regional scale (Mabalane district in Mozambique)	Primary data (Household survey)	9 out of 26 selected indicators revealed statistically significant relationship with vulnerability of households
Livelihood Vulnerability Index	Amos et al. (2013)	Equal Weight (Balance Weight) Approach	Farming and fishing	Regional scale (Coastal area of Akwa Ibom State, Nigeria)	Primary data (Household survey, structured interviews, or focused group discussions, 101 households)	Timing and duration of the average rainy season have varied over the period.
Vulnerability Index (No specific name)	Kienberger, S. (2012)	Expert Weighting and Community Knowledge	Social, economic, environmental and physical dimensions	Regional scale (District level, Central Mozambique)	Primary data (Expert interviews by arranging brainstorming sessions)	Proper measures and weights are determined for representing vulnerability according to different perceptions of experts or community members.
Agricultural Vulnerability Index	Dong et al. (2015)	Unit Vulnerability Concept	Crop yields (wheat)	Regional scale (Wuchuan County in Inner Mongolia)	Secondary data (Meteorological and yield data from national institutions)	Developed approach provides researchers with evaluating the vulnerability of a specific crop through objective indicators. Vulnerability of the same crop in different districts can be measured and compared to each other by the approach.

Table 2-1: Previous Studies Related to Climate Vulnerability based on Different Weighting Methods and Scales (continued)

Index name	Reference	Weighting (Method)	Sector/Area	Region	Data Gathering Method (Data Type)	Main Result
Socioeconomic Vulnerability Index	Ahsan and Warner (2014)	Pressure and Release (PAR) Model and Weighted Quantitative Assessment (Assigning Relative Weights)	Demographic, economic, social, physical and natural hazard exposure	Regional scale (South-western coastal Bangladesh)	Primary data (Household survey, 60 households)	People living in the southern and south-eastern communities are more vulnerable to climate change since they are suffering from natural hazards.
Livelihood Vulnerability Index	Shah et al. (2013)	Equal Weight Approach	Natural disasters and climate variability, health, water, food, socio demographic profile, livelihood strategies	Regional scale (Two wetland communities in Trinidad and Tobago)	Primary data (Household survey and interview)	Caroni community was less vulnerable than the other community Nariva in terms of socio-demographics, health and water security, natural disaster and climate variability assets.
Livelihood Vulnerability Index	Mwakalila, S. (2011	Equal Weight Approach	Water resources	Regional scale (Semi-arid rural area of Tanzania)	Primary data (interviews)	Alterations in intensity and duration of precipitation lead to water stress and making the region more vulnerable.

2.2 Climate Change and Food Security

2.2.1 Overview of Climate Change and Its Impacts

Climate change is a global challenge that threatens the globe and mankind (Godfray et al., 2010). The atmospheric amounts of carbon dioxide, methane, and nitrous oxide have risen to dangerous levels that have not been precedent for the last 800,000 years. In addition, 1983–2012 was probably the warmest 30-year period of the last 1400 years (IPCC, 2013 WG1). Its impacts are easily determined and measured. Oceans have absorbed about some amount of the emitted anthropogenic carbon dioxide which lead to ocean acidification. The decline in the amount of snow and ice, the change in frequency of the heavy climate events, the rise in sea level are easily detected evidences of human induced climate change. Furthermore, according to Stern (2006), concentration of CO_2 is mainly caused by developed countries through various production and consumption activities. However, the impact of climate change is mainly faced by developing countries which are mostly located in tropical regions and relying heavily on agriculture sector (Stern, 2006). In other words, developing countries are more vulnerable to climate change than developed countries, because of the large share of agriculture in the economies of these countries, the scarcity of capital for adaptation strategies and their exposure to heavy meteorological events (Fischer et al., 2002).

United Nation Framework Convention on Climate Change (UNFCCC) defines climate change as, "A change of climate which is attributed directly or indirectly to human activity that alters the composition of the global atmosphere and which is in addition to natural climate variability observed over comparable time periods". Moreover, IPCC (2007a) defines climate change more technically and specifically as "A change in the state of the climate that can be identified (e.g. using statistical tests) by changes in the mean and/or the variability of its properties, and that persists for an extended period, typically decades or longer".

Climate change will likely have a serious impact on water resources and agriculture which are directly linked to each other. According to IPCC (2007b) report; in the world, precipitation has increased significantly from the year of 1900 to 2005 in east parts of North and South America, northern Europe and Northern and Central Asia but declined in the Mediterranean, southern Africa and some parts of southern Asia. Furthermore, this report revealed that, globally, the regions affected by drought have increased since the 1970's. Moreover, about 70% of the world's fresh water is used for agricultural purposes and 90% of countries in the world rely on extensive irrigation. 30 developing countries are almost facing water shortages, and by 2050 this number may rise to over 50 countries (Fischer, 2002). According to climate scenarios, water availability is reduced by 2050's in climate scenarios in Mediterranean, Central and South America and in South Africa (Arnell, 2004).

Climate change will influence agriculture in several ways. Alterations in temperature and precipitation will have impact on timing and length of growing seasons and yields. It will also affect water availability for agriculture. In addition, rise in carbon dioxide concentrations may have a direct effect on certain crops. Alterations in climate variability, especially changes in the intensity and/or frequency of floods, drought and storms, evapotranspiration, sowing and harvesting dates are also expected to influence agricultural production significantly. Responses of climate change to agriculture can vary in different parts of the world. While regional yields increase in mid to high latitudes due to rise in temperature, in low latitudes they are expected to decline for any warming (IPCC, 2007b). Moreover, global average temperature increases in excess of 3°C are likely to lead to decline in yields in all regions of the world. Another impact of climate change is that, temperature rise above 3°C could result in upward force on world price of cereals (Parry et al, 2007).

2.2.2 Climate Models

Numerical models (General Circulation Models or GCMs) reveal physical processes in the atmosphere, ocean, cryosphere and land surface. They are the most advanced tools for simulating the impact of the world climate system to rise in greenhouse gas concentration. Climate models are based on physical laws and large number of observations. Four types of climate models with their properties are explained below (Fischer, 2002).

Hadley Centre for Climate Prediction and Research (HadCM3): HadCM3 is a coupled atmosphere-ocean general circulation model (GCM) improved at the Hadley Centre in Britain.

Commonwealth Scientific and Industrial Research Organisation (CSIRO): The CSIRO Climate Change Research Program is the largest and most comprehensive program of Australia to understand the interactions between land and atmosphere. Annual outputs of monthly weather parameters of CSIRO experiments were obtained from DDC for simulations using the IPCC emission scenarios (Fischer, 2002).

Canadian Centre for Climate Modeling and Analysis (CCCma): The Canadian Centre for Climate Modelling and Analysis (CCCma) is a part of the Climate Research Division of Environment Canada. Outputs were obtained with the second version of the Canadian Global Coupled Model (CGCM2). The IPCC provides annual time-series of monthly climate parameters for the scenarios (Fischer, 2002).

National Center for Atmospheric Research (NCAR): The Parallel Climate Model is founded by the US Department of Energy (DOE). The main objective is simulating the earth's climate system. Annual time series of monthly climate parameters for a grid of 68 by 128 grid-cells for IPCC emission scenarios are obtained from IPCC (Fischer, 2002).

Comparisons of results from HadCM3, CSIRO, CGCM2, and NCAR have been done for all land and current agricultural land separately in terms of "Temperature change (◦C) versus CO_2 concentration levels (ppm)" and for "Temperature change (◦C) versus precipitation change (%)". There is a close relationship between CO_2 concentration levels and forecasted temperature impacts for the results of HadCM3, CSIRO, and CGCM2. However, temperature effect for increased CO_2 is lower in the case of NCAR's PCM model. Moreover, relationship between temperature change and change in precipitation levels is different from each other.

Most of these studies are based on climate change experiments with General Circulation Models (GCMs), but they vary according to their baseline data, methods of analysis and scenarios of climate change.

2.2.3 Special Report on Emissions Scenarios (SRES)

Scenario of climate change is produced as a physically consistent set of alterations in meteorological parameters and it is determined according to projections of CO_2 (and other trace gases) levels. Scenarios of climate change are generated in order to predict the impact of climate change on crop yields and the type of crop mixtures that may be cultivated. The evaluations of the effects of climate change on agriculture are performed according to four baselines. They are modeled based on the IPCC SRES such as A1, A2, B1, and B2. Each story explains different aspects such as demographic, social, economic and environmental improvements (IPCC, 2000). These base scenarios reveal alternative extrapolations of the global climate system into the future. The system is simulated for the period of the year 1990–2080. Simulation is conducted in one-year intervals. All scenarios of climate-change effect begin in 1990 and are obtained relative to a reference climate of the period of the year 1961–1990. The emission scenarios, A1, A2, B1, and B2 are briefly summarized below (IPCC, 2007a).

SRES A1: In this scenario, rapid economic growth of world in the future is taken into account. It is ''business-as-usual scenario,'' which refers to the highest emissions.

Moreover, it includes low population growth and fast introduction of new and more efficient technology. People choose personal wealth rather than environmental quality. The A1 scenario family is classified into three groups that determine alternative directions of technological change in the energy system. They are fossil-intensive (A1FI), non-fossil energy sources (A1T) or a balance across all sources (A1B) (IPCC, 2007a).

SRES A2: This scenario describes high population growth among other scenarios so it requires highest food demand and also there is less worries for fast economic improvement in the future for SRES A2 scenario.

SRES B1: This scenario includes the same low population growth as in the A1 storyline but with fast alteration in economic aspects. Moreover, development of clean technologies is described in this scenario. In fact, the important issue is related to global solutions to environmental and social sustainability. Therefore, this scenario corresponds to the lowest emission scenario.

SRES B2: In this scenario, local solutions to economic, social, and environmental sustainability are taken into account. Fossil fuels are changed by low-carbon fuels at a much faster rate than under A2. This scenario describes also less fast and broader technological change than in the B1 and A1 storylines. In this scenario, a world with average population growth and economic development is described.

According to SRES emission scenario and general climate models, temperature is forecasted to rise in a range from 1.8°C for SRES B1 (with a range from 1.1°C to 2.9°C) to 4.0°C for SRES A1 (with a range from 2.5°C to 6.5°C) by 2100. Moreover, the atmospheric CO_2 concentration is forecasted to rise from about 380 ppm today to 550 ppm by 2100 in SRES B1 while it will increase to 800 ppm in SRES A1FI.

According to IPCC, projected temperatures for each scenario are given in Table 2-2 below. From the table it is certain that, temperature will rise by the end of 21st century for all SRES scenarios.

Table 2-2: Summary of Forecasted Temperature (°C) changes per SRES Scenario (B1, B2, A1B, A1T, A2, A1F1) by the end of the 21st Century

	B1	**B2**	**A1B1**	**A1T**	**A2**	**A1F1**
Temperature (°C)	+1.8 (1.1-2.9)	+2.4 (1.4-3.8)	+2.8 1.7-4.4)	+2.4 (1.4-3.8)	+3.4 (2.0-5.4)	+4.0 (2.6-6.4)

2.2.4 CO_2 Impact on Agriculture

The impacts of climate and increased emission concentrations will lead to developed growing conditions in some regions and thus, crop production may rise. CO_2 levels are expected to raise crop yield due to rise in photosynthetic activity and developed water use technology. Crop productivity in some countries may also be influenced by drier land and rise in water stress (Rosenzweig and Parry, 1994).

As mentioned above, temperature, solar radiation, water, and atmospheric CO_2 concentration are the climate parameters that influence crop productivity. Plant species vary in their response to CO_2 because of changing photosynthetic mechanisms. There are significant distinctions in temperature requirements and effects to concentration of CO_2 between C3 and C4 plants. In fact, C3 plants (temperate and boreal) reveal an relative response to rise in CO_2 concentrations while C4 plants (warm tropical) reveal only a restricted response to rise in CO_2 concentrations (Rosenzweig and Parry, 1994).

Lobell and Field (2007) found out that the impact of climate change was likely balanced by fertilization impacts of increased CO_2 levels, in spite of the uncertain magnitude of these impacts. They asserted that the effects of CO_2 and climate trends have likely offset each other over the past two decades, with a little impact on yields. The historical temperature–yield relationships revealed that at the global scale, increase in temperature from 1981 to 2002 very likely offset some of the yield increases from technological developments, increasing CO_2 and non-climatic factors.

2.2.5 Food Security

Food is a necessary for life and food security is a basic common interest in the world. The Food and Agriculture Organization (FAO) defines food security as a "Situation that exists when all people, at all times, have physical, social, and economic access to sufficient, safe, and nutritious food that meets their dietary needs and food preferences for an active and healthy life". It is composed of four key aspects of food supply which are availability, stability, access, and utilization. The first dimension is availability of enough food. Stability is related to people who are at high risk of temporarily or permanently lacking their access to the resources needed to obtain enough food. The third dimension, access, covers access by individuals to sufficient resources to obtain proper foods for a nutritious feed. The last dimension, utilization includes all food safety and quality conditions of nutrition (FAO, 2002). Climate change will influence all four dimensions of food security. The importance of the many dimensions and the effect of climate change on food security will change from region to region and time to time. It will rely on the socio-economic condition of a country (FAO, 2006).

The six most commonly cultivated crops in the world are rice, wheat, maize, soybeans, barley and sorghum. Cultivation of these crops explains over 40% of world cropland area (FAO, 2006). Moreover, in temperate latitudes, increase in temperature is expected to lead to benefits to agriculture. In fact, Schmidhuber and Tubiello (2007) stated that. "The areas potentially suitable for cropping will expand, the length of the growing period will increase, and crop yields may rise". In addition, more specifically, studies indicate that the largest losses in suitable cropland are more likely to be in Africa, whereas the largest expansion of suitable cropland will take place in the Russian Federation and Central Asia in the world due to climate change (Fischer et al., 2002).

Furthermore, irrigated agriculture covers only 19% of cropland and agricultural land cultivated through irrigation supplies 40% of the world's food. Therefore, water for agriculture is very important for food security (Molden et al., 2010). Furthermore, as mentioned above, developing countries are more vulnerable to climate change particularly to the agriculture production lacking adequate resources for the adaptation and substituting the production factors, agriculture based economy, food insecurity and poverty (Acharya and Bhatta, 2013).

Climate change will influence precipitation, runoff and the availability of water for irrigation in many regions and countries in the world. A decrease in precipitation with an increase in temperature will lead to increase in crop water requirement due to high evapotranspiration. Less rainfall will rise crop net irrigation water requirements. As a result, the existing water scarcity problem will emerge in many regions and countries, and influence food production. The strongest impact will be in the areas such as the arid countries of sub-Saharan Africa, Mediterranean region of Africa and some parts of South Asia. These regions are prone to malnutrition, poverty, and episodes of hunger (Brown and Funk, 2008). Mendelson et al. (1994) have concluded that temperature and rainfall are suitable variables for understanding climate change impacts on crop yields in the temperate and tropical regions respectively. Growing of wheat (crop grown in cool area), corn, and rice rely on the temperature.

2.2.6 Food Security and Climate Change in Mediterranean Region

One region that influenced by climate change is the Mediterranean Basin that is mostly warm and rainy during winter, dry and hot during summer. The region is situated in a transition part between the arid and hot climate of North Africa and the temperate and wet climate of central part of Europe. Interactions between mid-latitude and tropical processes have an effect on the climate of the region. The climate simulations reveals that it will be notably warmer and drier in mild season of the year except some northern parts such as Alps where an increase in rainfall is expected in winter. Projections obtained from general circulation models and regional models show that inter-annual variability for both temperature and precipitation will increase over the Mediterranean Basin, which makes the region more sensitive to climate change (Giorgi & Lionello, 2008).

According to IPCC 2014 Report, there is great evidence that agriculture in Northern Africa and watersheds around the Mediterranean Basin will become more sensitive to climate change in the future. Due to high rate of evapotranspiration in the region, it is reported that water stress will be a serious problem (Arnell, 2004; Boko et al., 2007, Moriondo et al., 2010). In fact, the annual precipitation is expected to decrease in most of the Mediterranean Africa, northern Sahara, and southern Africa (Christensen et al., 2007). In the rural part of the Mediterranean Basin, agriculture is the main activity for rural people and water resources are crucially important for sustainable crop cultivation. Decrease in water availability due to climate change may lead to greater stress on agricultural production in the region. Addition to all, Iglesias et al., (2011), Giorgi & Lionello (2008), and Giannakopoulos et al. (2009) discuss that climatic changes will lead to reduction in growing periods of crops produced.

Since Mediterranean Basin covers a large area surrounded by different climatic conditions, the effect of climate change is expected to be different for parts of the region. Agricultural activities in the southern Mediterranean region will most probably be affected by climate change more than the northern part of Europe (Giannakopoulos et al., 2009, Moriondo et al., 2010). In fact, an increase in temperature about +2°C will induce a more serious effect on agriculture in the Mediterranean region than the middle and northern Europe due to drier and hotter climate. In the Mediterranean part of Europe, there may be a reduction about %5 for summer wheat and sunflower crop and also %13 for soybean in the period of 2030-2060 according to CropSyst Model Simulation which is a temperature dependent model that takes into account agricultural parameters such as soil water budget, duration of grain filling, leaf area index, and CO_2 concentration in the atmosphere.

To sum up, Mediterranean region of Europe will be exposed to higher amount of extreme climatic conditions in the next decades and this will probably exacerbate unsustainable agriculture in the region (Moriondo et al., 2010). Besides, Mediterranean part of the North Africa is also likely to become vulnerable to climate change by 2050. In fact, it is expected that precipitation will reduce about between %10 and %20 and temperature of the region will increase about 2-3◦C by 2050. Thus, it is expected that many crops cultivated in this region will decline and shift in cultivation patterns will be inevitable (Schilling et al., 2012; Sowers, et al., 2011). These shifts will raise the food security problems. As reported in FAO (2012), the climate change has been threatening the food security in the Northern Africa and Western Asia.

2.2.7 Crop Models

The impact of climate change on agriculture can be investigated by crop models which incorporate three different common methods. These are “process based models”, “Ricardian approach” and “empirical (statistical) models”.

Process-based crop models were developed to simulate crop responses to environmental conditions at field level. They are limited by bio-physical processes. In fact, they use farm level data such as quality of soil, nutrition, nitrogen use efficiency, canopy structure and water. Moreover, these models are used for regional scales like tens to a couple of hundred kilometers (Tubiello and Ewert, 2002).

Statistical models take into account the historical data on crop yields and climate to obtain statistical relationships. They assess climate change effects at large spatial scale. The important advantage of statistical models is their restricted dependence on field data. In fact, planting and harvesting dates are not taken into account in these models. They measure the model uncertainties by using of coefficient of determination and confidence intervals. Moreover, these models forecast the future responses based on historical relationships between the climate and crop data. These models are alternative to process-based models. There are three main types of statistical approaches in the literature.

These are “time series”, “panel” and “cross-section” methods. Time series methods are based purely on time series data from a single point or area. Panel methods are based on changes both in time and space and cross section methods are only related to variations in space (Lobell and Burke, 2010).

Ricardian approach focuses on the economic effect of climate change on agriculture. This method is used for relating the climate change with alterations in land value. Moreover, it includes direct effect of climate on crop and also adaptation response by farmers to climate (Mendelson et al., 1994).

Most of the studies use agronomic models, e.g. CERES-Wheat, C-CAM, EPIC, etc. It is difficult to apply these models in most cases because agronomic models use farm-level data such as quality of soil, nutrition, water, daily minimum/maximum temperatures, precipitation. These are not available at national scale. Therefore, it is reasonable to use econometric approach for the projection of impact of different variables on agricultural production (Janjua et al., 2014).

Time-series models have the advantage of holding the properties related to the given area. However, panel and cross-section methods must assume common parameter values for all locations. Moreover, cross-section methods are especially prone to errors from omitted variables such as soil quality or fertilizer inputs that change region to region. In addition, time-series models are often restricted by data while panel and cross-section methods can combine data from multiple sites (Lobell and Burke, 2010).

2.2.7 Literature Review about Crop Models

There are many studies done based on three different types of crop models which are Ricardian approach, process based and statistical models. Moreover, these studies can also be classified according to their scale or area coverage which are regional, national and global based models. In last decade, there have been several globally scaled studies in which variety of crop models are developed (Blanc et al., 2012; El-Maayar and

Lange, 2013; Parry et al., 2004; Schlenker and Lobell; 2010; Lobell et al., 2008; Moriondo et al.; 2010; Lobell and Field, 2007; Van Passel et al., 2014). The brief summaries of these studies are given as below.

Blanc (2012) studied the effect of climate change on yields for the four most widely cultivated crops in Sub-Saharan Africa. These crops are millet, maize, sorghum and cassava. Panel data approach has been employed for 37 countries for the period of 1961-2002. Firstly, unit root tests and Westerlund Panel Cointegration approach have been conducted. Then, error correction model has been developed to determine the relationship between the yield and explanatory climatic variables and area harvested. Finally, crop yields by 2100 have been forecasted by integrating the estimates from panel data analysis with climate change projections from general circulation models (GCMs). Results showed that there will be no change in cassava yield by 2100. However, yield alterations changes from–19% to +6% for maize, from –38% to –13% for millet and from 47% to –7% for sorghum under climate change scenarios in 2100.

In another study, El-Maayar and Lange (2013) have investigated the impact of climate change on three Mediterranean countries (Egypt, Greece ant Morocco) by using first difference method. The aim of the used methodology in this study is removing the impact of non-climatic factors on crop yield and determining the observed climate change between 1961 and 2006 on three widely crops cultivated which are namely wheat, corn and potato. Results revealed that methodology used in the study decrease uncertainties in estimation of climate change impacts on agricultural production. Moreover, they found out that while increase in temperature has negative impact on maize cultivated in Egypt, it has positive impact on wheat cultivated on Greece. Moreover, rise in temperature has positive effect on potato harvested in Morocco.

In another work in which process based model has been used, Parry et al. (2004) globally analyzed the future influence of climate change on maize, wheat, rice and soybean crop yields which constitutes the 85% of the cereal production in the world.

While they measured the responses of crop yields in the first part of the study, they simulate the agro-economic results of the possible alterations in crop yields in the second part. In fact, they considered alterations in regional productivity, global commodity prices and total number of people suffering from hunger in the world in this part of the research. Future climate data were obtained from climate change scenarios attained from the HadCM3 global climate model under the Intergovernmental Panel on Climate Change Special Report (IPCC) on Emissions Scenarios (SRES) A1FI, A2, B1, and B2. According to results, generally, there will be a great reduction in yield by the 2080's under the A1F1 scenario which is developed based on large increase in global temperatures. Moreover, yield change between the developed and developing countries is largest under the A2a–c scenarios.

Schlenker and Lobell (2010) analyzed the future yield response to climate change for maize, sorghum, millet, groundnut, and cassava crops cultivated in Sub-Saharan countries by conducting panel data analysis. They used the average annual temperature, precipitation and area harvested data as independent variable and yield data as dependent variable for the period of 1961-2002. Results revealed that there will be significant decline in crop production about 22%, 17%, 17%, 18%, and 8% for maize, sorghum, millet, groundnut, and cassava, respectively. Another interesting finding is that countries having highest yields will experience the highest forecasted yield losses which indicate that well-fertilized crops are more sensitive to weather related losses.

Lobell et al. (2008) made a global climate risk analysis related to maize, wheat, sorghum, rice and cassava crop production in 12 food-insecure regions determined by the Food and Agriculture Organization (FAO). They specified the adaptation strategies according to statistical crop models and climate projections for 2030 from twenty GCM's. A hunger importance ranking (HIR) was created by ranking the hunger importance (HI) values for all crop-by-region integration alternatives. They found out that climate change, with insufficient adaptation strategies, will have adverse impacts on several crops cultivated in South Asia and Southern Africa. Moreover, results demonstrated that uncertainties change extensively by crop and priorities will rely on risk factors of investment organizations.

In another globally scaled study, Moriondo et al. (2010) explored the response of a climate change on agricultural yield in Europe corresponding to a global warming of +2°C, considering possible changes in mean climate. CropSyst Model (a multi-year, multi-crop, daily time-step crop-growth simulation-model) is used to forecast the future climate. Soil-water budget, soil-plant nitrogen budget, crop canopy and root growth, phenology, dry matter production, yield, residual production and decomposition, and erosion are also taken into account in this model. In the study, the outputs of general circulation models were combined with the process-based CropSyst model to simulate responses of sunflower, soybean and wheat to climate change and variability. As a result of the simulations, a +2°C scenario will have a greater impact on crops harvested over the Mediterranean basin than on those harvested in central and northern Europe. Furthermore, results revealed that in the present period agriculture in the northern Europe has been temperature-restricted while it has been water-restricted in the south. In addition, projections revealed that while growing season temperatures are almost same in the northern part of Europe, there will be likely decline in rainfall and rise in temperature in the Southern part of the continent.

Lobell & Field (2007) examined the global influence of climate change on crop yields by creating statistical models of yield response to climate change. Rather than using annual averages for each climatic variable, global growing season is defined for each crop. The selected growing seasons were May–October (for wheat), January–October (for rice), July–August. (for maize and soy), May–August. (for barley) and August. (for sorghum). In the study, first difference method and multiple linear regressions with method of de-trending were used. Results indicated that simple measures of growing season temperatures and precipitation account for nearly 30% or more of year-to-year variations in global average yields for the six most widely cultivated crops 35üte35s the world. There exists an obvious negative impact of global yields to increased temperatures for wheat, maize and barley.

In a FP-7 European project, Van Passel et al. (2012) explored the effect of climate variability on European agriculture by conducting Ricardian analysis. Data related to climate, soil, geography and regional socio-economic characteristics were gathered from the 37612 individual farms in the EU-15 countries. The results revealed that seasonal climate variables strongly affected current farmland values in those countries. Moreover, the impact of climate change is not homogeneous but mixed across Europe. Another finding is that rise in spring temperature will have positive impact but increase in summer temperature will have negative effect on agricultural land value.

After reporting the studies conducted globally scaled, there are also studies done in national level by employing different types of crop models (Yoji et al., 2014; Iglesias and Minguez, 1997; McCarl et al., 2013; Janjua et al.; 2014; Chen and Chang, 2005; Gaál et al., 2014; Kucharik and Serbin, 2008; Eregha et al., 2014; Dellal et al., 2011).

Yoji et al. (2014) have investigated the effect of climate change on rice total factor productivity (TFP) in Japan by panel data analysis. They have developed a regression model in order to understand the relationship between rice TFP and climate factors. Then, the future levels of rice TFP is forecasted by using model for interdisciplinary research on climate (MIROC). TFP is obtained by using the Tornqvist-Theil index for each region of Japan. The results reveal that climate change has positive impact in the northern part of Japan. However, in western regions, it is expected that there will be a reduction in rice TFP. In addition, they asserted that regional gaps for rice TFP are broadened over time due to varied effects of climate and socio-economic factors and these can be used for restructuring the Japanese agricultural policy.

In another study, Iglesias and Minguez (1997) have assessed the effect of climate change on production of two crops (maize and wheat) and water use of them in Spain. They used CERES crop simulation models in connection with the climate change scenarios obtained from general circulation models. They claimed that impact of climate change on crops is the interaction of many factors which are crop growth duration, precipitation pattern, daily evapotranspiration rate, CO_2 effect and water use efficiency. They found out that wheat yield increases significantly in some regions of Spain and in the future wheat production shifts the northern parts of the present cultivated regions. It is concluded that there may be reduction in maize yield in the future due to water deficiency in the region.

McCarl et al. (2013) investigated the general impact of climate change on agricultural production, water resources, sea level rise and growing population in Egypt. They used a partial equilibrium model, ASME (Agricultural Sector Model of Egypt) that simulated crop and livestock production with water resources. Moreover, possible adaptation strategies related to climate change such as technological progress in agriculture, coastal protection against sea level rise and water supply distribution are examined. The main result of the study is that climate change will have a great impact on Egypt agriculture. What is more, prices of agricultural commodities will rise which has adverse effect on consumers but a positive effect on producers.

Janjua et al. (2014) examined the impact of climate change on wheat production in Pakistan by using Autoregressive Distributed Lag (ARDL) model. They mainly considered the wheat production, temperature, precipitation, fertilizer and CO_2 historical data from 1960 to 2009. The results revealed that climate change doesn't affect the wheat production in Pakistan in the short and long run. Nevertheless, in the short run, wheat production and fertilizers have positive impact on wheat production which balanced the any negative climate shock on it. In the long run in the case of a decrease in wheat production, use of fertilizers may prevent this decline. Moreover, authors also stated that proper adaptive measures should be taken into account for any possible sudden climate shock on wheat production.

Chen and Chang, (2005) analyzed the effect of climate change on the seven crop yields in for 15 regions in Taiwan by employing pooled panel data. The unclear yield outcome is included in discrete stochastic programming model to make reliable comparisons between sector analyses by taking into account crop insurance policy based on different climate scenarios. Moreover, in the study unit root tests and maximum likelihood methods are performed to obtain robust estimates. Results showed that crop insurance can balance revenues and it protects farmers from climate shocks that they may suffer.

Gaál et al., (2014) examined the impact of climate change on crop production in Hungary in terms of socio-economic measures by conducting integrated panel data analysis. They also focused on the effect of climate related stimuli such as drought, flood or excess surface water on crop yields. Moreover, five crops (maize, sunflower, potato, green peas and grapevines with varied water needs were selected for the study. The main results revealed that irrigation is crucially important for green peas, maize and potato production. Another finding is that maize production will be possible with improved irrigation systems in the second half of the century.

Kucharik and Serbin, (2008) investigated the effect of temperature and precipitation trends on corn and soybean yield trends in Wisconsin, USA for the period of 1976 -2006 They used multiple regression models in order to determine the relationship between the precipitation & temperature trends and corn &soybean yields. They discovered that crop productivity for the northern part of the Corn Belt may be influenced negatively due to rise in temperature during the summer growing season. Moreover, the results indicated that one degree increase in temperature during summer months may bring about reduction in 13% and 16% for corn and soybean crop yields, respectively. In addition, medium increase in total summer precipitation may lead to rise in crop yield about 5–10% which offsets the negative impacts related to increased temperature.

Eregha et al. (2014) investigated the impact of climate change on crop production in Nigeria. Temperature, rainfall and also CO_2 emission data were used as climate variables. Ten crops were selected. These are beans, cassava, cocoa, groundnut, maize, millet, potato, rice, sorghum and yam. Cointegration approach and error correction techniques are employed to determine the response of climate change on these crops. As a result, study revealed that effect of climatic variables on crop production changes relying on the crop type of and seasonal properties and length of days of the crop. Some seasonal crops that are cultivated during raining seasons have been negatively affected by precipitation. Almost production of all crops was found to have been influenced by the carbon emission in atmosphere during the period. The author also claimed that policy implications about mitigation and adaptation strategies should be taken into account by farmers in order to increase the crop production.

Dellal et al. (2011) investigated the five major crop (wheat, barley, corn, sunflower, and cotton) production produced in seven regions of Turkey and economic implications of projected climate change on Turkish agricultural sector. In the study, projected climate data obtained by general circulation model of HADCM which is projected for each region of Turkey for 2050's. Turkish Agricultural Sector Model (TARSEM), a mathematical program simulating economic factors in the Turkish agricultural sector involving prices, production, and trade of the main crops (wheat, barley, corn, sunflower and cotton) was computed for Turkey and yield responses were determined for each crop. Moreover, each region of Turkey with base climate yield and the projected climate change yield are compared by biophysical model. Finally, projected climate change yields were integrated into economic model by changing yields in the TARSEM. The authors concluded that crop yields alterations are negatively influenced by 3.8% to 10.1% in Turkey. For instance, while area cultivated for barley and corn have increased, area harvested for sunflower has declined. Moreover, wheat and cotton area cultivated have remained unchanged. Besides, it is expected that there will be a shift from barley and sunflower to corn in the Black Sea region according to model results. Another finding is that Turkey experiences a welfare loss of about $0.1 million per year based on simulation outputs. There are also studies done in regional scale by employing Ricardian approach and statistical models (Mishra, D., 2015; Mougou et al., 2011; Amikuzino and Donkoh 2012).

Mishra, D. (2015) investigated the impact of climate change on net revenue obtained from agricultural production of crops such as wheat, millet, maize, paddy and potato in the east coast of the India by employing the Ricardian approach. Then, panel data method is used to examine the relationship between the climatic factors (temperature and precipitation) and other control variables affecting net revenue. Data were collected from the related institutions at a district level. Results of the study indicated that climate has a significant impact on the agricultural production in the east coast of the India. The future climate scenarios will have a negative effect on the net revenue from agricultural production the end of twenty-first century.

Mougou et al. (2011) analyzed the impact of climate change on wheat cultivated in Kairouan region of Tunisia by employing simple regression analysis between the climate factors and wheat yield. The results showed that increase in temperature during the growing season of wheat leads to direct effect on rain-fed wheat production. Moreover, the authors concluded that alterations in temperature and precipitation patterns with higher evapotranspiration rates may lead to decrease in wheat production and quality. As a result, these findings may have adverse impact on socioeconomic development and social stability in Tunisia.

Amikuzino and Donkoh (2012) examined the long-term relationship between climatic variables (temperature and rainfall) and yields of the most important staple crops which are millet, maize, sorghum, rice and groundnut. Pooled panel data of seasonal rainfall, temperature and yield for 1976 to 2010 are used. Johansen’s Variance Autoregressive (VAR) approach and Granger Causality Analysis are conducted. The results revealed that there exists strong evidence of cointegration between seasonal rainfall and crop yields and there is causality from rainfall to crop yields in the Sudano-Guinea Savannah and Guinea Savannah zones of Northern Ghana. They also asserted that these findings indicated that inter-annual yields of the crops have been affected by the total amounts of precipitation in the planting season.

As a result of examination of the literature about crop models, the studies of different authors related the topic, reported in details above, are classified in Table 2-3 as a summary and given below.

Table 2-3: Previous Studies Related to Crop Models Based on Different Methods and Scales

Reference	Crop Model (Method)	Crop type	Area coverage	Study period	Used variables	Main result
Blanc et al. (2012)	Statistical (Panel Data Model) (Panel Cointegration Tests, Error Correction Model)	Millet, maize, sorghum and cassava	Global scale (Sub-Saharan countries)	1961-2002	Temperature, rainfall, evapotranspiration, flood, drought, area harvested, yield	There will be no change in cassava yield by 2100. However, yield alterations range from –19% to +6% for maize, from –38% to –13% for millet and from –47% to –7% for sorghum under climate change scenarios in 2100.
El-Maayar and Lange (2013)	Statistical (First Difference Method)	Wheat, corn and potato	Global scale (Mediterranean countries)	1961-2006	Yield, temperature and precipitation	While increase in temperature has negative impact on maize cultivated in Egypt, it has positive impact on wheat cultivated on Greece. Rise in temperature has positive effect on potato harvested in Morocco.
Parry et al. (2004)	Process based (CERES and SOYGRO)	Maize, wheat, rice and soybean	Global scale (World)	Future climate data from general circulation models	Temperature, precipitation and crop simulation data	There will be a great reduction in yield by the 2080's under the A1F1 scenario which is developed based on large increase in global temperatures. Yield change between the developed and developing countries is largest under the A2a–c scenarios.
Schlenker and Lobell (2010)	Statistical (Panel Data Analysis) (Fixed Effect Model)	Maize, sorghum, millet, groundnut, and cassava	Global scale (Sub-Saharan countries)	1961-2006	Yield, area harvested, average temperature and precipitation	There will be significant decline for each crop by mid-century. There will be significant decline in crop production about 22%, 17%, 17%, 18%, and 8% for maize, sorghum, millet, groundnut, and cassava, respectively.
Lobell et al. (2008)	Statistical	Maize, wheat, sorghum, rice and cassava	Global scale (World)	Climate projections for 2030 (Outputs of process-based models)	Temperature, precipitation, crop production	Climate change, with insufficient adaptation strategies, will have adverse impacts on several crops cultivated in South Asia and Southern Africa.

Table 2-3: Previous Studies Related to Crop Models Based on Different Methods and Scales (continued)

Reference	Crop Model (Method)	Crop type	Area coverage	Study period	Used variables	Main result
Moriondo et al. (2010)	Process Based (Crop-Syst Model)	Wheat, soybean and sunflower	Global scale (Europe)	1975-2005	Daily minimum and maximum temperature, rainfall and global radiation	A +2°C scenario will have a greater impact on crops harvested over the Mediterranean basin than on those harvested in central and northern Europe. While growing season temperatures are almost same in the northern part of Europe, there will be likely decline in rainfall and rise in temperature in the Southern part.
Lobell and Field (2007)	Statistical Model(First Difference Method, Multiple Linear Regression)	Rice, wheat, maize, soybean, barley and sorghum	Global scale	1961-2002	Yield and growing season temperature and rainfall	Simple measures of growing season temperatures and precipitation account for nearly 30% or more of year-to-year variations in global average yield six most widely cultivated crops across the world. There exists an obvious negative impact of global yields to increased temperatures for wheat, maize and barley.
Van Passel et al. (2014) FP-7 Project	Ricardian Analysis	No specific crops	Global scale (37.612 individual farms in Europe)	2007	Agricultural land value per hectare, seasonal temperature and precipitation, population density, mean elevation and distance from urban areas	Seasonal climate variables strongly affected current farmland values in those countries. The impact of climate change is not homogeneous but mixed across Europe. Another finding is that rise in spring temperature will have positive impact but increase in summer temperature will have negative effect on agricultural land value.
Yoji et al. (2014)	Statistical (Crop Growth model, Panel Data Analysis (Fixed Effect, Random Effect Estimation)	Rice	National scale (Japan)	1979-2009	Climate factors (flood data), rice production (TFP)	Climate change has positive impact in the northern part of Japan. In western regions, there will be a reduction in rice TFP.

Table 2-3: Previous Studies Related to Crop Models Based on Different Methods and Scales (continued)

Reference	Crop Model (Method)	Crop type	Area coverage	Study period	Used variables	Main result
Iglesias and Minguez (1997)	Process based (CERES crop simulation model)	Wheat and maize production	National scale (different regions of Spain)	1971-1990	Daily maximum and minimum temperatures, precipitation and hours of sunshine, solar radiation	Wheat yield increases significantly in some regions of Spain Wheat production shifts the northern parts of the present cultivated regions. There may be reduction in maize yield in the future due to water deficiency in the region.
McCarl et al. (2013)	Process based (Agricultural Sector Model of Egypt (ASME))	No specific crop, total agricultural production	National scale (Egypt)	Outputs of general circulation models, period of 2030-2060	Crop yield change, population, water use	Climate change will have a great impact on Egypt agriculture. Prices of agricultural commodities will rise.
Janjua et al. (2014)	Statistical (Time Series, ARDL Method)	Wheat	National scale (Pakistan)	1960-2009	Temperature, precipitation, CO2, water and wheat production	Climate change doesn't affect the wheat production in Pakistan in the short and long run. In the short run, wheat production and fertilizers have positive impact on wheat production which balanced the any negative climate shock on it.
Chen and Chang, (2005)	Statistical (Panel Data Analysis)	Taiwan's seven major field crops (rice, corn, soybeans, peanuts, adzuki beans, sweet potatoes and potatoes)	National scale (15 regions of Taiwan)	1977-1996	Temperature, precipitation, crop production	Crop insurance can balance revenues and protects farmers from climate shocks that they may suffer.

Table 2-3: Previous Studies Related to Crop Models Based on Different Methods and Scales (continued)

Reference	Crop Model (Method)	Crop type	Area coverage	Study period	Used variables	Main result
Gaál et al., (2014)	Statistical (Panel Data (Fixed Effect Model, Random Effect Model))	Maize, sunflower, potato, green peas and grapevines	National scale (Hungarian countries)	2001-2011	Harvested area, crop yield, net income per capita, amount of irrigated water, average temperature, precipitation, etc.	Irrigation is crucially important for green peas, maize and potato production
Kucharik and Serbin (2008)	Statistical (Multiple Regression Analysis)	Corn and soybean	National scale (USA-Wisconsin)	1976–2006	Temperature, precipitation, corn and soybean crop data	Crop productivity in northern part of the Corn Belt may be influenced negatively due to temperature during the summer growing season. One degree increase in temperature during summer months may bring about reduction in 13% and 16% for corn and soybean crop yields.
Eregha et al. (2014)	Statistical (Time Series Analysis, (Johansen Cointegration and Error Correction Model))	Beans, cassava, cocoa, groundnut, maize, millet, potato, rice, sorghum and yam	National scale (Nigeria)	1970-2009	Crop production, temperature, rainfall and CO2 emission data	Effect of climatic variables on crop production changes relying on the crop type of and seasonal properties and length of days of the crop.
Dellal et al. (2011)	Process Based Models (TARGEM)	Wheat, barley, corn, sunflower, and cotton	National scale (Turkey)	Future climate data from general circulation models	Temperature, rainfall and evapotranspiration	Crop yields alterations are negatively influenced by 3.8% to 10.1% in Turkey.

Table 2-3: Previous Studies Related to Crop Models Based on Different Methods and Scales (continued)

Reference	Crop Model (Method)	Crop type	Area coverage	Study period	Used variables	Main result
Amikuzino and Donkoh (2012)	Statistical (Pooled Panel Data (Johansen's Variance Autoregressive (VAR) Approach and Granger Causality Analysis))	Maize, millet, rice, sorghum, groundnuts and yam	Regional scale (Nothern Gana, six climatically-unique geographical locations)	1976-2010	Seasonal rainfall, seasonal temperature and yield	There exists strong evidence of cointegration between seasonal rainfall and crop yields There is causality from rainfall to crop yields in the Sudano-Guinea Savannah and Guinea Savannah zones of Northern Ghana.
Mishra (2015)	Ricardian Analysis and Panel Regression Model	Paddy, wheat, maize, millet, greengram, blackgram, horsegram, sesame, groundnut, mustard, potato and sugarcane	Regional scale (Odisha, a state at the east coast of India)	1993–2009	Temperature and rainfall, agricultural production	Climate has significant impact on the agricultural production in the east coast of the India. The future climate scenarios will have negative effect on the net revenue from agricultural production at the end of twenty-first century.
Mougou et al. (2014)	Statistical (Simple Regression Analysis)	Wheat and maize production	Regional scale (Tunisia, Kairouan region)	1980-2000	Temperature, precipitation and yield	Alterations in temperature and precipitation patterns with higher evapotranspiration rates may lead to decrease in wheat production and quality.

CHAPTER 3

DATA AND METHODOLOGY

In this section, the data and method employed for analyses are briefly explained. As stated in Figure 3-1, in the first step, agricultural vulnerability index is developed for by employing PCA. Then, countries are grouped by conducting cluster analysis based on index scores. In the second step, panel data analysis is applied to clusters for wheat, maize and potato crops in order to determine the impact of climate change in agriculture by using three estimators which are pooled mean group, mean group and dynamic fixed effect estimators.

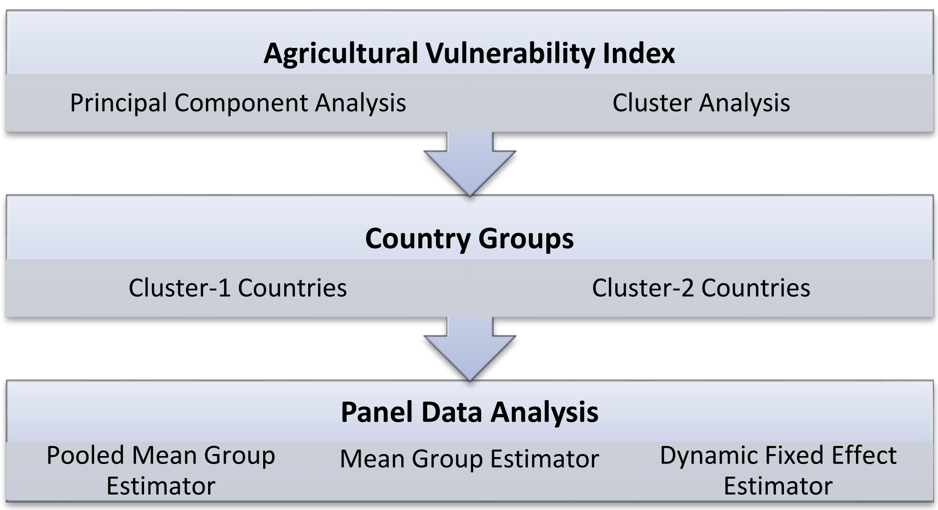

Figure 3-1: Framework for Methodology

3.1 Vulnerability Analysis

3.1.1 Data

An agricultural vulnerability composite index will be developed for 50 countries since they have a share of 90.8% of the world cereal production and were inhabited almost by 80% of the world population Table 3-1 reports the population and cereal production of each country. By using the data of the 50 countries around the world, we could determine the vulnerability of 20 Mediterranean countries [1] to climate change in agriculture and group them by cluster analysis. In this scope, with this analysis, we have the opportunity to compare Mediterranean countries with the other 30 countries having the highest cereal production.

The vulnerability has three major components; namely exposure, sensitivity, and adaptive capacity. Each of these components needs to be determined by a set of different indicators. Indicators are chosen from literature, however the final decisions are based on the data availability. While data related to exposure is mostly obtained from the International Disaster Database (EM-DAT), the data for the indicators of sensitivity and adaptive capacity components are sourced to the World Bank, Food and Agriculture Organization (FAO), AQUASTAT and World Fact Book of Central Intelligence Center (CIA). Some missing data are completed from different sources.[2][3][4] The list of indicators for each component and the data sources are presented in Table 3-2.

[1] Montenegro declared independence and separated from Serbia in 2006. However, in this study it is not taken into account as a separate country since the exposure component of the vulnerability is calculated for the period of 2000-2013.
[2] Data of GDP of Syria and Myanmar for 2012 are obtained from the website of https://data.un.org.
[3] Datum of improved water source of Libya for 2012 is obtained from the website of https://goo.gl/IsGp4b
[4] Datum of total renewable water resources per capita for Montenegro for 2012 is obtained from the website of https://goo.gl/htVpX7

Table 3-1: Cereal Production and Population of 50 Countries

Countries	Cereal Production	Population	Countries	Cereal Production	Population
Albania	697,400	2,900,489	***Kazakhstan***	12,788,049	16,791,425
Algeria	5,137,455	38,481,705	***Libya***	306,900	6,154,623
Argentina	43,389,294	41,086,927	***Lebanon***	188,695	4,424,888
Australia	43,371,698	22,728,300	***Malta***	18,200	419,455
Bangladesh	52,802,619	154,695,368	***Mexico***	33,615,012	120,847,477
Brazil	89,908,244	198,656,019	***Morocco***	5,311,130	32,521,143
Bosnia and Herzegovina	905,975	3,833,916	***Myanmar***	30,175,000	52,797,319
Cambodia	10,241,849	14,864,646	***Nigeria***	21,435,636	168,833,776
Canada	51,781,300	34,752,128	***Pakistan***	33,728,400	179,160,111
China	541,440,900	1,350,695,000	***Philippines***	25,440,136	96,706,764
Croatia	2,688,345	4,267,558	***Poland***	28,269,372	38,535,873
Cyprus	60,921	1,128,994	***Romania***	12,831,307	20,058,035
Denmark	9,485,400	5,591,572	***Russia***	68,762,551	143,178,000
Egypt	23,755,745	80,721,874	***Serbia***	5,934,015	7,199,077
Ethiopia	19,651,152	91,728,849	***Slovenia***	579,806	2,057,159
France	70,981,606	65,649,570	***South Africa***	14,266,240	52,341,695
Germany	45,396,500	80,425,823	***Spain***	16,981,441	46,773,055
Greece	4,288,269	11,092,771	***Syria***	4,599,397	22,399,254
Hungary	10,072586	9,920,362	***Thailand***	42,809,933	66,785,001
India	293,290,000	1,236,686,732	***Tunisia***	2,305,900	10,777,500
Indonesia	88,443,148	246,864,191	***Turkey***	33,371,844	73,997,128
Iran	22,010,000	76,424,443	***Ukraine***	45,739,700	45,593,300
Israel	323,445	7,910,500	***England***	19,515,000	63,700,300
Italy	19,039,442	59,539,717	***USA***	356,932,761	313,873,685
Japan	11,729,460	127,561,489	***Vietnam***	48466,766	88,772,900
Total 50 countries	2,325,265,944	5,642,907,886			
Total World	2,561,544,811	7,019,919,414			
Percentage (%)	**90.8**	**80.4**			

Table 3-2: Sources of the Data Used for Three Components of Vulnerability

Component	Indicators	Source
Exposure	# of Total Affected (2000-2013)	EM-DAT
	# of landslides (2000-2013)	EM-DAT
	# of floods (2000-2013)	EM-DAT
	Droughts, floods, extreme temp (% of population average (2000-2013)	World Bank
	# of droughts (2000-2013)	EM-DAT
	Total Damage (2000-2013)	EM-DAT
	# of storms (2000-2013)	EM-DAT
Sensitivity	Food Production index (2012)	World Bank
	Crop production index (2004-2006 = 100) (2012)	World Bank
	Agriculture, value added (% of GDP) (2012)	World Bank
	Cereal production (metric tons) (2012)	World Bank
	Land under cereal production (hectares) (2012)	World Bank
	Fertilizer consumption (kilograms per hectare of arable land) (2012)	World Bank
	Average precipitation in depth (mm per year) (2012)	FAO
	Forest area (% of land area) (2012)	World Bank
	Cereal yield (kg per hectare) (2012)	World Bank
Adaptive Capacity	GDP per capita (current US$) (2012)	World Bank
	Health expenditure, total (% of GDP) (2012)	World Bank
	Government effectiveness (2012)	World Bank
	Internet users (per 100 people) (2012)	World Bank
	Rural population (% of total population) (2012)	World Bank
	Access to electricity, rural (% of population) (2012)	World Bank
	Literacy rate, adult total (% of people ages 15 and above) (2012)	World Bank
	Improved water source, rural (% of rural population with access) (2012)	World Bank
	Improved sanitation facilities, rural (% of rural population with access) (2012)	World Bank
	Life expectancy at birth, total (years) (2012)	World Bank

3.1.2 Methodology

The framework for developing agricultural vulnerability index is given in Figure 3-2. In the first step, related indicators are selected from different sources. At the next, indicators are normalized since each one is measured in different scales. After determining the weight of the each indicator by applying principal component analysis (PCA), sub-indices for each component of vulnerability are created. At the final step, three sub-indices are combined in order to develop one single agricultural vulnerability index (CAVI).

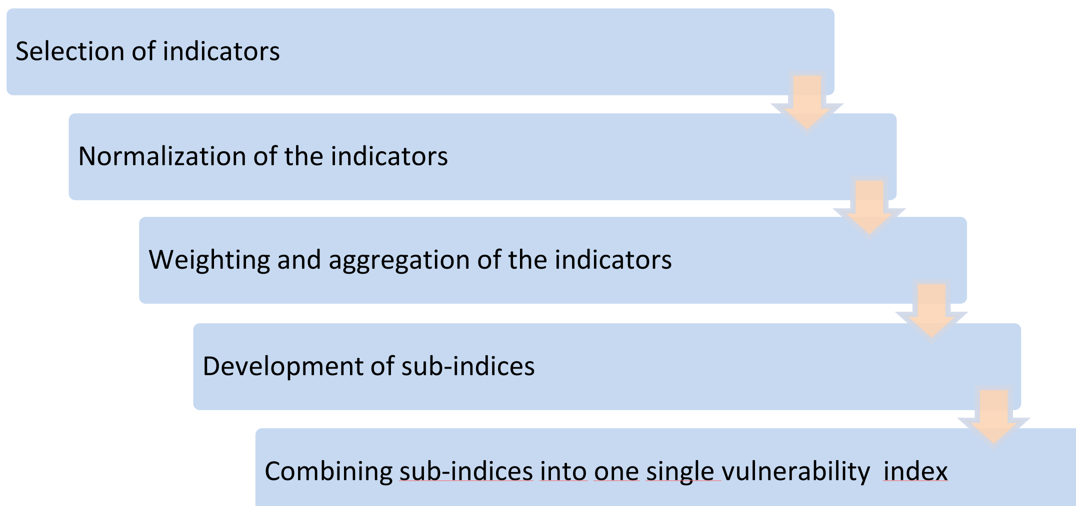

Figure 3-2: Framework for Developing Composite Agricultural Vulnerability Index (CAVI)

3.1.2.1 Construction of Composite Indices

Composite indicators are common performance evaluations of countries for comparing and ranking them, especially, in terms of energy, environmental, economic, social, and/or technological development. They provide researchers for reducing the size of indicator groups and making fast comparisons about relevant areas much easier and more reliable than the separate indicators measurements (Freudenberg, 2003). Moreover, composite indicators explain multi-dimensional issues briefly and help evaluating the progress of countries about complicated issues for future. However, the calculations of the composite index are very sensitive to errors; thus, they should have some properties such as being measurable, reliable, and hard to manipulate (Sumner, 2004).

When variables are aggregated into a composite index, they should be weighted according to some methods (Freudenberg, 2003). These methods can be classified into three parts; (i) equal weighting, (ii) weighting based on (expert) opinions, and (iii) weighting based on statistical models such as principal component analysis, factor analysis, data envelopment analysis, benefit-of-the-doubt approach and hybrid methods (Greyling, 2013). Equal weighting is the most frequently used method to weight composite indicators (Hagerty and Land, 2007). According to this method, all dimensions are equally important. However, if there is a high correlation among the variables identifying the same dimension, equal weighting method leads to double counting in the index (OECD, 2008). In the second method, the opinions of expert are related to development of an index by considering the expert's own judgment. However this approach has some disadvantages. For different experts, the weighting of different indices may change and it is difficult to find a weighting system that is approved by most of the policy makers and researchers (OECD, 2008). The final method is statistical approaches which are known as objective methods of weighting. Statistical methods can be used to cope with inadequacies arose from subjective computations of weighting indices encountered in the method of "weighting based on opinions". By using statistical methods, weights are determined according to information included in the data set (Greyling, 2013). The analyses in this dissertation are based on the third approach; hence the Principle Components Analyses and Cluster Analyses will be employed which are explained in detail in the following sections.

3.1.2.1.1 Description of Principal Component Analysis

Principal Component Analysis (PCA) is a variable reduction technique that maximizes the amount of variances accounted for the explanatory variables by using the smallest possible number of principal components (Nardo, Saisana, Saltelli, & Tarantola, 2005).

In fact, the main goal is to account for the variance of the explanatory data through a few linear combinations of the original data and evaluate the correlations among indicators (OECD, 2008; Hudrlikova, 2013). The raw correlated set of indicators is transformed into a new smaller set of uncorrelated variables. This method has been applied since the beginning of the century for different purposes. It was first defined by Karl Pearson in 1901. However, practical application was firstly done by Hotelling in 1933. After Hotelling's applications, the method has been used widely especially at the last quarter of the century (Nardo et al., 2005).

Before applying PCA, it is necessary to standardize indicators since each one is measured on a different scale or different units. By standardization, domination of the outliers in the data set and problems arising from poor data quality can be prevented (Freudenberg, 2003). There are several standardization methods such as ranking, standard deviation from the mean method, minimum-maximum method, distance from mean method and categorical scales methods. Each method has some advantages and disadvantages. For instance, standard deviation from the mean method changes indicators to a common scale, assuming normal distribution with a mean of zero and one standard deviation. If the data-set have extreme values, this will influence the composite indicator. However, this is not suitable when the aim is to emphasize the importance of exceptional behavior. In addition, minimum-maximum method is calculated by subtracting the minimum value from the indicator value, then dividing the outcome by the range of indicator values. Although outliers may create imperfections about transformed indicator, this method can enlarge the range of indicators found in a small interval. It leads to a higher impact on composite indicator than the standard deviation from the mean method (Nardo et al., 2005; OECD, 2008).

We use minimum-maximum method as explained below:

$$\text{Indicator}_{\text{standardized}} = \frac{\text{Indicator}_{\text{value}} - \text{Indicator}_{\text{minimum}}}{\text{Indicator}_{\text{maximum}} - \text{Indicator}_{\text{minimum}}} \quad (1)$$

Since adaptive capacity reduces vulnerability, its contribution to the index is negative. Therefore, inverse values, that is to say, 1- "indicator values", are calculated for most of the selected adaptive capacity indicators. This is also valid for some of the sensitivity indicators. Clearly; indicators, whose rising values have negative effect on agricultural vulnerability, are normalized as shown below:

$$\text{Indicator}_{\text{standardized}} = 1 - \frac{\text{Indicator}_{\text{value}} - \text{Indicator}_{\text{minimum}}}{\text{Indicator}_{\text{maximum}} - \text{Indicator}_{\text{minimum}}} \quad (2)$$

3.1.2.1.2 Stages of Principal Component Analysis

The *first* stage in applying PCA is confirmation of a sufficient correlation between the explanatory variables to conduct analysis. In fact, PCA requires that there should be some correlations greater than 0.3 between each two variables. In addition, Kaiser-Meyer-Olkin (KMO) measure and the Bartlett test of sphericity are two tests to determine the correlation between the variables. The KMO measure of sampling adequacy statistic is used for evaluating the magnitude of the observed correlation coefficients and magnitude of partial correlation coefficients (Tabachnick and Fidell, 2007). The value should be at least greater than 0.5 to obtain good result from PCA (Kaiser & Rice, 1974). Besides, the Bartlett Test of Sphericity is calculated to test the null hypothesis that the correlation matrix is an identity matrix (it is a matrix in which magnitude of all diagonal elements is 1 and magnitude of all off-diagonal elements is 0). If the test statistic is less than 0.05, it suggests that the significance level is small enough to reject the null hypothesis (Greyling, 2013). Furthermore, in the next stage of the analysis, communality of each indicator is calculated. It represents the proportion of the variance of each original indicators explained by extracted components. Any indicator which has lower communality value than 0.5 should be excluded from the analysis.

Determining the number of components to extract is the *second* stage of the PCA. The important point about this step is that extracted components should account for as much of the variance as possible in the main data set. Kaiser's criterion or the eigenvalue rule can be applied for the decision of number of components. The eigenvalue of each principal component represents the percentage of variation explained in the main data set. According to this rule, components having an eigenvalue of one or higher than one are selected. Furthermore, extracted principal components should account for higher than 50 % of overall variance as another option (Nicoletti et al., 1999; Greyling, 2013, Tabachnick & Fidell, 2007). Another technique to identify the number of components is to take the scree test into account. It is the graphical representation of incremental variance explained by each component. In fact, it reveals the combination of component number versus eigenvalues of each component. According to this method, it is important to determine the place in the graph where the scree plot starts to level off. While components that are found after the break should be excluded from the model, the ones before the level part should be retained (Cattell, 1966; Walker & Maddan, 2009). After specifying the number of components extracted, how much of each variable loads on the components will be calculated. Each component measures the correlation between the original indicator and the component (Nicoletti et al., 1999).

The *third* stage of the principal component analysis is related to rotation of the data which is applied to minimize the number of original indicators that have a high loading on the same component. In fact, it is a transformation of the factorial axes to get a simpler structure of the components which provides that each indicator is loaded with only one of the extracted components. This leads to obtain clear form of component loadings (OECD, 2008; Nicoletti et al., 1999; Greyling, 2013).

The rotation attempts to minimize the number of basic indicators that have a high loading on the same factor. It is a transformation of factorial axes that makes it possible to approximate a "simple structure" of the factors, in which each indicator is “loaded” exclusively on one of the retained factors. It enhances the interpretability of these factors. There are two methods of rotation which are “oblique” and “orthogonal solution”. The most common use of orthogonal rotation is Varimax procedure. If components are uncorrelated, it can be assumed that data is orthogonal. Thus, Varimax method can be chosen. However, if it is expected that components are correlated, oblique methods such as Direct Oblimin is preferred (Walker & Maddan, 2009; Field, 2005; Greyling, 2013; Tabachnick & Fidell, 2007). In this study, we prefer to use Varimax method.

3.1.2.1.3 Determination of Weighting Factors

Weights of each selected indicator for each three component of vulnerability are determined after the principle components are extracted. Then, intermediate agricultural vulnerability indicators (IAVI) related to each component is determined. A series of calculations are performed to determine the weighted aggregation of indicators. We have used the same methodology developed in Gomez-Limon and Riesgo (2008):

$$\mathrm{IAVI_J} = \sum_{k=1}^{n} \mathrm{w_{kj} I_k} \tag{3}$$

where, $\boldsymbol{IAVI_J}$ is intermediate agricultural vulnerability indicator, $\boldsymbol{w}$ is weight of indicator $\boldsymbol{I}$ is normalized indicator, $\boldsymbol{j}$ is number of principle component, and $\boldsymbol{k}$ is number of indicator.

The weights w_{kj} are derived from division of square of the factor loading to the related eigenvalue of each component:

$$w_{kj} = \frac{(\text{factor loading}_{\text{kj}})^2}{\text{eigenvalue}_{\text{j}}}$$

(4)

Sub-indices are obtained from weighted aggregation of the intermediate sustainability indicators by multiplying the related intermediate sustainability indicator by the percentage proportion of the eigenvalue of the related component:

$$\mathrm{I} = \sum_{\mathrm{j}=1}^{\mathrm{m}} \alpha_{\mathrm{j}} \mathrm{IAVI}_{\mathrm{J}} \qquad (5)$$

where, ***I*** is the value of subindex, ***j*** is the number of principle component, ***IAVI*** is intermediate agricultural vulnerability indicator, $\boldsymbol{\alpha}$ is weight applied to intermediate agricultural vulnerability indicator. This weight is calculated as below:

$$\alpha_{\mathrm{j}} = \frac{\text{eigenvalue}_{\mathrm{j}}}{\sum_{\mathrm{j}=1}^{\mathrm{m}} \text{eigenvalue}_{\mathrm{j}}} \qquad (6)$$

After the calculations of each sub-index to find the agricultural vulnerability of each 50 countries, it is essential to constitute a composite index that includes the vulnerability components, exposure, sensitivity, and adaptive capacity. Thus, agricultural vulnerability sub-indices are aggregated into one final composite agricultural vulnerability index (***CAVI***) (Gomez-Limon and Riesgo, 2008).

$$\mathrm{IAVI}_J = \sum_{k=1}^{n} w_{kj} I_k \tag{7}$$

where, $\boldsymbol{IAVI_J}$ is intermediate agricultural vulnerability sub index, ***w*** is weight of sub-index, ***I*** is the value of sub-index, ***j*** is the number of principle components, ***k*** is the number of sub-indices.

The weights w_{kj} are derived from division of square of the factor loading to the related eigenvalue of each component:

$$w_{kj} = \frac{(\text{factor loading}_{kj})^2}{\text{eigenvalue}_j}$$

(8)

Composite agricultural vulnerability index (***CAVI***) is obtained from weighted aggregation of the intermediate sustainability sub-indices by multiplying the related intermediate sustainability sub-index by the percentage proportion of the eigenvalue of the related component of agricultural vulnerability:

$$\mathrm{CAVI} = \sum_{j=1}^{m} \alpha_j \mathrm{IAVI}_J \tag{9}$$

where, ***CAVI*** is composite agricultural vulnerability index, ***j*** is number of principle component, ***IAVI*** is intermediate agricultural vulnerability sub-indices, $\boldsymbol{\alpha}$ is weight applied to intermediate vulnerability sub-indices.

This weight is calculated as below:

$$\alpha_j = \frac{\text{eigenvalue}_j}{\sum_{j=1}^{m} \text{eigenvalue}_j} \tag{10}$$

3.1.2.2 Cluster Analysis

Cluster analysis is a statistical tool to constitute groups that share similar characteristics (Manly, 2005). In this study, countries are classified according to value of their vulnerability index and the countries that have similar values are clustered into one group. While principal component analysis decreases the number of variables by grouping them into a smaller set of components, cluster analysis decreases the number of cases by grouping them into a smaller set of clusters.

There are three types of clustering methods; (i) hierarchical, (ii) nonhierarchical, and (iii) two step cluster analysis. Hierarchical method is the mostly used one. In this method, at first step, the number of clusters is the same with the number of variables/cases. Then, the most similar clusters are merged at successive steps and this continues recurrently until all cases gather in one main cluster. At successive steps, similar clusters are merged. Finally, optimum number of clusters is determined by examining all possible cluster choices (Everitt, et al., 2001). However, in non-hierarchical technique (k mean clustering), the number of clusters is decided before start of the analysis. This method is efficient when the aim is dividing the sample into k clusters, which provides the largest possible distinction, by analyzing the variance of each cluster. This procedure begins with k random clusters and brings the objects in and out of the clusters. The goal is reducing the variance of variables in the clusters and increasing the variance of the variables out of the cluster as much as possible (Nardo et al., 2005). In this dissertation, we prefer to use hierarchical method.

There are some methods to determine the distance between the clusters like nearest, farthest neighbor, unweighted pair-group average, weighted pair-group average and Ward's method. In nearest neighbor method, the distance between two closest cases in different clusters is taken into account. In Ward's method, clusters are identified according to variance of the cases. In fact, in this method, sum of the squared Euclidean distance in cluster is calculated and these distances are summed for all cases (Hair, et al., 2006). This distance method is the most commonly used measure of distance and it is the recommended measure for Ward's method of clustering.

The related equation of the squared Euclidean distance is given below:

$$D_{i,J} = \sum_{k=1}^{n} \left(X_{ik} - X_{Jk}\right)^2 \tag{11}$$

where, X_{ik} is the measurement of i^{th} cases for k^{th} variable, X_{Jk},is the measurement of J^{th} cases for k^{th} variable; n is the number of variables.

In this method, the combination which produces the lowest sum of squares is selected. The process of forming clusters generates a tree like diagram. It represents combination of clusters to produce complete range of cluster solutions. In the end, this method will generate a complete set of cluster solutions ranging from all single-member clusters to one cluster solution and provide an excellent framework since it will be possible to compare the set of cluster solutions (Hair, et al., 2006). Therefore, we prefer to use Ward's method.

While employing cluster analysis, it is essential to choose the best cluster solution. The process of clustering can be represented on a diagram called "dendogram". The dendogram portrays graphically how the clusters are combined at each step of the procedure until all are included in a single cluster. If there is big jump in the distance between clusters from one stage to another, joined clusters will be relatively close to each other at one stage while at the flowing stage they will be relatively far from each other. The stage that reveals the optimum number of cluster is just before the big jump in the distance (Manly, 2005).

3.2. Econometric Analysis

3.2.1 Data

3.2.1.1 Food Production Data

Agricultural crops are selected according to global distribution of area harvested data for 18 major crop types derived in Leff et al. (2004). Among 18 major crops, we choose three mostly cultivated crops in Southern Europe and Northern Africa which are wheat, maize and potato based on data obtained from FAO, 2012. Area harvested (in hectares, Ha) and production (tonnes) data are used to calculate the yield (tonnes/Ha) for each crop for Mediterranean countries from the period of 1992 to 2013. In this scope, we prefer to use the area harvested (in hectares, Ha) and yield (tonnes/Ha) data in econometric models.

3.2.1.2 Weather Data

For each country gridded monthly temperature and precipitation data (0.5° degree resolution, 55*55 kilometers) obtained from Climate Research Unit (CRU) of the University of East Anglia dataset for the period of 1992-2013 are used. The average annual temperature and precipitation data is calculated from monthly data for each grid of countries. Grids are selected according to crop growing areas determined by using satellite-derived land cover data (Leff et al, 2004). Therefore, only relevant weather data related to area where crop is grown are taken into account. Deserts, lakes or area that is not allocated to cultivation of related crop are not considered. The crop data are also gridded at 0.5° degree resolution and each grid cell represents the fraction of area where related crop is cultivated. Weather data are weighted by regarding proportion of area harvested to total area within the cell for each crop. For example, an imaginary country is composed of 3 gridded cells as shown below. Area harvested data (%) for a crop and temperature data that belong to grids are given in the Table 3-5 and Table 3-6.

Table 3-3: Area Harvested (%) Data for Crop

Grid #1	Grid #2	Grid #3
20%	40%	60%

Table 3-4: Temperature (°C) for Crop

Grid #1	Grid #2	Grid #3
10°C	15°C	20°C

Average temperature data is calculated as (0.2*10+0.4*15+0.6*20)/(0.2+0,4+0,6) = 16.7 °C. So, the average temperature is 16.7 °C for that country where that crop is cultivated. Same procedure is also applied for precipitation data for each country having different grid numbers. Since arranging data based on procedure given above is labor intensive work and requires attention, a software program is written in Visual Basic to compute reliable final country temperature and precipitation average data from monthly data for each country and crop.

In the study, we prefer to use yield and area harvested data in their log form in order to homogenize the variances. However, we use climate data (temperature and precipitation) in their level form; that is to say, they are not logged in order to generate semi-elasticities as in Blanc, 2012; Quiroga and Iglesias, 2009. The semi-log transformation, widely used in economic and climate change studies, develops the distribution of variables by decreasing the presence of outlying data and removing the effect of the unit of account on the coefficient estimates. It helps the comparison of the effect of different variables. What is more, a log transformation makes the parameters more easily interpretable since it generates constant elasticities of the dependent variable with respect to each independent variable. In other words, the proportional change over the dependent variable is determined when a unit change has been generated over the independent variable. In identifying the responses of climate change on crop yield, semi-elasticities enable us to interpret more simply than elasticities since they provide us with direct identification of the effect of, “1ºC increase in temperature” (Gaál et al., 2014). In this study, inverse of the natural logarithm of the coefficients are taken in order to measure the impact of increase in temperature and precipitation by one unit.

We do not include some explanatory variables such as maximum and minimum temperature, the number of wet days and cloud cover in order to focus on the major determinants of agricultural production. Fertilizer effect, soil related parameters and mechanization parameters are not considered due to technical difficulties and data limitations. Solar radiation is also excluded due to correlation of it with other weather parameters such as temperature. This makes difficult to investigate the specific effect of sunlight on crops (Evans, 1996). In addition, we do not incorporate the evapotranspiration due its larger collinearity with the temperature. In addition, at the beginning of the study we prefer to include flood and drought variables into the model. They are calculated by standardized precipitation index and according to their occurrence in a year, dummy variables are added. However, while computing the models, multi-collinearity with precipitation is determined. Therefore, they are removed from the all analyses. Another point is that the study considered the crop zones in Mediterranean Basin defined by Leff et al. (2004) which represent the areas of the early 1990’s. Thus, we do not take into account the possible migration of crop zones by farmers.

3.2.2 Methodology

For the econometric analysis part, we firstly conduct first generation panel unit root tests (The Levin and Lin-Chu Test, The Im-Pesaran-Shin test and the Fisher-type tests of using ADF and PP tests) to determine the stationary of the data. Then, we check whether there is a cross-sectional dependence (CD) among the variables or not, by four test groups which are Breusch-Pagan LM test, Pesaran scaled LM test, Baltagi, Feng, and Kao bias-corrected scaled LM test and finally Pesaran CD test. After applying these tests, if there exists cross-section dependence among the variables under consideration, we employ Pesaran's cross-sectionally augmented ADF (CADF) test to determine the order of integration for all variables. Then, based on results, we proceed with panel data analysis with three different estimators which are pooled mean group estimator (PMG), mean group estimator (MG) and dynamic fixed effect estimator (DFE) to identify the short run and long run relationships among the variables considered. As a result, we are able to interpret the future impact of temperature and precipitation on each crop yield in the short and long term.

Although Johansen (1995) pointed out that long run relationships exist only in the case of the cointegration across variables having the same order of integration, an important point related to methodology set we conduct in the dissertation is that, Pesaran and Shin (1999) stated that panel ARDL method can be conducted with variables having different order of integration regardless of the variables under consideration are I(0) or I(1) as long as they do not exceed I(1). Note that I(2) variables are not allowed to include in panel ARDL analysis. Therefore, we do not employ standard panel data cointegration tests such as Pedroni's test or Kao's test which require the same order of integration. Instead, we determine the existence of long run relationship by taking into account the error correction coefficient obtained from the estimators. To sum up, details of the methods briefly mentioned above are explained in the following sections.

3.2.2.1 Data Stationarity (Unit Root Tests)

In panel data econometrics, before estimating the model, it is essential to determine whether the data are stationary or not. If a series is not stationary in level, first difference of it is calculated to make it stationary. If satisfied, it is said to be integrated of order d, or I(d) in which d is the number times that the series should be differenced to become stationary. There are several panel unit root tests to identify whether the main data have unit root or not. These are Levin-Lin-Chu (Levin et al., 2002) test, Harris Tzavalis (HT) test (Harris and Tzavalis, 1999), the Im-Pesaran-Shin (IPS) test (Im et al., 2003) the Fisher-type tests of Maddala and Wu (Maddala and Wu, 1999) test, Hadri residual-based

LM test (Hadri, 2000). These tests are called “First generation panel unit root tests” in the econometrics literature and based on the assumption of cross-sectional independence. Use of the first generation tests in the presence of cross-sectional dependence may cause over-rejection of the null hypothesis (O’Connell, 1998).

Therefore, it is needed to determine whether cross-sectional dependence problem exists or not. Therefore, Breusch-Pagan (1980) LM test, Pesaran (2004) scaled LM test, Baltagi, Feng, and Kao (2011) bias-corrected scaled LM test and Pesaran (2004) CD Pesaran (2004) are applied to data. For these tests, the null hypothesis is that there exists no cross-sectional dependence. If it is concluded that cross-sectional dependence problem exists, one of the second generation panel unit root test, Pesaran (2007)’s CADF unit root test can be preferred to use. It describes a very simple procedure to explain cross-sectional dependency in panel unit root tests (Pesaran, 2007).

Four types of first generation unit root tests are used in this dissertation.

3.2.2.1.1 The Levin and Lin-Chu Test:

The Levin and Lin-Chu Test (Levin et al., 2002) is based on three-step procedure. In the first step, ADF regressions for each cross-section are employed. Estimation of the ratio of long-run to short-run standard deviations is the second step of the test. In the third step, panel test statistics are calculated by running pooled regression (Baltagi, 2008). This test is valid under cross-sectional independence.

For The Levin and Lin-Chu panel unit root test, the following general model is considered (Asteriou and Hall, 2011):

$$\Delta Y_{it} = a_i + \rho Y_{i,t-1} + \sum_{k=1}^{n} \emptyset_k \Delta Y_{i,t-k} + \delta_i t + \theta_t + \mu_{it} \tag{12}$$

where, $\boldsymbol{n}$ is number of lags, $\boldsymbol{i}$ denotes cross section, $\boldsymbol{t}$ represents time, $\boldsymbol{Y}$ is the variable being tested, $\boldsymbol{\theta}$ is deterministic component.

The model above allows for two way fixed effects, one is coming from $\boldsymbol{a_i}$, the second is coming from θ_t. The null and alternative hypotheses of this test are reported below;

H_0 : ρ=0 (null hypothesis is that all panel contains unit roots)
H_a : ρ<0 (alternative hypothesis is that panels are stationary)

3.2.2.1.2 The Im, Pesaran and Shin (IPS) Test:

Im et al., (1997) extended the Levin and Lin (LL) test, providing heterogeneity on the coefficient of the Y_{it} variable. They suggest a basic testing procedure based on the average of the individual unit root test statistics (Asteriou and Hall, 2011). The IPS test can be used in relation with any parametric unit-root test as long as the panel is balanced and all the t-statistics for the unit-root in every cross section are identically distributed; so that they have the same variance and mean (Hoang and McNown, 2006).

The following general model is considered for IPS unit root test (Asteriou and Hall, 2011):

$$\Delta Y_{it} = a_i + \rho Y_{i,t-1} + \sum_{k=1}^{n} \emptyset_{ik} \Delta Y_{i,t-k} + \delta_i t + \theta_t + \mu_{it} \tag{13}$$

where, n is number of lags, i denotes cross section, t represents time, Y is the variable being tested, θ is deterministic component.

The null and alternative hypotheses of this test are reported below;

H_0 : ρ=0 for all i (null hypothesis is that all series are non-stationary)

H_a : ρ<0 for at least one i (alternative hypothesis is that some of the series are assumed to be stationary)

3.2.2.1.3 The Maddala and Wu (MW) Test:

Maddala and Wu (1999) suggested the use of the Fisher test which is based on combining the p-values of the test-statistic for a unit root in each cross section unit. This test can be conducted with any unit root test on a single time-series. It is important that the MW test does not require using the same unit-root test in each cross section. Another remarkable feature of this test is that it does not require a balanced panel as the other tests like IPS test so time period can change over cross sections (Hoang and McNown, 2006). The null and alternative hypotheses are the same as in the IPS test.

The following general model is considered for MW unit root test (Asteriou and Hall, 2011):

$$\pi = -2\sum_{i=1}^{N} ln\pi_i \qquad (14)$$

where, $\boldsymbol{\pi_i}$ is the probability limit values from regular DF panel unit root tests for each individual, $\boldsymbol{i}$ denotes the cross section.

3.2.2.2 Cross-sectional Independence:

There is an opinion in panel data literature that large cross-sectional dependence is likely emerged in panel data sets. This problem has arisen from the existence of common shocks and unobserved components which become part of the error term and spatial dependence. Pair-wise dependence found in the disturbances without particular pattern of common components or spatial dependence is another reason causes cross-sectional dependence. Much of the recent studies have focused on this problem (Robertson and Symons, 2000; Pesaran, 2004; Baltagi, 2005). Presence of cross-sectional correlations is identified by cross-sectional independence test. The Breusch-Pagan test is conducted in which null hypothesis of cross-sectional independence is tested (Greene, 2008). The problem related to this test is that when the number of cross sections is larger than the number of period, it cannot be applied. In this situation, there are also other tests developed to determine cross-sectional dependence. These tests are Pesaran (2004) scaled LM test, Baltagi, Feng, and Kao (2012) bias-corrected scaled LM test and finally Pesaran (2004) CD test. In these tests, null hypothesis is no cross section dependence (correlation) in residual. When the null hypothesis of cross-sectional independence is rejected, it is concluded that error terms are not independent among countries.

3.2.2.2.1 Cross-Sectionally Augmented ADF (CADF) Test:

First generation panel unit root tests may over-reject the null hypothesis of presence for unit root excessively if there exists of cross-section dependence among variables. In this case, CADF test is suggested by Pesaran (2007). The test is associated to the mean of individual ADF t-statistic of each unit in the panel. It removes the cross sectional dependence by augmenting the ADF regression with the lagged individual mean and its first differences of the individual series (CADF statistics) to hold cross sectional dependence by a single factor model (Burret et al., 2014). In this test, lag can be determined by using Newey and West's (1994) plug-in procedure at $(4*(T/100)^{2/9})$, as also stated in the study done by Hoechle (2007).

3.2.2.3 Panel Data Analysis

Panel data has become commonly used among researchers because it allows the inclusion of data for N cross sections such as countries, firms and T time periods such as years and months. The combined panel data matrix set includes time series for each cross-sectional member in the data set. Furthermore, the main idea behind panel data analysis stem from the notion that the individual relationship have same parameters like pooling assumption. In fact, all individuals are pooled into one set and common set of parameters is created. When this assumption is verified, then, panel data estimation has advantages like attainment of better estimates by means of increase in sample size. However, if it is not verified, there may be some problems since in this case, parameters vary among the individuals. This kind of data set is known as heterogeneous panel (Asteriou and Hall, 2011).

Some of the advantages of panel data are listed below (Hsiao, 2014; Baltagi, 2008):

- ✓ Large number of data is used in panel data.
- ✓ It provides more degrees of freedom than time series or cross section analysis.
- ✓ It decreases the collinearity among the independent variables so it develops the efficiency of the econometric estimates.
- ✓ It has ability to control for individual heterogeneity and time effects that cannot be determined by time series or cross-sectional data.
- ✓ Panel data give information about time-ordering of events.
- ✓ It enables to control for variables that cannot be observed or measured.

Panel data has also some disadvantages in spite of the many advantages explained above. These are related to problems of data collection and measurement errors as well as cross-sectional dependence, serial correlation and limited time series dimension (Baltagi, 2008).

There are different types of models based on structural heterogeneity. These models can be classified into two groups which are static and dynamic models. While static models such as fixed effect and random effect models impose homogeneity in the slope coefficients of the models, dynamic models do not restrict the slope parameters, that is to say, allow coefficients vary across individuals (Samargandi et al., 2013).

Static Models

The ordinary panel models such as pooled ordinary least square (OLS), fixed effects and random effects models have some deficiencies or disadvantages. Pooled OLS is limited model that does not allow intercept and slope coefficients to vary across cross sections, thus ignores individual heterogeneity. Moreover, fixed effect model investigates group differences in intercepts. It allows the individual-specific effects to be correlated with independent variables. In fact, each individual (group or entity) has different intercept term and the same slope parameters with constant variance (Park, 2011). However, this approach encounters with several problems due to the loss of degrees of freedom (Baltagi, 2008). Another important point related to this estimator is that parameter estimates obtained can be biased when some independent variables are endogenous and correlated with error term (Campos et al., 2008). In random effects model, the variation across individuals is assumed to be random unlike the fixed effect model. This model assumes that individual-specific effect (heterogeneity) is not correlated with any independent variable and it is has composite error term. In fact, each individual has the same slope parameters and a composite error term (Park, 2011). However, the random effects model has a limitation that it takes into account the model to be time invariant. This indicates that error at any term is uncorrelated with the past and future (Arellano, 2003). However, this circumstance may not be valid in reality. Besides, for standard panel data models, there exists a homogeneity for the coefficients of lagged dependent variables which leads to serious bias when there is heterogeneity between the cross section (Holly and Raissi, 2009).

To sum up, static panel estimators can not hold the dynamic nature of the data which is a principal issue in climate change studies, particularly researches related to crop yield analyses.

Dynamic Models

A dynamic model is characterized by the existence of lagged dependent variable among the repressors (Asteriou and Hall, 2011). When the data is composed of large number of cross sections relative to time period (N>T), two estimators are proposed by Arellano and Bond (1991) and by Arellano and Bover (1995). They are referred to as Generalized Method of Moments (GMM) estimators. However, Roodman (2006) pointed out that, GMM estimators may provide spurious results for small cross sections and large time period since due to unreliable autocorrelation test (Arrelano-Bond estimator is based on the assumption that there does not exist second-order serial correlation in the residuals). Therefore, it may not be possible to obtain efficient and consistent results. As Christopoulos and Tsionas (2004) stated, GMM only holds the short run dynamics and these models may not produce nonspurious long run relationships. When the coefficients of the variables are not identical, GMM approaches generate incoherent and incorrect results (Pesaran and Smith, 1995; Pesaran and Shin, 1999).

To sum up, since we have doubts about reliability and consistency of the estimators mentioned above, we prefer to choose panel ARDL model in this dissertation. In the following part, panel ARDL approach and the methodology dealing with the heterogeneous dynamic panels are explained.

3.2.2.3.1 Panel ARDL Model

Dynamic heterogeneous panel regression model can be converted into the error correction model using the autoregressive distributed lag ARDL (p,q) (p denotes the lag of the dependent variable, q denotes the lags of independent variables) technique (Asteriou and Hall, 2011).

Unrestricted specification of ARDL model is given as follows:

$$Y_{it} = \sum_{j=1}^{p} \gamma_{ij} Y_{i,t-j} \sum_{j=0}^{q} \delta_{ij} X_{i,t-j} + \mu_i + \varepsilon_{it} \tag{15}$$

Vector error correction model representation of equation above is given by;

$$\Delta(Y_i)_t = \sum_{j=1}^{p=1} \gamma_j^i \, \Delta(Y_i)_{t-j} + \sum_{j=0}^{q=1} \delta_j^i \, \Delta(X_i)_{t-j} + \varphi^i \left[(Y_i)_{t-1} - \left\{ \beta_0^i + \beta_1^i (X_i)_{t-1} \right\} \right] \in_{it}$$

(16)

Where, $\boldsymbol{Y}$ is logarithm of yield, $\boldsymbol{X}$ is set of independent variables including temperature, precipitation and logarithm of area harvested, $\boldsymbol{\gamma}$ is a short run coefficient of lagged dependent variable, $\boldsymbol{\delta}$ is a short run coefficient of the lagged independent variable which are temperature, precipitation and logarithm of area harvested, $\boldsymbol{\beta}$ is long run coefficients of independent variables; $\boldsymbol{\varphi}$ is an error correction coefficient (the coefficient of speed of adjustment), **i** and **t** represents the country and time, respectively. The term in the square brackets includes the long run regression.

Equation 16 can be estimated by three different estimators which are the mean grouped estimator (MG) (Pesaran and Smith, 1995), the pooled mean group estimator (PMG) (Pesaran et al., 1999) and the dynamic fixed effects estimator (DFE). These approaches are proposed to resolve the bias due to heterogeneous slopes in dynamic panels. All estimators require the selection of the proper lag lengths for the individual cross section equations using one of the criterion methods, i.e., Akaike Information Criterion (AIC), Schwarz Bayesian Criterion (SBC), and Hannan-Quinn Criterion (HQ).

Furthermore, the error correction coefficient (speed of adjustment coefficient) defined in the models (Equation 16) reveals the adjustment speed to hold equilibrium in the dynamic model. The speed of adjustment coefficient indicates how quickly variables converge or diverge to equilibrium. In order to have a valid, consistent and efficient model, error correction term should be negative (not lower than -2) and statistically significant (Hoang and Barker, 2012). Highly significant error correction coefficient is an indication of existence of a stable long-run relationship. Another important point for the consistency of the panel ARDL model is that residual of the error-correction model should be serially uncorrelated and independent variables can be placed as exogenous. These circumstances can be performed by involving the lags of dependent and independent variables in ARDL model as error correction representation (Samargandi et al., 2014).

3.2.2.3.1.1 Mean Group Estimator (MG)

The mean group estimator (MG) allows all slope coefficients and error variances to vary across cross sections, providing considerable heterogeneity. The MG approach employs an OLS method to estimate separate regression for each cross sections to obtain individual slope coefficients. Then, the country-specific coefficients are averaged to produce a long-run parameter for the panel model (Huang and Barker, 2012). MG estimator is consistent for large time period and cross sections (Pesaran et al., 1999). Nevertheless, MG approach may not produce efficient results for small cross sections and small time period (Hsiao et al., 1999). Besides, the error correction coefficient estimate for MG approach may be exposed to downward lagged dependent variable bias (Pesaran et al., 1999).

3.2.2.3.1.2 Pooled Mean Group Estimator (PMG)

The pooled mean group approach (PMG) is an intermediate estimator between the MG method, in which both slopes and intercepts are allowed to vary across cross sections, and standard fixed effect model in which slopes do not change but intercepts are allowed to differ. In PMG approach, long run coefficients are restricted to be unchanged across cross sections. However, the short run coefficients, intercepts, the speed of adjustment terms and error variances are allowed to differ (Asteriou and Hall, 2011).

3.2.2.3.1.3 Dynamic Fixed Effects Estimator (DFE)

The dynamic fixed effects estimator (DFE) and PMG estimator have similar properties in that they constraint the slope coefficient and error variances to be equal across cross sections in the long run. However, DFE also constraints the error correction coefficient and short run coefficients, that is to say, they are equal for different cross sections. Furthermore, DFE only allows intercepts to vary. Baltagi et al. (2000) stated that DFE model is exposed to simultaneous equation bias because of the endogeneity between the error term and the lagged dependent variable when the number of cross section is in small size. Furthermore, as also valid for PMG and MG estimators, DFE estimator is computed by maximum likelihood estimations (Asteriou and Hall, 2011).

CHAPTER 4

RESULTS

In this chapter, the results of Principal Component Analysis (PCA), Cluster Analysis (CA) and Econometric Analysis are reported.

4.1 Results of Principal Component Analysis (PCA) and Cluster Analysis (CA)

In this part, the results of the vulnerability analysis are reported. As mentioned in Data and Methodology part of the dissertation, different indicators related to agriculture and food security are obtained based on three components of vulnerability. After normalizing all indicators that have been measured at different scale, principal component analysis is employed in order to identify the weights of the indicators. Then, the methodology given in the study of Gomez-Limon and Riesgo (2008) is applied. The results of the composite index for all 50 countries are presented in Table 4-2. For each three components of vulnerability Index; Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMSA), final communality values, component loadings, and weight of the indicators are reported. Some of the indicators related to each three components (exposure, sensitivity and adaptive capacity) of vulnerability are excluded from the analysis since they do not meet the requirements of the PCA. Then, the analyses have been recomputed until the requirements are satisfied[5].

For the exposure part of the index, as mentioned in Chapter 3, the first stage in applying PCA is to confirm that there is a sufficient correlation between the explanatory variables to conduct analysis. It is seen from the Table 4-1 that there are correlations among the variables in medium level. The "*extreme temperatures*" indicator is excluded from the analysis since KMSA value of the indicator is smaller than 0.5. Then, the KMSA test is repeated. According to new results, since all

[5] We do not report the outcomes of the repeated analyses; however they are available upon request. We only include the final PCA results.

KMSA variable values are larger than 0.5, this rule is satisfied at this round. In addition, as is seen from the Table 4-2, the overall KMSA for the set of indictors of exposure is 0.723, which exceeds the minimum requirement of 0.50 for overall KMSA. In the next stage of the analysis, communalities of each value, which represents the proportion of the variance of the original indicators explained by extracted factors, are calculated. The values should be 0.5 or higher. Since the value belonging to "*total death*" indicator is less than 0.5, it is also excluded from the analysis. Moreover, the Principal Component Analysis requires that the probability related with Bartlett's Test of Sphericity should be less than the level of significance. As reported in Table 4-3, the probability associated with the Bartlett Test is less than 0.001 which satisfies the requirement. After these tests, the number of components to extract should be determined and the rule suggests that the components having an eigenvalue of one or higher should be selected.

Table 4-1: Correlation Matrix for Indicators Determining the Exposure Component of Vulnerability

	Flood	**Storm**	**Landslide**	**Drought**	**Total Death**	**Extreme events (% of population affected**	**Total Damage**
Flood	1.000						
Storm	0.641	1.000					
Landslide	0.804	0.395	1.000				
Drought	0.689	0.577	0.600	1.000			
Total Death	0.159	0.080	0.156	0.057	1.000		
Extreme events* (% of population affected)	0.580	0.456	0.484	0.594	0.077	1.000	
Total Damage	0.428	0.839	0.200	0.523	0.018	0.149	1.000

Note: *Extreme events refer to droughts, floods, extreme temp occurred between 2000-2013 period.

Table 4-2: PCA Results and Weight of Indicators Based on PCA

Component	Kaiser-Meyer-Olkin measure (KMSA)	Indicators	Communalities	Loading on component-1	Loading on component-2	Loading on component-3	Weight of the indicators
Exposure	0.723	# of Total Affected (2000-2013)	0.813	**0.879**	0.200	—	0.153
		# of landslides (2000-2013)	0.762	**0.868**	0.093	—	0.149
		# of floods (2000-2013)	0.816	**0.819**	0.381	—	0.133
		Droughts, floods, extreme temp (% of population average (2000-2013)	0.588	**0.757**	0.120	—	0.113
		# of droughts (2000-2013)	0.748	**0.748**	0.453	—	0.111
		Total Damage (2000-2013)	0.958	0.088	**0.975**	—	0.188
		# of storms (2000-2013)	0.905	0.362	**0.880**	—	0.153
Sensitivity	0.586	Food Production index (2012)	0.887	**0.93**	0.138	-0.053	0.141
		Crop production index (2004-2006 = 100) (2012)	0.825	**0.899**	0.123	-0.036	0.133
		Agriculture, value added (% of GDP) (2012)	0.674	**0.817**	-0.075	-0.032	0.109
		Cereal production (metric tons) (2012)	0.936	0.091	**0.962**	-0.054	0.151
		Land under cereal production (hectares) (2012)	0.870	0.195	**0.910**	0.067	0.135
		Fertilizer consumption (kilograms per hectare of arable land) (2012)	0.583	0.33	**-0.553**	0.410	0.050
		Average precipitation in depth (mm per year) (2012)	0.785	-0.385	0.065	**0.796**	0.103
		Forest area (% of land area) (2012)	0.617	-0.073	0.026	**0.782**	0.099
		Cereal yield (kg per hectare) (2012)	0.698	-0.333	0.311	**-0.700**	0.080
Adaptive Capacity	**0.911**	GDP per capita (current US$) (2012)	0.856	**0.894**	0.241	—	0.125
		Health expenditure, total (% of GDP) (2012)	0.778	**0.845**	0.252	—	0.112
		Government effectiveness (2012)	0.814	**0.839**	0.332	—	0.110
		Internet users (per 100 people) (2012)	0.865	**0.79**	0.492	—	0.098
		Rural population (% of total population) (2012)	0.628	**0.633**	0.477	—	0.063
		Access to electricity, rural (% of population) (2012)	0.776	0.242	**0.847**	—	0.112
		Literacy rate, adult total (% of people ages 15 and above) (2012)	0.745	0.256	**0.824**	—	0.107
		Improved water source, rural (% of rural population with access) (2012)	0.750	0.324	**0.803**	—	0.101
		Improved sanitation facilities, rural (% of rural population with access) (2012)	0.757	0.367	**0.789**	—	0.090
		Life expectancy at birth, total (years) (2012)	0.726	0.516	**0.678**	—	0.072
Vulnerability Index	0.506	Exposure sub-index	—	—	—	—	0.447
		Sensitivity sub-index					0.320
		Adaptive capacity sub-index					0.232

Table 4-3: KMO and Bartlett's Test for Exposure Component of Vulnerability

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0,723
	Approx. Chi-Square	275,719
Bartlett's Test of Sphericity	df	21
	Sig.	0,000

Table 4-4: Total Variance Explained for Exposure Component

Component	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	**4.356**	62.235	62.235	**3.469**	49.557	49.557
2	**1.249**	17.848	**80.083**	**2.137**	30.526	**80.083**
3	0.577	8.237	88.320			
4	0.421	6.015	94.335			
5	0.182	2.598	96.933			
6	0.144	2.062	98.995			
7	0.070	1.005	100.000			

A close inspection of Table 4-4 indicates that there are two components to be extracted from these variables, because only two components have a value of eigenvalue greater than 1. As explained before, examining scree plot is another way of deciding on number of components that should be retained in the analysis. The scree plot test given in Figure 4-1 shows that curve begins to tail off after two components, conforming the first method. After specifying the number of components to extract, the next step is the rotation of the data to minimize the number of original indicators that have a high loading on the same component. Varimax rotation method is carried out for the purpose. Component loadings which are determined from rotated component matrix are given in Table 4-2. While five variables (*number of total affected people*; *number of landslides*; *number of droughts, number of floods*; *droughts, floods, extreme temperatures, % of population average (2000-2013) affected*) load on the first component, two variables (*number of storms, total damage*) load only on the second component. Thus, it reveals a clear form of component loadings.

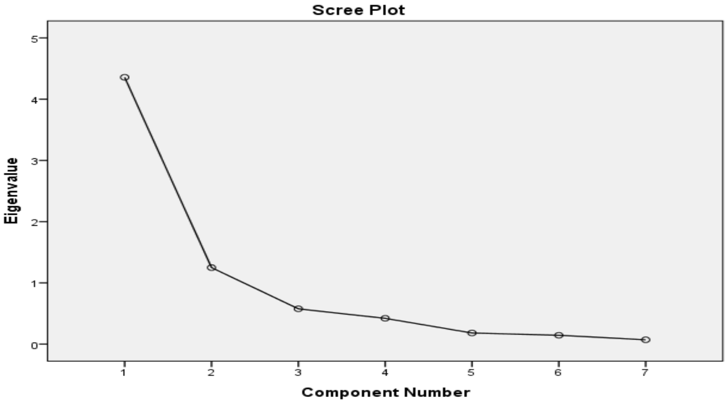

Figure 4-1: Scree Plot Test for Indicators Related to Exposure Component of Vulnerability

For the sensitivity part of the vulnerability, correlation matrix of selected indicators is reported in Table A-1 in Appendix. It is seen that there exists sufficient correlation among the variables. Thirteen indicators are selected firstly and for each indicator KMSA values are examined. It is realized that there are four indicators which have KMSA value smaller than 0.5. These are "*Arable land (% land area)*", "*Agricultural land (% of land area)*", "*Arable land (hectares per person)" and* "*Total renewable water resources per capita actual) (m3/inhab/yr)*" indicators which should be removed from the PCA analysis. As is seen from the Table 4-2, communality value of all variables is larger than 0.5 which is a precondition before deciding to number of components to be extracted. The overall KMSA is 0.586. The Bartlett Test of Sphericity is smaller than 0.001 which is suitable for the requirement as reported in Table A-2 in Appendix. Results of the total variance explained for sensitivity component are given in Table 4-5. There are three components which have eigenvalues higher than 1 and these components account for almost 76 % of the total variance.

Table 4-5: Total Variance Explained for Sensitivity Component

Component	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	**2.829**	31.438	31.438	**2.760**	30.669	30.669
2	**2.387**	26.523	57.961	**2.200**	24.447	55.116
3	**1.659**	18.430	**76.392**	**1.915**	21.276	**76.392**
4	0.906	10.070	86.462			
5	0.528	5.872	92.334			
6	0.312	3.468	95.801			
7	0.270	3.001	98.802			
8	0.058	0.645	99.447			
9	0.050	0.553	100.000			

The next stage is related to rotated component matrix which is obtained from Varimax method. According to results given in Table 4-2, three variables (*Food Production index; Crop production index; Agriculture, value added (% of GDP))* loads on the first component, three other variables; (*Cereal production (metric tons), Land under cereal production (hectares), Fertilizer consumption (kilograms per hectare of arable land*)) load on the second component, the last three variables (*average precipitation in depth (mm per year), Cereal yield (kg per hectare), Forest area (% of land area)*) have a loading on the third component. To sum up, there are three groups of variables; each group is loading on three different components.

The PCA results for adaptive capacity are reported in Table 4-6. There is sufficient correlation among the variables as seen in Table A-3 in Appendix. Based on the KMSA tests, the *population density* and *unemployment total (% of total labor force)* indicators are excluded from analysis. The overall KMSA value is 0.911, the value of the Bartlett Test is less than 0.001 as reported in Table A-4 in Appendix.

Table 4-6: Total Variance Explained for Adaptive Capacity Component

Component	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	**6.559**	65.593	65.593	**3.870**	38.699	38.699
2	**1.135**	11.351	**76.944**	**3.825**	38.245	**76.944**
3	0.505	5.052	81.996			
4	0.422	4.216	86.212			
5	0.361	3.613	89.825			
6	0.290	2.900	92.726			
7	0.250	2.497	95.223			
8	0.218	2.183	97.406			
9	0.144	1.436	98.841			
10	0.116	1.159	100.000			

The results indicate that there are two eigenvalues greater than 1 and these two components explain for almost 77 % of the total variance. The first component is loaded by the five variables; *GDP per capita (current US$), Health expenditure total (%) of GDP*, *Government effectiveness*, *Internet users (per 100 people), Rural population (% of total population)*. The second component is also loaded by the other five variables (*Access to electricity, rural (% of population), Improved water source, rural (% of rural population with access), Life expectancy at birth, total (years), Improved sanitation facilities, rural (% of rural population with access, Literacy rate, adult total (% of people ages 15 and above)*).

After weight of the each component is determined, indicators in each dimension aggregated into three sub-indices. In the later stage, these sub-indices were weighted and aggregated into one index, CAVI (Composite Agricultural Vulnerability Index)[6]. The values belonging to indices are between zero and one. The calculated indices are depicted in Figure 4-2. The results reveal that China has the highest index value of

[6] We conduct the same analysis with equal weighting approach and we almost reach the same ranking of countries based on the index results. The rank of the countries changes at most three sequences forward or backward.

0.6 which makes it the most vulnerable country among the all countries. On the other hand, Slovenia has the lowest index of 0.098, which makes it the least vulnerable country. Besides, Algeria was ranked as the highest vulnerable country among the Mediterranean countries. When the results are examined further, it can be seen that North African countries have the highest vulnerability scores. Spain and most of the Balkan states such as Croatia, Greece and Slovenia have lower vulnerability values than the others. Our findings are in line with the results obtained globally scaled study of Krishnamurthy, et al. (2014) in which vulnerability index is obtained related to food security. It is found out that North African countries are more vulnerable to climate change in both studies.

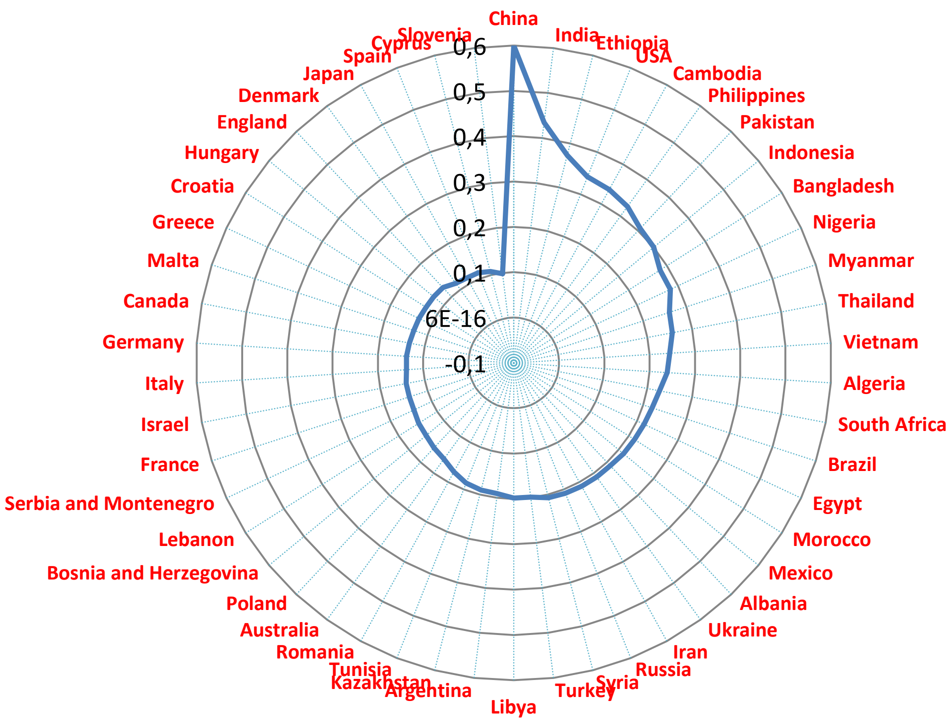

Figure 4-2: Vulnerability Index Scores for 50 Countries

In order to group countries on a common base, clustering technique is used and dendograms are taken into account. Countries are clustered according to the vulnerability index and its components; exposure, sensitivity and adaptive capacity. Figure 4-3 shows the dendogram for the grouping of countries according to vulnerability index from which the number of clustered groups can be determined. The groups are presented in Table 4-7. Dendogram results suggest that there should be five groups when hierarchical clustering technique is employed. Group-1 and Group-2 does not include Mediterranean countries, China is in Group-1 countries due to its high exposure and sensitivity. Group-2 includes USA, India, Philippines, Ethiopia and Cambodia. This group is composed of a developed country, USA, due to increase in frequency of extreme climate events at one side; and Ethiopia and the other countries having low adaptive capacity at the other side. Group 3 includes Algeria as Mediterranean country. Its index value is high since its high sensitivity value is higher when compared to other Mediterranean countries. In fact, it has restricted water resources such as rainfall and renewable water resources. Most of the land area of this country is under desert. In addition, the European countries of Mediterranean Basin are in Group-5. The main reason behind this is that; they have high adaptive capacities to recover from the adverse impact of climate change although being exposed to climate related stimuli more when compared to North African countries.

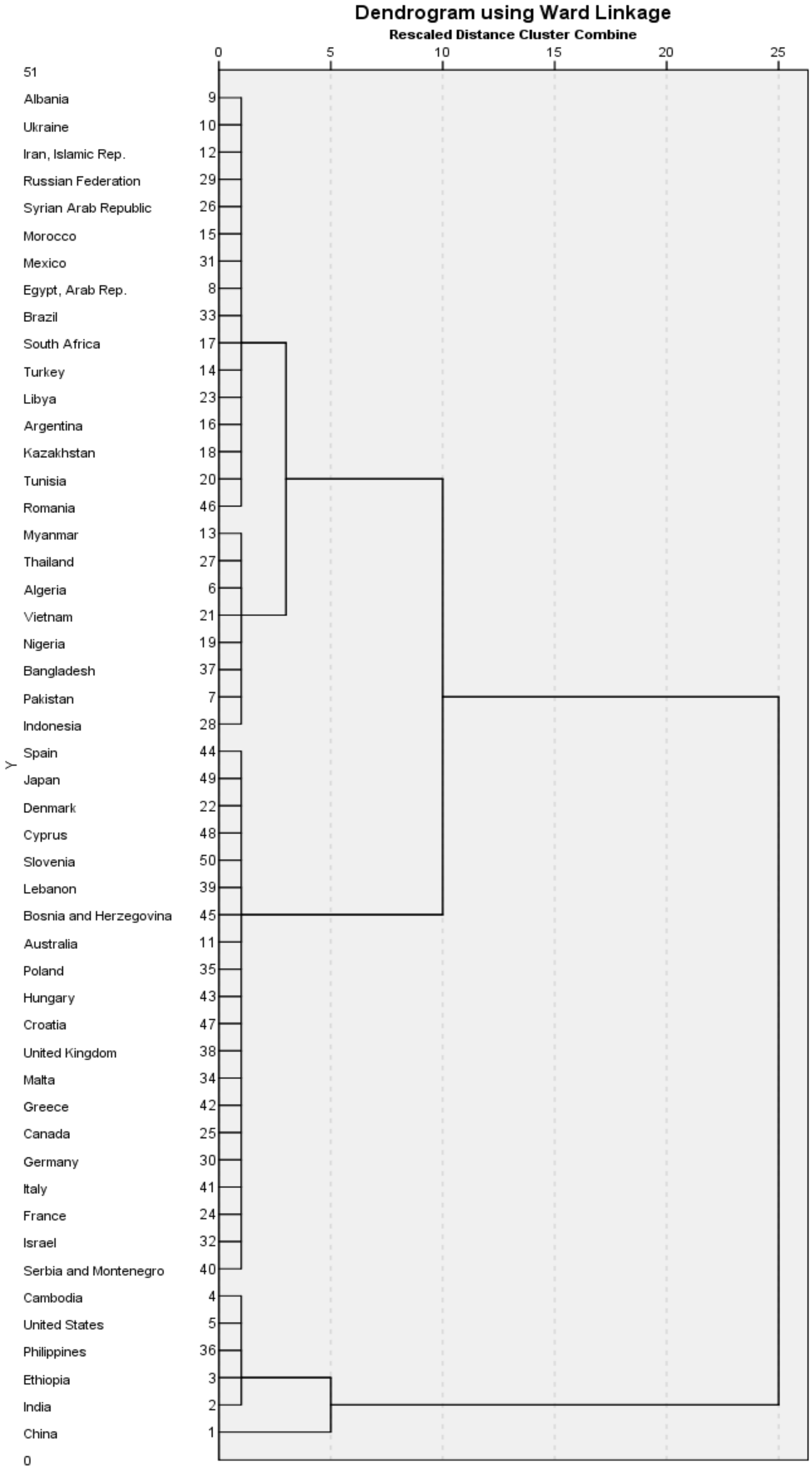

Figure 4-3: Dendogram of Agricultural Vulnerability Index for 50 Countries

Table 4-7: Clustering of Countries

Vulnerability Index	**Clusters**				
Degree of vulnerability	**Most vulnerable**				**Less vulnerable**
Groups	**Group 1**	**Group 2**	**Group 3**	**Group 4**	**Group 5**
	China	India	Pakistan	Mexico	Australia
		USA	Vietnam	Brazil	**France**
		Philippines	Thailand	**Albania**	Canada
		Ethiopia	Indonesia	Iran	Germany
		Cambodia	Bangladesh	**Turkey**	**Israel**
			Algeria	Argentina	United Kingdom
			Myanmar	South Africa	**Italy**
			Nigeria	Russia	**Bosnia & Herzegovina**
				Romania	Japan
Countries				**Egypt**	Denmark
				Ukraine	**Malta**
				Morocco	Poland
				Kazakhstan	**Lebanon**
				Tunisia	**Serbia & Montenegro**
				Libya	**Greece**
				Syria	Hungary
					Spain
					Croatia
					Cyprus
					Slovenia

Note: Countries written in bold are the Mediterranean countries.

The geographical distribution of the vulnerability indices are depicited in a World map as in Figure 4-4. The map indicates that geographical location is a distingushing factor for the level of vulnerability. It is seen that the most vulnerable countries take part in Northern Hemisphere. However Southern Hemisphere countries have lower index values. Furthermore, the map portrays that almost all European countries are clustered in the same group with lower index values.

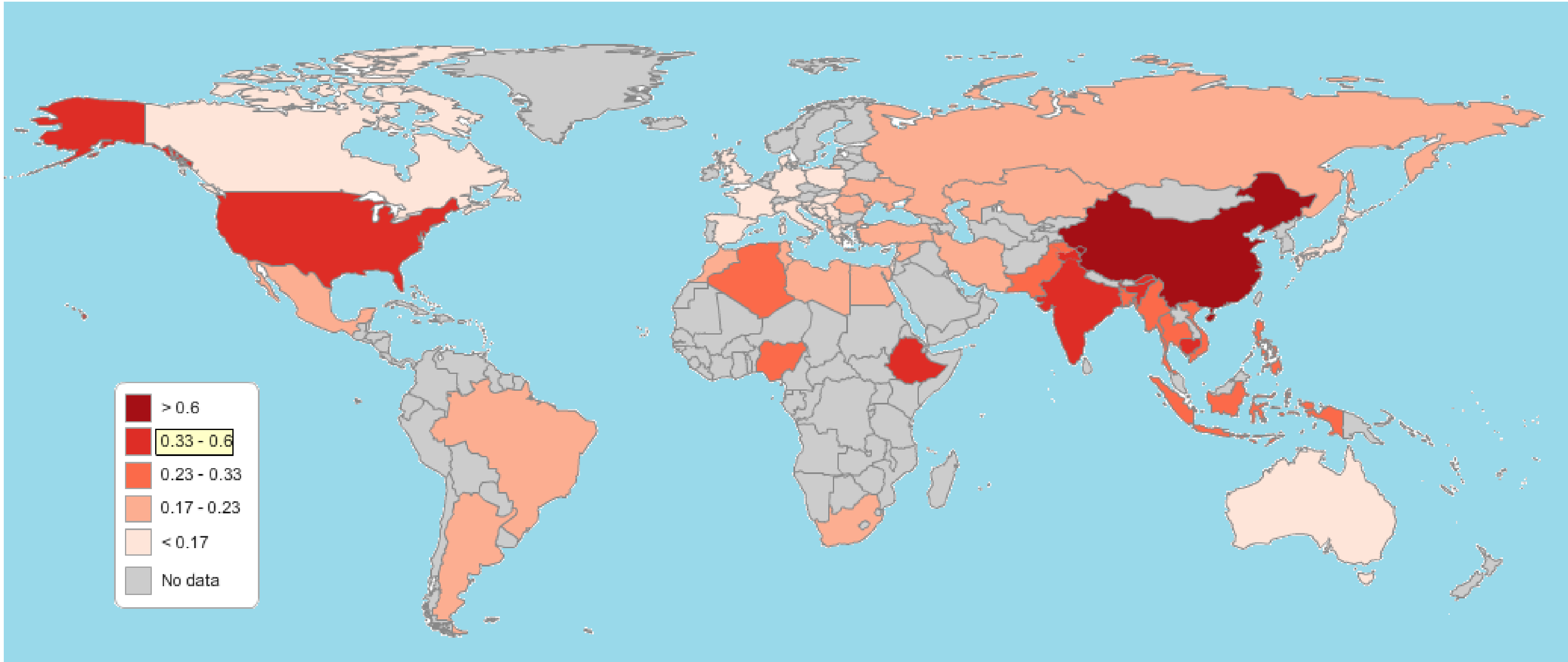

Figure 4-4: World Map According to Vulnerability Index Results

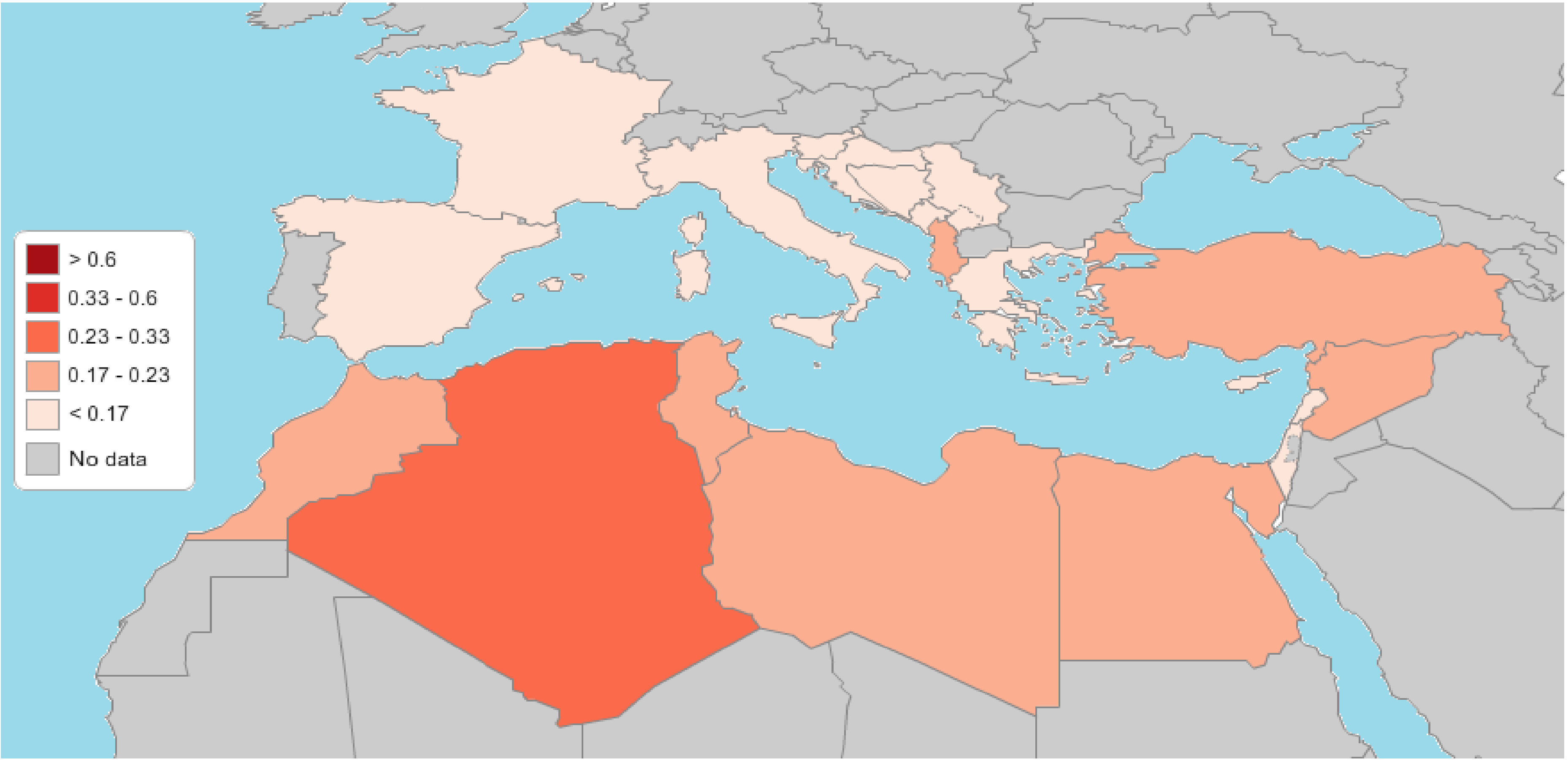

Figure 4-5: Map Focused on Mediterranean Region Based on Vulnerability Index Scores

In addition, it can be understood from Figure 4-5 that Mediterranean countries can be divided into two regions. Southern European countries have low index values, while Northern African countries and Eastern Mediterranean countries such as Turkey have higher index values. Albania has the highest index value among the Southern European countries since its sensitivity component value is larger than the others. In spite of its lower exposure and higher adaptive capacity value compared to other Mediterranean countries, magnitude of sensitivity component of Albania contributes largely to its index value.

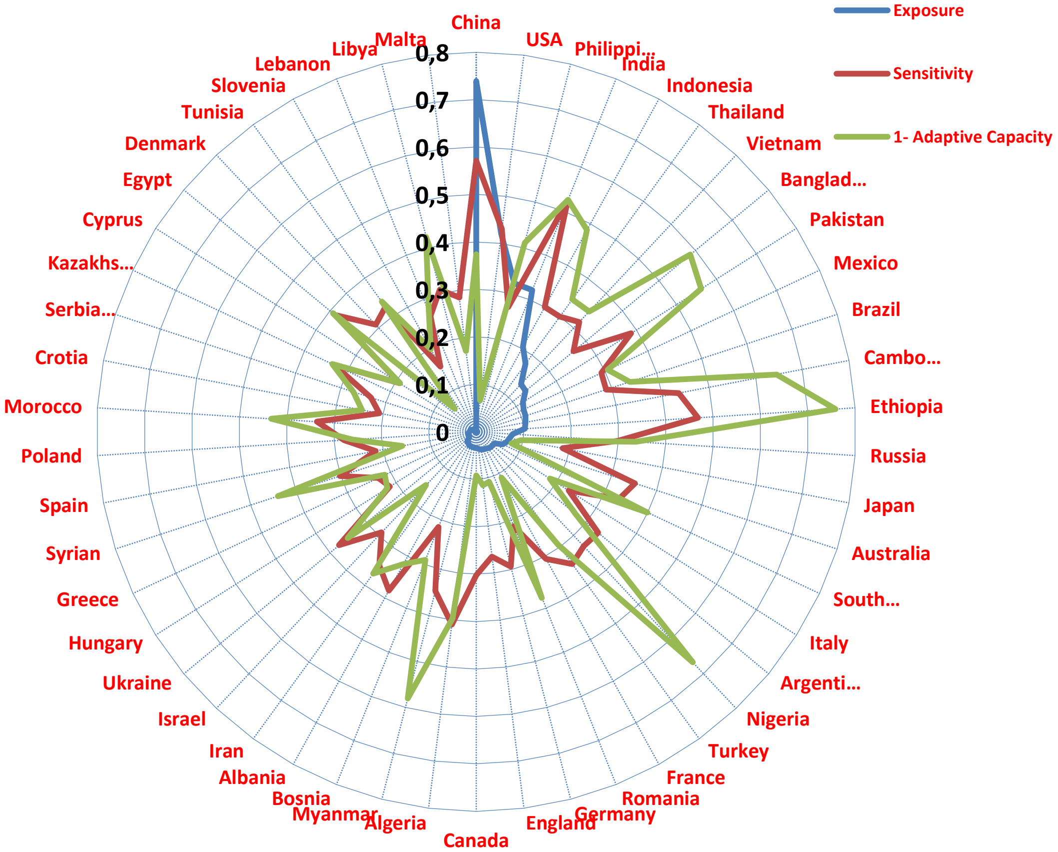

Figure 4-6: Component Indices Score according to 50 Countries

Figure 4-6 displays the component values of each country. It can be concluded that the countries have different magnitude of component scores. There is not any country that have the higher scores for all components. While, major contribution to index value comes from the sensitivity component for Mediterranean European countries, low adaptive capacity component values make Northern African countries have higher index results.

Table 4-8: Clusters of Countries according to Exposure Component

Exposure Component	**Clusters**				
Degree of Exposure	**Most exposed**	→			**Less exposed**
Groups	**Group 1**	**Group 2**	**Group 3**	**Group 4**	**Group 5**
	China	India	Ethiopia	**Algeria**	**Egypt**
		USA	Cambodia	**Albania**	Ukraine
		Philippines	Pakistan	Australia	**Morocco**
			Vietnam	Iran	Kazakhstan
			Thailand	Myanmar	**Tunisia**
			Indonesia	**Turkey**	Denmark
			Mexico	Argentina	**Libya**
			Brazil	South Africa	**Syria**
			Bangladesh	Nigeria	**Malta**
				France	Poland
Countries				Canada	**Lebanon**
				Russia	**Serbia & Montenegro**
				Germany	**Greece**
				Israel	Hungary
				United Kingdom	**Spain**
				Italy	**Croatia**
				Bosnia & Herzegovina	**Cyprus**
				Romania	**Slovenia**
				Japan	

Note: Countries written in bold are the Mediterranean countries.

According to Table 4-8 above, clustering countries based on exposure component produces five groups. It is obtained from the dendogram given in Table A-5 in Appendix. Countries in Group 1 are the most exposed due to climatic stimuli while countries in Group 5 are the least exposed. China is the only country taking part in Group 1. India, the Unites States, and Philippines are in Group 2, the second most exposed countries. In fact, the number of climatic events such as drought, flood, and storms are larger for these four countries relative to other countries. Mediterranean countries are placed in Group 4 and 5. Since Mediterranean countries do not have different complex climatic zones or longer oceanic coast that can make them more experienced to sudden climatic shocks and the people living in this region do not encounter with a continuous and heavy droughts, floods or storms; the number of people influenced by those shocks is not so high. France and Italy, having the highest exposure values among the Mediterranean countries, fall into Group 4. Their high adaptive capacity to climate change decreases the vulnerability of those countries. However, high population intensity in countries located in Southern European region of Mediterranean makes them susceptible to possible climatic shocks in the future.

Table 4-9 displays the country groups according to their sensitivity values. There are five groups as seen from the dendogram in Table A-6 in Appendix. China is the most sensitive country in terms of agricultural activities among all countries. Algeria has the highest sensitivity sub-index value among the Mediterranean countries and found in Group 2. In fact, deficiency in average annual precipitation, total renewable water resources and lack of forest area are the factors that make Algeria more vulnerable to climate change in terms of agricultural activities. Albania and Egypt are the other two countries in the second group. Agricultural activities are the major driver of the economy of Albania and the value of it in GDP and the share of agricultural areas in total land are high. Therefore, its vulnerability index value is larger than the other European countries. Turkey, Morocco, and Tunisia are the three Mediterranean countries that are placed in Group 3, while Israel, Malta, Lebanon, Libya, Syria, and France are in Group 4. Similar to clustering according to vulnerability index, Hungary, Romania, and Japan are located in the Group 5 as the least sensitive countries.

Table 4-9: Clusters of Countries according to Sensitivity Component

Sensitivity Component			**Clusters**		
Degree of Sensitivity	**Most vulnerable**				**Less vulnerable**
Groups	**Group 1**	**Group 2**	**Group 3**	**Group 4**	**Group 5**
	India	**Albania**	**Turkey**	**Israel**	**Italy**
	China	Ethiopia	Argentina	**Malta**	**Greece**
		Cambodia	Nigeria	Poland	Hungary
		USA	Australia	**Lebanon**	**Spain**
		Pakistan	Myanmar	Mexico	**Cyprus**
		Egypt	Iran	**France**	**Slovenia**
		Ukraine	South Africa	Canada	**Bosnia & Herzegovina**
		Algeria	**Morocco**	Germany	**Serbia & Montenegro**
Countries			Kazakhstan	United Kingdom	**Croatia**
			Tunisia	Denmark	Japan
			Vietnam	Indonesia	Romania
				Bangladesh	
				Russia	
				Libya	
				Syria	
				Brazil	
				Thailand	
				Philippines	

Note: Countries written in bold are the Mediterranean countries.

As seen in Table 4-10, there are six groups when adaptive capacity values used for clustering based on dendogram presented in Table A-7 in Appendix. In Group 1 there are countries with the highest adaptive capacity values, while Group 6 includes countries with the lowest values. Nigeria, Ethiopia, and Cambodia are the three countries in Group 1; African countries lying on the Mediterranean region are in Group 3. They have low adaptive capacity scores. It is because the degree of government effectiveness and poverty, access to infrastructure are the major insufficient factors for those countries to recover in a short time from any climatic shock. Furthermore, Turkey, Lebanon and Balkan States are in Group 4 as Mediterranean countries. They are also in risky group in terms of their adaptive measures to climatic shock. Furthermore, Group 5 includes Italy, Greece, Spain, Slovenia, Israel, Malta and Cyprus. They are less adaptive to climate related stimuli than developed countries such as France Japan, United Kingdom and United States involved in Group 6.

Table 4-10: Clusters of Countries according to Adaptive Capacity Component

Adaptive Capacity Component			**Clusters**			
Degree of Adaptive Capacity	**Less adaptive**		→			**Most adaptive**
Groups	**Group 1**	**Group 2**	**Group 3**	**Group 4**	**Group 5**	**Group 6**
	Nigeria	Myanmar	Romania	**Bosnia & Herzegovina**	**Italy**	Japan
	Ethiopia	Indonesia	Iran	**Serbia & Montenegro**	**Greece**	Australia
	Cambodia	Bangladesh	South Africa	**Croatia**	Hungary	**France**
		Pakistan	**Morocco**	**Turkey**	**Spain**	Canada
		India	Kazakhstan	Argentina	**Cyprus**	Germany
			Tunisia	Poland	**Slovenia**	United Kingdom
			Vietnam	**Lebanon**	**Israel**	Denmark
Countries			Russia	Mexico	**Malta**	USA
			Libya	**Albania**		
			Syria			
			Brazil			
			Thailand			
			Philippines			
			Egypt			
			Ukraine			
			Algeria			
			China			

Note: Countries written in bold are the Mediterranean countries.

4.2 Results of Econometric Analysis

In this section, the results of econometric analysis are reported. Econometric analysis is applied to nine country groups which are created by cluster analysis according to vulnerability index reported in the previous section. As reported in Table 4-11, for each crop, there are three country groups which are *Cluster-1* and *Cluster-2* countries, as well as another group disregarding the cluster analysis incorporating all countries in one group named as "*all countries*". While explaining the model results in this part, instead of saying "the effect on natural logarithm of yield (lnyield)", we prefer to say "effect on yield" so as to report results fluently.

Table 4-11: Country Groups according to Vulnerability Index Created for Each Crop

Wheat		Maize		Potato	
Cluster-1	**Cluster-2**	**Cluster-1**	**Cluster-2**	**Cluster-1**	**Cluster-2**
Albania	Bosnia	Albania	Bosnia	Albania	Bosnia
Algeria	Croatia	Algeria	Croatia	Algeria	Croatia
Egypt	France	Egypt	France	Egypt	Cyprus
Libya	Greece	Libya	Greece	Libya	France
Morocco	Israel	Morocco	Israel	Morocco	Greece
Syria	Italy	Syria	Italy	Syria	Israel
Tunisia	Lebanon	Turkey	Lebanon	Tunisia	Italy
Turkey	Serbia		Serbia	Turkey	Lebanon
	Slovenia		Slovenia		Serbia
	Spain		Spain		Slovenia
					Spain

Note: Bosnia and Herzegovina is written as "Bosnia". Serbia and Montenegro is written as "Serbia" Tunisia is not taken part in Cluster-1 for maize due to lack of production and yield data. Cyprus is not taken part in Cluster-2 for wheat and maize due to lack of production and yield data.

4.2.1 Descriptive Statistics

Data summary statistics for each crop type are reported in Table 4-12. Potato yields are higher than yields for the other crops taken into account. The most widely harvested crop is wheat. What is more, the highest temperature is observed for maize cultivated areas, and the lowest temperature is observed for wheat areas. Furthermore, the highest annual precipitation amount is seen for wheat and the lowest one is seen for maize. In general, average temperature and precipitation amounts are almost the same.

Table 4-12: Data Summary Statistics (1992-2013)

Variable	Crop	Observation	Mean	St Dev	Minimum	Maximum
Yield (Hg/ha)	Wheat	396	30362	16282	4564	76058
	Maize	374	72625	66317	1303	352943
	Potato	418	211293	81524	59440	468991
Area harvested (ha)	Wheat	396	1578618	2208308	23595	9800000
	Maize	374	354974	485372	120	1916000
	Potato	418	60534	55707	3307	257152
Temperature ©	Wheat	396	13.996	4.028	6.356	23.655
	Maize	374	13.851	4.455	6.632	23.761
	Potato	418	14.059	4.123	6.573	23.352
Precipitation (mm)	Wheat	396	650.482	309.934	19.439	1426.364
	Maize	374	652.136	313.598	24.266	1382.051
	Potato	418	656.575	296.200	36.223	1424.069

Note: Data of 18 countries, 17 countries and 19 countries are used for wheat, maize and potato, respectively, regarding data availability.

In this section, the results of the econometric analysis will be given for wheat, maize, and potato, respectively. Panel ARDL Method is applied to cluster groups obtained in the first part of the study for each crop. Before employing Panel ARDL Method, unit root tests and cross section dependence tests are also conducted. PMG approach for panel ARDL models with appropriate lag selection produces consistent results disregarding the order of integration as long as long run relationship among variables exists as stated by Kim et al. (2008). Therefore, for nine models, there is no series which is order of integration, either I(2) or higher. We present the unit root test results for the first models in detail. However, for the following models, we make a brief summary of unit root test results for each model. Furthermore, we emphasize the results of the PMG estimator, regarding its advantages in consistency and efficiency over the other estimators when the long run homogeneity restriction holds and the short run adjustments are expected to differ across countries. Based on our findings from Hausman test for the appropriate estimator, we develop our interpretations in that direction for all nine models. Therefore, in this section, we are more focused on exclusive feature of PMG model for all crops while reporting the model results.

4.2.2 Wheat

4.2.2.1 Wheat for Cluster-1 Countries

Cluster-1 is composed of eight countries which are Albania, Algeria, Egypt, Libya, Morocco, Syria, Tunisia and Turkey as suggested by cluster analysis.

In the first step, we discuss panel unit root tests in order to determine the stationarity properties of panel series or determine the integration order of series. Levin-Lin-Chu (Levin et al., 2002) test, the Im-Pesaran-Shin (IPS) (Im et al., 2003) test and the Fisher-type tests of using ADF and PP tests (Maddala and Wu, 1999) are performed for the data of natural logarithm of yield, natural logarithm of area harvested, temperature and precipitation so as to determine the order of integration. As reported in Table 4-13, temperature and precipitation series are stationary at level according to all types of unit root tests, that is to say, variables are I(0). However, series of logarithm of yield and logarithm of area are stationary when their first differences are taken into account for all unit root tests so they are I(1) with intercept and trend as reported in Table 4-14.

Table 4-13: Unit Root Results (Level) for Wheat for Cluster-1 Countries

Intercept	lnyield	Lnarea	Temp	Prep
Levin-Lin-Chu	-0.0628	-0.7761	-8.2828[a]	-5.8993[a]
Im, Pesaran and Shin W-stat	-0.6272	-1.3029[c]	-8.7363[a]	-6.9268[a]
ADF - Fisher Chi-square	31.2128[b]	25.3835[c]	95.5311[a]	75.8660[a]
PP - Fisher Chi-square	39.6481[a]	56.3837[a]	148.9130[a]	85.0545[a]
Intercept and trend	lnyield	Lnarea	Temp	Prep
Levin-Lin-Chu	-1.5287[c]	-1.7563[b]	-9.2039[a]	-4.5081[a]
Im, Pesaran and Shin W-stat	-3.8106[a]	-3.5586[a]	-9.0962[a]	-5.8561[a]
ADF - Fisher Chi-square	50.9779[a]	40.6586[a]	91.7897[a]	60.7594[a]
PP - Fisher Chi-square	75.5247[a]	91.2675[a]	126.7890[a]	70.4656[a]

Note: a, b and c denote significance at the 1%, 5% and 10% level, respectively. For Levin-Lin-Chu unit root test, null hypothesis is that there exists unit root (assumes common unit root process). For Im, Pesaran and Shin W-stat, ADF - Fisher Chi-square and PP - Fisher Chi-square unit root tests, null hypothesis is that there exists unit root (assumes individual unit root process). Automatic lag length is selected based on AIC. EViews-9 software program is used.

Table 4-14: Unit Root Results (First Difference) for Wheat for Cluster-1 Countries

Intercept	lnyield	Lnarea	Temp	Prep
Levin-Lin-Chu	13.3488[a]	-15.0581[a]	-11.4670[a]	-8.6994[a]
Im, Pesaran and Shin W-stat	-14.1841[a]	-15.1403[a]	-14.1841[a]	-10.5148[a]
ADF - Fisher Chi-square	160.1240[a]	196.3990[a]	158.5540[a]	118.6850[a]
PP - Fisher Chi-square	815.4230[a]	676.9730[a]	403.0240[a]	818.4820[a]
Intercept and trend	lnyield	Lnarea	Temp	Prep
Levin-Lin-Chu	-8.6353[a]	-12.9823[a]	-9.5841[a]	-6.6021[a]
Im, Pesaran and Shin W-stat	-10.2056[a]	-12.8865[a]	-12.1562[a]	-8.5624[a]
ADF - Fisher Chi-square	103.9630[a]	132.8310[a]	122.6090[a]	90.0848[a]
PP - Fisher Chi-square	441.3560[a]	518.5050[a]	434.4130[a]	555.6540[a]

Note: a, b and c denote significance at the 1%, 5% and 10% level, respectively. For Levin-Lin-Chu unit root test, null hypothesis is that there exists unit root (assumes common unit root process). For Im, Pesaran and Shin W-stat, ADF - Fisher Chi-square and PP - Fisher Chi-square unit root tests, null hypothesis is that there exists unit root (assumes individual unit root process). Automatic lag length is selected based on AIC. EViews-9 software program is used.

However, as mentioned in Chapter 3, if cross-sectional dependence exists among variables, it may lead to over rejection of the null hypothesis of unit root nonstationary (O'Connell, 1998). In this regard, according to Table 4-14, it can be concluded that there may be over-rejection much more than it is expected. Therefore, cross-sectional dependence tests should be conducted and then, if it exists, cross-sectional dependence can be removed partially by subtracting cross-sectional means from each series. After that, first generation panel unit root tests are performed to demeaned series as proposed by Hsiao (1986) and Levin et al. (2002). However, it is not possible to correct cross-sectional dependence completely by this methodology. Therefore, Pesaran (2007)'s CADF test, not sensitive to cross-sectional dependence, can be used to identify the order of integration.

Breusch-Pagan LM, Pesaran scaled LM, Bias-corrected scaled LM and Pesaran CD cross-sectional dependence test results tests reject the null hypothesis of no cross-section dependence (correlation) in residuals, as indicated by results in Table 4-15. We may conclude that there exists cross-sectional dependence in all panel series. When Pesaran (2007)'s CADF unit root test, as a second generation panel unit root test, is conducted, it can be inferred from Table 4-16, the majority of series under consideration are stationary in first differences except for temperature. Thus, we can conclude that series have a mixed order of integration, either I(0) or I(1).

Table 4-15: Residual Cross-Section Dependence Test for Wheat for Cluster-1 Countries

Test	**Statistic**
Breusch-Pagan LM	1014083***
Pesaran scaled LM	8740547***
Bias-corrected scaled LM	8550071***
Pesaran CD	5337690***

Note: The asterisks ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Null hypothesis is that there exists no cross-section dependence (correlation) in residuals. EViews-9 software program is used.

Table 4-16: Pesaran (2007) CADF Unit Root Test for Wheat for Cluster-1 Countries

Variables	Pesaran Z[t-bar]	
	level	first difference
lnyield	2.319	-1.554[c]
lnarea	3.272	-3.714[a]
temp	-2.384[a]	-3.720[a]
prep	0.932	-1.145[c]

Note: a, b and c denote significance at the 1%, 5% and 10% level, respectively. Following Hoechle (2007), we choose the ideal lag length by using Newey and West's (1994) plug-in method at (4*(T/100)^$^{(2/9)}$ =~3). We use Stata routine "pescadf".

To sum up, when performing Panel ARDL model, order of integration of variables is not crucially important as long as related variables are I(0) and/or I(1) (Pesaran and Smith, 1995; Pesaran et al, 1999). We conduct these tests to ensure that there does not exist any series that exceed I(1). Therefore, we prefer Panel ARDL model to traditional panel cointegration tests due to mixed orders of integration.

Autoregressive distributed lag (ARDL) model has been applied by using PMG, MG and DFE estimators in order to determine the effects of climatic variables and area harvested on agricultural yield. Before applying the three approaches, it is necessary to determine the lag orders of the variables. We perform the lag selection procedure and Akaike Information Criterion (AIC) suggested 4 as the maximum lag length. Based on the results presented in Table 4-17, it is concluded that the most appropriate model can be written in the form of the ARDL(3,3,3,3). For the models of maize and potato, we prefer to choose lag length based on AIC.

Table 4-17: Model Selection Criteria Table for Wheat for Cluster-1 Countries

Model	LogL	AIC*	BIC	HQ	Specification
9	228.577064	**-1.688570**	0.518166	**-0.791877**	**ARDL(3, 3, 3, 3)**
12	235.464154	-1.673113	0.698613	-0.709378	ARDL(4, 3, 3, 3)
6	203.326541	-1.448980	0.592767	-0.619329	ARDL(2, 3, 3, 3)
3	176.868275	-1.192615	0.684142	-0.430007	ARDL(1, 3, 3, 3)
11	175.690770	-1.176261	0.700496	-0.413653	ARDL(4, 2, 2, 2)
8	163.787994	-1.122055	0.589712	-0.426490	ARDL(3, 2, 2, 2)
5	154.644395	-1.106172	0.440606	-0.477649	ARDL(2, 2, 2, 2)
7	138.137091	-1.099126	0.117672	-0.604688	ARDL(3, 1, 1, 1)
4	128.835857	-1.081054	-0.029245	-0.653658	ARDL(2, 1, 1, 1)
2	144.301824	-1.073636	0.308152	-0.512156	ARDL(1, 2, 2, 2)
10	142.185956	-1.044249	0.337539	-0.482769	ARDL(4, 1, 1, 1)
1	116.375634	-1.019106	**-0.132287**	-0.658753	**ARDL(1, 1, 1, 1)**

Note: AIC, SBC, HQ represent Akaike Information Criterion, Schwarz Bayesian Criterion, Hannan-Quinn Criterion, respectively. Dependent variable is lnyield.

Table 4-18 reports the results of PMG, MG and DFE estimation for Cluster-1 countries for the crop wheat. Furthermore, Hausman h-Test result is reported in the same table to identify the efficiency and consistency among the PMG and MG estimators. As explained in Chapter 3, the PMG estimator restricts the long run coefficients to be same but allows all slope coefficients, error variances and coefficient of error correction term (speed of adjustment) to differ among countries. However, MG estimator allows all slope coefficients and error variances for both short and long run to change across countries. In addition, DFE estimator allows the intercepts to vary across groups, but does not impose heterogeneity of all slope coefficients and error variances. In this scope, the results in Table 4-18 indicate that the coefficients of temperature (-1.1908) and precipitation variables (0.0001) are significantly negative and positive, respectively. It reveals that while temperature has a significant negative effect on yield, precipitation has positive impact on yield in the long run. The reason is due to high annual average temperature in cluster 1 countries (including North African countries) which leads to more transpiration of plants and thus, it increases the need of much water for wheat crop. In addition, temperature and precipitation have no significant impact on yield in the short run based on PMG estimator. The reason behind it may be small fluctuations in temperature and precipitation balances each other and do not cause loss of yield in the short term. On the other hand, MG estimator suggests insignificant and positive coefficient in both long and short run. According to DFE model, precipitation has a small effect on yield in the long run. In addition, as explained in Chapter-3 the coefficient of the error correction term should be negative for the existence of long run relationship (dynamic stability). Highly significant error correction term confirms the existence of stable long-run relationship based on DFE approach. DFE estimates of the speeds of adjustment about 38% which means that adjustment is slow, with 38% occurring within one year. Hausman h-Test is performed to decide between the PMG and MG estimators. According to test results displayed in Table 4-18, null hypothesis of homogeneity restriction on the variables in the long run is strongly failed to reject and it reveals that PMG is more efficient estimator than MG estimator. Long run homogeneity restrictions of PMG estimator leads to decrease in standard errors of error correction term and long run coefficients of PMG, which are higher in MG estimator.

To sum up, based on PMG estimator, precipitation and temperature have inverse impact on wheat yield in Cluster-1 countries which have arid and dry climatic conditions. That is to say, while temperature has adverse effect on wheat yield, precipitation affect positively wheat crop.

Table 4-18: ARDL(3,3,3,3) Results with PMG, MG, DFE Estimators for Cluster-1 Countries

Dependant variable: lnYield Crop: Wheat	PMG		MG		DFE	
	Coef	Std error	Coef	Std error	Coef	Std error
Long run coefficients						
lnArea	6.3778***	0.7344	0.3985	0.9972	-0.2764	0.3459
Temperature	-1.1908***	0.2544	0.7395	0.7457	0.1848	0.1604
Precipitation	0.0001	0.0005	-0.0003	0.0014	0.0010*	0.0006
Error correction coefficient	-0.2199	0.2273	- 1.2243***	0.3366	-0.3848***	0.1207
Short run coefficients						
Δ Yield(-1)	-0.5142**	0.2074	0.2269	0.2714	-0.5144***	0.1146
Δ Yield(-2)	-0.2457**	0.1147	0.1067	0.2760	-0.1206	0.0871
Δ Area	-0.4279	0.8004	-0.2667	0.9053	0.1888	0.1314
Δ Area(-1)	0.0778	0.3019	0.7938	0.5276	0.0467	0.1110
Δ Area(-2)	0.1744	0.2154	0.7783	0.5460	-0.0394	0.0880
Δ Temp	-0.0402	0.0319	0.2303	0.2123	-0.0312	0.0603
Δ Temp(-1)	0.0317	0.1043	0.1606	0.1720	-0.0185	0.0488
Δ Temp-2)	0.0933	0.1400	0.1745	0.1435	0.0020	0.0346
Δ Prep	0.0002	0.0002	0.0016	0.0014	0.0001	0.0002
Δ Prep(-1)	-0.0002	0.0004	0.0010	0.0008	0.0001	0.0002
Δ Prep(-2)	0.0000	0.0003	0.0008***	0.0003	0.0001	0.0002
C	-23.3953	24.1631	-3.6443	24.9584	3.9375***	2.4762
Hausman Test	1.05 (0.999)					
Observations	176		176		176	
Number of countries	8		8		8	

Note: The table reports the results for the pooled mean group (PMG), mean group (MG) and dynamic fixed effect estimators. The dependent variable is yield. The asterisks ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. The Hausman test is the statistic for the null hypothesis that the slope is homogeneous across countries ($\beta_i=\beta$) under the null hypothesis that, the PMG estimator is better than the MG estimator. PMG estimate outputs are both obtained by using E-Views-9 and Stata-13 software programs in order to check the accuracy of the results. For MG and DFE estimates; Stata-13 routine xtpmg is used.

4.2.2.2 Wheat for Cluster-2 Countries

Cluster-2 countries are Bosnia and Herzegovina, Croatia, France, Greece Israel, Italy, Lebanon, Serbia and Montenegro, Spain and Slovenia.

Results of first generation panel unit root tests, cross section dependence test and Pesaran (2007) CADF test are given in this section for the Cluster-2 countries. Table 4-19 and Table 4-20 report the results of unit root tests conducted for the series under consideration both in levels and first differences, respectively. For the series yield, according to all unit root tests except for IPS test, hypothesis for unit root non-stationary is rejected at the 1% level of significance. Thus, we can conclude that yield series are stationary at their level. Moreover, for the series of temperature and precipitation, it can be inferred from the Table 4-19 that they do not have unit root in their level, that is to say, they are stationary. Therefore, they are I(0). In addition, results in Table 4-19 indicates that null hypothesis cannot be rejected when the series of area is taken in level. However, when the tests are applied to the first differenced series, as shown in Table 4-20, it is stationary and the order of integration is 1, I(1). To sum up, according to first generation unit root tests, the series have mixed order of integrations, either I(1) or I(0).

Table 4-19: Unit Root Results (Level) for Wheat for Cluster-2 Countries

Intercept	lnyield	Lnarea	Temp	Prep
Levin-Lin-Chu	-2.8976[a]	2.0911[b]	-8.1386[a]	-10.4930[a]
Im, Pesaran and Shin W-stat	-2.2204[b]	-0.5575	-7.7824[a]	-10.7290[a]
ADF - Fisher Chi-square	38.0862[a]	27.1371	94.6730[a]	132.9420[a]
PP - Fisher Chi-square	85.2079[a]	33.2221[b]	113.8610[a]	196.2530[a]
Intercept and trend	lnyield	Lnarea	Temp	Prep
Levin-Lin-Chu	-4.7543[a]	-4.1099[a]	-8.8318[a]	-8.5798[a]
Im, Pesaran and Shin W-stat	-4.5025[a]	-4.6019[a]	-8.6675[a]	-8.4564[a]
ADF - Fisher Chi-square	53.9483[a]	57.4150[a]	97.6210[a]	98.0175[a]
PP - Fisher Chi-square	279.7830[a]	80.1413[a]	102.6500[a]	183.1020[a]

Note: a, b and c denote significance at the 1%, 5% and 10% level, respectively. For Levin-Lin-Chu unit root test, null hypothesis is that there exists unit root (assumes common unit root process). For Im, Pesaran and Shin W-stat, ADF - Fisher Chi-square and PP - Fisher Chi-square unit root tests, null hypothesis is that there exists unit root unit root (assumes individual unit root process). Automatic lag length is selected based on AIC. EViews-9 software program is used.

Table 4-20: Unit Root Results (First Difference) for Wheat for Cluster-2 Countries

Intercept	lnyield	Lnarea	Temp	Prep
Levin-Lin-Chu	-13.8089[a]	-10.9196[a]	-14.1143[a]	-6.6767[a]
Im, Pesaran and Shin W-stat	-16.3847[a]	-12.2772[a]	-14.4866[a]	-10.9390[a]
ADF - Fisher Chi-square	205.5190[a]	152.3180[a]	181.2420[a]	138.6820[a]
PP - Fisher Chi-square	1009.0000[a]	295.3070[a]	660.7850[a]	1297.4400[a]
Intercept and trend	lnyield	Lnarea	Temp	Prep
Levin-Lin-Chu	-7.3854[a]	-7.4019[a]	-9.9610[a]	-4.4283[a]
Im, Pesaran and Shin W-stat	-11.0176[a]	-8.4379[a]	-11.2878[a]	-9.0359[a]
ADF - Fisher Chi-square	126.8990[a]	99.3730[a]	129.3960[a]	107.0140[a]
PP - Fisher Chi-square	1048.4700[a]	239.4560[a]	857.6050[a]	927.1550[a]

Note: a, b and c denote significance at the 1%, 5% and 10% level, respectively. For Levin-Lin-Chu unit root test, null hypothesis is that there exists unit root (assumes common unit root process). For Im, Pesaran and Shin W-stat, ADF - Fisher Chi-square and PP - Fisher Chi-square unit root tests, null hypothesis is that there exists unit root unit root (assumes individual unit root process). Automatic lag length is selected based on AIC. EViews-9 software program is used. PMG estimate outputs are both obtained by using E-Views-9 and Stata-13 software programs in order to check the accuracy of the results. For MG and DFE estimates; Stata-13 routine xtpmg is used.

According to results of cross-sectional dependence tests presented in Table 4-21, null hypothesis of no cross-sectional dependence is rejected at 1% significance level. We can conclude that there exists cross-sectional dependence in all panel series. Therefore, Pesaran (2007)'s CADF unit root test is employed. As indicated in Table 4-22, all series except for temperature are stationary at their level. However, series of temperature has unit root at level. When it is first differenced, it becomes stationary so it is I(1). To sum up, series have mixed order of integration based on Pesaran (2007) CADF test results.

Table 4-21: Residual Cross-Section Dependence Test for Wheat for Cluster-2 Countries

Test	Statistic
Breusch-Pagan LM	1304997***
Pesaran scaled LM	7958368***
Bias-corrected scaled LM	7720272***
Pesaran CD	9667565***

Note: The asterisks ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Null hypothesis is that there exists no cross-section dependence (correlation) in residuals. EViews-9 software program is used.

Table 4-22: Pesaran (2007) CADF Unit Root Test for Wheat for Cluster-2 Countries

Variables	Pesaran Z[t-bar]	
	level	first difference
lnyield	-2.538[a]	-3.023[a]
lnarea	-1.693[b]	-3.962[b]
temp	-1.111	-2.440[a]
prep	-1.693[c]	-3.962[a]

Note: a, b and c denote significance at the 1%, 5% and 10% level, respectively. Following Hoechle (2007) respectively we choose the ideal lag length by using Newey and West's (1994) plug-in method at (4*(T/100)^(2/9) =~3). Stata routine "pescadf" isused.

Panel ARDL model results with different estimators, for the crop wheat cultivated in Cluster-2 countries, are reported in this part. Before conducting these approaches, we perform the lag selection based on AIC to determine the model as mentioned in the previous part of the section. Table 4-23 indicates the results of appropriate model selection according to three criteria. Based on AIC, the most appropriate model can be written in the form of the ARDL(4,3,3,3) model.

Table 4-23: Model Selection Criteria Table for Wheat for Cluster-2 Countries

Model	LogL	AIC*	BIC	HQ	Specification
12	262.000107	**-1.322223**	1.214403	-0.293730	**ARDL(4, 3, 3, 3)**
9	239.712157	-1.185691	1.173550	-0.229120	ARDL(3, 3, 3, 3)
6	220.845346	-1.087171	1.094683	-0.202523	ARDL(2, 3, 3, 3)
1	142.804665	-0.997830	**-0.057681**	**-0.616640**	**ARDL(1, 1, 1, 1)**
3	201.662165	-0.985135	1.019332	-0.172410	ARDL(1, 3, 3, 3)
4	146.821033	-0.931345	0.186190	-0.478233	ARDL(2, 1, 1, 1)
2	166.210002	-0.924556	0.547752	-0.327598	ARDL(1, 2, 2, 2)
5	174.043185	-0.900480	0.749215	-0.231600	ARDL(2, 2, 2, 2)
10	156.223719	-0.813597	0.658711	-0.216639	ARDL(4, 1, 1, 1)
11	184.712233	-0.796803	1.207665	0.015923	ARDL(4, 2, 2, 2)
8	160.000898	-0.633343	1.193738	0.107459	ARDL(3, 2, 2, 2)
7	126.854465	-0.598383	0.696538	-0.073348	ARDL(3, 1, 1, 1)

Note: AIC, SBC, HQ represent Akaike Information Criterion, Schwarz Bayesian Criterion, Hannan-Quinn Criterion, respectively. Dependent variable is lnyield.

Table 4-24 displays the results of PMG, MG and DFE estimation and Hausman test for Cluster-2 countries for the crop wheat cultivated. Long run coefficients of temperature (0.0896) and precipitation (0.0013) are positive and significant according to PMG approach, but are not statistically significant based on the MG estimator. We can conclude that temperature and precipitation have a positive effect on the wheat cultivated in Cluster-2 countries according to PMG estimator. As indicated in Table 4-24, Hausman test results revealed that homogeneity restriction imposed on the long-run coefficients cannot be rejected. Thus, we can conclude that PMG provides more consistent and efficient estimate than MG. Hsiao et al., (1999) revealed that the MG approach is likely to be inefficient for small samples and short time series which confirms the results of Hausman test we conduct. Nevertheless, we found almost no significant short run relationship between climatic variables and yield for the PMG estimator. The reason may be due to temperature and precipitation can offset the impact of each other in the short term.

Furthermore, the error correction coefficient is negative and significant within the unit circle which is an indication of long term relationship between the yield and the independent variables. In fact, about 50 % of the imbalances will become removed in the next year and converge the long run equilibrium. In addition, sign of coefficients of the parameters obtained from DFE estimator are same with the results of PMG. Standard errors of the PMG estimators are the smallest when compared to results of other estimators which is a result of long run homogeneity restrictions. Furthermore, short run coefficient of lagged yield variables are statistically significant revealing that yield obtained in the last three years have negative impact on yield at present according to PMG estimator.

To sum up, in the long run, temperature and precipitation have positive effect on wheat yield based on the results of PMG for Cluster-2 countries which are composed of Southern European countries. The common feature of those countries is that it is generally mild and warm during the growing season of the wheat crop and increase in temperature has positive impact on wheat during the growing season of it. Besides, precipitation influences positively the wheat yield since in the last decades frequency for droughts has increased in Southern European countries.

Table 4-24: ARDL(4,3,3,3) Results with PMG, MG, DFE Estimators for Cluster-2 Countries

Dependant variable: lnYield Crop: wheat	PMG		MG		DFE	
	Coef	**Std error**	**Coef**	**Std error**	**Coef**	**Std error**
Long run coefficients						
lnArea	-0.8426***	0.0635	-0.4061	0.4263	-0.2630*	0.1384
Temperature	0.0896***	0.0268	-1.2123	1.1279	0.1190**	0.0601
Precipitation	0.0013***	0.0004	0.0031	0.0036	0.0006*	0.0007
Error correction coefficient	-0.5047***	0.1761	0.0279	0.4694	-0.8554***	0.1335
Short run coefficients						
Δ Yield(-1)	-0.3565**	0.1757	-1.2232***	0.4373	-0.0092	0.1218
Δ Yield(-2)	-0.3339**	0.1542	-0.9763***	0.3196	0.1124	0.1049
Δ Yield(-3)	-0.2496*	0.1313	-0.2661	0.2330	0.0409	0.0754
Δ Area	0.3517	0.2835	2.0130	2.1340	0.3982***	0.1384
Δ Area(-1)	0.0171	0.1915	1.2645	1.3094	-0.1158	0.1380
Δ Area(-2)	0.0201	0.2473	0.2468	0.5414	-0.1096	0.1263
Δ Temp	-0.0459	0.0334	-1.0641	0.7597	-0.0525	0.0436
Δ Temp(-1)	-0.0089	0.0497	-0.5479*	0.3144	-0.0488	0.0381
Δ Temp-2)	0.0239	0.0436	-0.2914	0.2076	-0.0021	0.0279
Δ Prep	-0.0003	0.0004	0.0045	0.0031	-0.0003	0.0003
Δ Prep(-1)	-0.0005*	0.0003	0.0031	0.0026	-0.0002	0.0002
Δ Prep(-2)	-0.0004	0.0002	0.0019	0.0017	-0.0001	0.0001
C	9.4883***	3.2782	-17.4286	16.7814	10.1518***	2.3664
Hausman Test	0.06 (0.9961)					
Observations	220		220		220	
Number of countries	10		10		10	

Note: The table reports the results for the pooled mean group (PMG), mean group (MG) and dynamic fixed effect estimators. The dependent variable is yield. The asterisks ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. The Hausman test is the statistic for the null hypothesis that the slope is homogeneous across countries (β_i=β) under the null hypothesis that, the PMG estimator is better than the MG estimator. PMG estimate outputs are both obtained by using E-Views-9 and Stata-13 software programs in order to check the accuracy of the results. For MG and DFE estimates; Stata-13 routine xtpmg is used.

4.2.2.3 Wheat for All Mediterranean Countries

Results of first generation panel unit root tests (Levin-Lin-Chu, Im-Pesaran-Shin, the Fisher-type tests of using ADF and PP tests), cross section dependence test and Pesaran (2007) CADF test are given in this section for the Cluster-2 countries. Table 4-25 and Table 4-26 present the unit root results of variables at their level and first differences, respectively.

Series of area, temperature and precipitation are stationary at level based on all first generation unit root tests. According to Levin-Lin-Chu unit root test, yield has unit root at level, but when the first difference of series is taken, it becomes stationary, that is to say it is I(1). In that case, there may be over-rejection due to presence of cross-sectional dependence. According to results of cross sectional dependence tests (Breusch-Pagan LM, Pesaran scaled LM, Bias-corrected scaled LM and Pesaran CD) displayed in Table 4-27, null hypothesis of no cross-section dependence is strongly rejected. Therefore, there exists cross-sectional dependence in series.

Table 4-25: Unit Root Results (Level) for Wheat for All Mediterranean Countries

Intercept	lnyield	Lnarea	Temp	Prep
Levin-Lin-Chu	-1.7337	-1.9655[b]	-11.6516[a]	-11.2932[a]
Im, Pesaran and Shin W-stat	-2.0768[b]	-1.2790[b]	-11.6301[a]	-12.6025[a]
ADF - Fisher Chi-square	69.2990[a]	52.5207[b]	190.2040[a]	208.8080[a]
PP - Fisher Chi-square	124.8560[a]	89.6057[b]	262.7740[a]	281.3080[a]
Intercept and trend	lnyield	Lnarea	Temp	Prep
Levin-Lin-Chu	-4.4029[a]	-4.1420[a]	-12.7692[a]	-9.4236[a]
Im, Pesaran and Shin W-stat	-5.8953[a]	-5.8008[a]	-12.5234[a]	-10.1647[a]
ADF - Fisher Chi-square	104.9260[a]	98.0737[a]	189.4110[a]	158.7770[a]
PP - Fisher Chi-square	355.3080[a]	171.4090[a]	229.4400[a]	253.5680[a]

Note: a, b and c denote significance at the 1%, 5% and 10% level, respectively. For Levin-Lin-Chu unit root test, null hypothesis is that there exists unit root (assumes common unit root process). For Im, Pesaran and Shin W-stat, ADF - Fisher Chi-square and PP - Fisher Chi-square unit root tests, null hypothesis is that there exists unit root unit root (assumes individual unit root process). Automatic lag length is selected based on AIC. EViews-9 software program is used.

Table 4-26: Unit Root Results (First Difference) for All Mediterranean Countries

Trend	lnyield	Lnarea	Temp	Prep
Levin-Lin-Chu	-19.0212[a]	-18.3613[a]	-18.1476[a]	-11.0467[a]
Im, Pesaran and Shin W-stat	-21.6704[a]	-19.1866[a]	-20.2513[a]	-15.1524[a]
ADF - Fisher Chi-square	365.6430[a]	348.7170[a]	339.7960[a]	257.3670[a]
PP - Fisher Chi-square	1824.4200[a]	972.2810[a]	1063.8100[a]	2115.9200[a]
Intercept and trend	lnyield	Lnarea	Temp	Prep
Levin-Lin-Chu	-11.1736[a]	-14.9989[a]	-14.0985[a]	8.0357[a]
Im, Pesaran and Shin W-stat	-15.0067[a]	-14.7556[a]	-16.4993[a]	-12.4326[a]
ADF - Fisher Chi-square	230.8620[a]	232.2040[a]	252.0050[a]	197.0990[a]
PP - Fisher Chi-square	1489.8300[a]	757.9620[a]	1292.0200[a]	1482.8100[a]

Note: a, b and c denote significance at the 1%, 5% and 10% level, respectively. For Levin-Lin-Chu unit root test, null hypothesis is that there exists unit root (assumes common unit root process). For Im, Pesaran and Shin W-stat, ADF - Fisher Chi-square and PP - Fisher Chi-square unit root tests, null hypothesis is that there exists unit root unit root (assumes individual unit root process). Automatic lag length is selected based on AIC. EViews-9 software program is used.

Table 4-27: Residual Cross-Section Dependence Test for Wheat for All Countries

Test	**Statistic**
Breusch-Pagan LM	4661235***
Pesaran scaled LM	1687109***
Bias-corrected scaled LM	1644252***
Pesaran CD	1579130***

Note: The asterisks ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Null hypothesis is that there exists no cross-section dependence (correlation) in residuals. EViews-9 software program is used.

Table 4-28 portrays the results of the Pesaran (2007) Unit Root test. According to results, for the yield, area and precipitation, the test does not reject the null hypothesis of a unit root. However, when they are first differenced, they become stationary. Thus, they are integrated of order one, I(1). Temperature variable is stationary at level. As a result, variables have mixed order of integration based on Pesaran (2007) CADF test results.

Table 4-28: Pesaran (2007) CADF Unit Root Test for Wheat for All Mediterranean Countries

Variables	Pesaran Z[t-bar]	
	level	first difference
lnyield	-0.820	-2.268[b]
lnarea	1.079	-2.621[a]
temp	-3.082[a]	-5.977[a]
prep	0.792	-6.782[a]

Note: a, b and c denote significance at the 1%, 5% and 10% level, respectively. Following Hoechle (2007), we choose the ideal lag length by using Newey and West's (1994) plug-in method at (4*(T/100)^$^{(2/9)}$ =~3). We use Stata routine "pescadf".

Panel ARDL model results with different estimators for the crop wheat cultivated in all Mediterranean countries are reported in this part. Before conducting these approaches, we perform the lag selection procedure. Table 4-29 reveals the results of proper model selection according to three criteria. Based on AIC, the most appropriate model can be written in the form of the ARDL(4,3,3,3) model.

Table 4-29: Model Selection Criteria Table for Wheat for All Countries

Model	LogL	AIC*	BIC	HQ	Specification
12	525.282414	**-1.668410**	1.307175	-0.480720	**ARDL(4, 3, 3, 3)**
9	458.492501	-1.367238	1.398306	-0.263385	ARDL(3, 3, 3, 3)
6	408.378678	-1.169004	1.386498	-0.148988	ARDL(2, 3, 3, 3)
4	274.416846	-1.008746	0.286509	-0.491752	ARDL(2, 1, 1, 1)
5	327.988228	-1.006100	0.919278	-0.237595	ARDL(2, 2, 2, 2)
1	255.392486	-1.002423	**0.082791**	**-0.569265**	**ARDL(1, 1, 1, 1)**
7	286.743487	-0.973725	0.531571	-0.372894	ARDL(3, 1, 1, 1)
3	356.829273	-0.961909	1.383552	-0.025730	ARDL(1, 3, 3, 3)
11	355.596624	-0.954300	1.391161	-0.018121	ARDL(4, 2, 2, 2)
2	297.543979	-0.929284	0.786054	-0.244616	ARDL(1, 2, 2, 2)
10	291.781564	-0.893713	0.821624	-0.209045	ARDL(4, 1, 1, 1)
8	321.025131	-0.852007	1.283413	0.000335	ARDL(3, 2, 2, 2)

Note: AIC, SBC, HQ represent Akaike Information Criterion, Schwarz Bayesian Criterion, Hannan- Quinn Criterion, respectively. Dependent variable is lnyield

Results of the Panel ARDL (4,3,3,3) model with PMG, MG and DFE estimators are reported in Table 4-30. Long run coefficients of temperature (-0.0113) and area harvested (-0.4459) are highly significant at 1% significance level according to PMG estimator. More clearly, based on PMG estimator, area harvested and temperature have negative impact on yield in all countries where wheat is cultivated. In addition, Hausman test results fail to reject the null hypothesis of the homogeneity restriction on the variables in the long run which ensures the cointegration relationship between considered variables. Furthermore, the coefficient of the error correction term should be negative for the presence of long run relationship. As reported in Table 4-30, estimated error coefficients are significantly negative and they are in dynamically stable range for PMG and DFE estimators. Furthermore, based on DFE estimators, all long run variables are significant at 5% significance level. Coefficients of area and precipitation based on PMG estimator are in line with the DFE estimator. When short run coefficients are taken into account, one lagged of the yield variable has significant impact on yield based on three estimators. In addition, as in the Cluster-1 and Cluster-2 groups, short run coefficients are not significant. The reason of it may be that small changes in temperature and precipitation balance each other and do not cause loss of wheat yield in the short term.

We also present the results of the panel data methodology applied for all countries without clustering. Thus, we are able to compare the results of clustered groups and the group of all countries. While increase in temperature and precipitation in Cluster-1 countries influences wheat yield negatively and positively, respectively; this increase affects wheat yield positively for Cluster-2 countries based on PMG estimator. However, based on the results of model including all countries, direction of impact of temperature and precipitation are not the same with the results of Cluster-2 countries. That is to say, according to model including all countries, temperature and precipitation have negative and positive impact on wheat yield. Accordingly, by employing cluster analysis, we group the Mediterranean countries with the same structural and climatic features in terms of agriculture. It provides us to measure the impacts of climate change on wheat yield that is specific to each cluster group. Hence, we can determine the impact properly by focusing on the related clustered countries.

Table 4-30: ARDL(4,3,3,3) Results with PMG, MG, DFE Estimators for All Countries

Dependant variable: lnYield Crop: wheat	PMG		MG		DFE	
	Coef	Std error	Coef	Std error	Coef	Std error
Long run coefficients						
lnArea	-0.4459***	0.0045	0.7665	0.7042	-0.3316**	0.1346
Temperature	-0.0113***	0.0016	-0.2430	0.7164	0.1364**	0.0597
Precipitation	0.0004	0.0000	0.0029	0.0021	0.0006**	0.0003
Error correction coefficient	-0.5042***	0.1707	-0.1528	0.5217	-0.6751***	0.0919
Short run coefficients						
Δ Yield(-1)	-0.3012*	0.1773	-0.9779**	0.4866	-0.1870**	0.0873
Δ Yield(-2)	-0.2184*	0.1271	-0.5965**	0.2675	0.0286	0.0771
Δ Yield(-3)	-0.1170	0.0788	-0.2114	0.1636	0.0369	0.0544
Δ Area	0.3855*	0.2098	0.1810	1.8322	0.3335***	0.0898
Δ Area(-1)	0.3347*	0.1892	0.2681	1.1359	0.0505	0.0808
Δ Area(-2)	0.0835	0.1744	0.4496	0.3994	-0.0217	0.0669
Δ Temp	0.1057	0.1143	-1.2465*	0.7170	-0.0439	0.0362
Δ Temp(-1)	0.0873	0.0899	-0.6725*	0.3555	-0.0357	0.0314
Δ Temp-2)	0.0657	0.0527	-0.2042*	0.1184	0.0008	0.0224
Δ Prep	0.0003	0.0002	0.0033*	0.0018	-0.0002	0.0002
Δ Prep(-1)	-0.0002	0.0002	0.0023*	0.0015	-0.0001	0.0001
Δ Prep(-2)	0.0000	0.0002	0.0014	0.0010	0.0000	0.0001
C	8.0248***	2.7322	-48.3496	41.1544	8.2637***	1.7302
Hausman Test	0.03 (0.9683)					
Observations	396		396		396	
Number of countries	18		18		18	

Note: The table reports the results for the pooled mean group (PMG), mean group (MG) and dynamic fixed effect estimators. The dependent variable is yield. The asterisks ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. The Hausman test is the statistic for the null hypothesis that the slope is homogeneous across countries ($\beta_i=\beta$) under the null hypothesis that, the PMG estimator is better than the MG estimator. PMG estimate outputs are both obtained by using E-Views-9 and Stata-13 software programs in order to check the accuracy of the results. For MG and DFE estimates; Stata-13 routine xtpmg is used.

4.2.3 Maize

4.2.3.1 Maize for Cluster-1 Countries

Cluster -1 is composed of eight countries which are Albania, Algeria, Egypt, Libya, Morocco, Syria and Turkey according to results reported in Chapter 3.

As reported in Table 4-31, the null hypothesis of the presence of a unit root is rejected for the series of temperature and precipitation indicating that series are stationary at their level. Variables of area and yield have unit root at level. However, when their first difference is taken (Table 4-32), they become stationary revealing that they areI(1).

Table 4-31: Unit Root Results (Level) for Maize for Cluster-1 Countries

Intercept	lnyield	Lnarea	Temp	Prep
Levin-Lin-Chu	0.8108	0.5443	-6.7361[a]	8.3438[a]
Im, Pesaran and Shin W-stat	-1.2840[c]	0.9923	-5.5176[a]	-6.5974[a]
ADF - Fisher Chi-square	27.1034[b]	14.6658	55.9728[a]	73.1152[a]
PP - Fisher Chi-square	27.5337[b]	28.7949[b]	67.2086[a]	84.0272[a]
Intercept and trend	lnyield	Lnarea	Temp	Prep
Levin-Lin-Chu	-2.4779[a]	-1.4331[c]	-7.0211[a]	-6.8164[a]
Im, Pesaran and Shin W-stat	-2.2495[b]	-2.2885[b]	5.9832[a]	-6.6691[a]
ADF - Fisher Chi-square	29.6128[a]	30.5905[a]	59.0737[a]	63.9538[a]
PP - Fisher Chi-square	29.0674[b]	40.0415[a]	72.9428[a]	88.6806[a]

Note: a, b and c denote significance at the 1%, 5% and 10% level, respectively. For Levin-Lin-Chu unit root test, null hypothesis is that there exists unit root (assumes common unit root process). For Im, Pesaran and Shin W-stat, ADF - Fisher Chi-square and PP - Fisher Chi-square unit root tests, null hypothesis is that there exists unit root unit root (assumes individual unit root process). Automatic lag length is selected based on AIC. EViews-9 software program is used.

Table 4-32: Unit Root Results (First Difference) for Maize for Cluster-1 Countries

Intercept	lnyield	Lnarea	Temp	Prep
Levin-Lin-Chu	-5.5097[a]	-5.4596[a]	-12.3610[a]	-6.2281[a]
Im, Pesaran and Shin W-stat	-7.9212[a]	-8.5484[a]	-12.9122[a]	-9.7210[a]
ADF - Fisher Chi-square	80.1601[a]	91.1749[a]	134.5020[a]	101.7990[a]
PP - Fisher Chi-square	361.1200[a]	178.1600[a]	337.5620[a]	784.1860[a]
Intercept and trend	lnyield	Lnarea	Temp	Prep
Levin-Lin-Chu	-1.9249[b]	-3.1201[a]	-10.1966[a]	-3.9584[a]
Im, Pesaran and Shin W-stat	-5.8988[a]	-7.2863[a]	-11.2361[a]	-8.0829[a]
ADF - Fisher Chi-square	56.1708[a]	72.2336[a]	105.8320[a]	78.6716[a]
PP - Fisher Chi-square	390.5570[a]	301.7830[a]	335.1020[a]	502.1580[a]

Note: a, b and c denote significance at the 1%, 5% and 10% level, respectively. For Levin-Lin-Chu unit root test, null hypothesis is that there exists unit root (assumes common unit root process). For Im, Pesaran and Shin W-stat, ADF - Fisher Chi-square and PP - Fisher Chi-square unit root tests, null hypothesis is that there exists unit root unit root (assumes individual unit root process). Automatic lag length is selected based on AIC. EViews-9 software program is used.

According to results reported in Table 4-33, null hypothesis of "cross-section dependence does not exist" is strongly rejected. Therefore, there is a cross-sectional dependency between the series. Regarding the presence of cross-sectional dependence, we apply Pesaran (2007)'s CADF unit root test, presented in Table 4-34. According to results, majority of the series are stationary when they are first differenced, except for the series of temperature which is stationary at level. Therefore, we can conclude that series have a mixed order of integration, I(0) and I(1).

Table 4-33: Residual Cross-Section Dependence Test for Maize for Cluster-1 Countries

Test	Statistic
Breusch-Pagan LM	58.65015***
Pesaran scaled LM	4.729421***
Bias-corrected scaled LM	4.562754***
Pesaran CD	5.883945***

Note: The asterisks ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Null hypothesis is that there exists no cross-section dependence (correlation) in residuals. EViews-9 software program is used.

Table 4-34: Pesaran (2007) CADF Unit Root Test for Maize for Cluster-1 Countries

Variables	Pesaran Z[t-bar]	
	level	first difference
lnyield	2.381	-1.044[c]
lnarea	1.056	-2.121[b]
temp	-3.078[a]	-3.670[a]
prep	0.165	-1.308[c]

Note: a, b and c denote significance at the 1%, 5% and 10% level, respectively. Following Hoechle (2007), we choose the ideal lag length by using Newey and West's (1994) plug in method at $(4*(T/100)^{(2/9)}$ =~3). Stata routine "pescadf" is used.

Panel ARDL model results with different estimators for the crop maize cultivated in all Cluster-1 countries are explained in this part. Table 4-35 displays the results of proper model selection according to three criterion. Based on AIC, the most appropriate model can be written in the form of the ARDL(4,3,3,3).

Table 4.35: Model Selection Criteria Table for Maize for Cluster-1 Countries

Model	LogL	AIC*	BIC	HQ	Specification
12	195.114484	**-1.493881**	0.779647	-0.570218	**ARDL(4, 3, 3, 3)**
9	178.117578	-1.335200	0.780757	-0.475553	ARDL(3, 3, 3, 3)
6	153.999241	-1.063480	0.894905	-0.267850	ARDL(2, 3, 3, 3)
1	97.146788	-0.938838	**-0.083451**	**-0.591321**	**ARDL(1, 1, 1, 1)**
4	101.835467	-0.902150	0.110808	-0.490617	ARDL(2, 1, 1, 1)
3	135.743062	-0.884811	0.916003	-0.153196	ARDL(1, 3, 3, 3)
7	106.174744	-0.859917	0.310612	-0.384367	ARDL(3, 1, 1, 1)
11	133.281703	-0.845741	0.955073	-0.114127	ARDL(4, 2, 2, 2)
2	111.704957	-0.836587	0.491514	-0.297021	ARDL(1, 2, 2, 2)
10	111.625163	-0.835320	0.492780	-0.295755	ARDL(4, 1, 1, 1)
5	111.044614	-0.714994	0.770678	-0.111412	ARDL(2, 2, 2, 2)
8	117.470556	-0.705882	0.937361	-0.038284	ARDL(3, 2, 2, 2)

Note: AIC, SBC, HQ represent Akaike Information Criterion, Schwarz Bayesian Criterion, Hannan-Quinn Criterion, respectively. Dependent variable is lnyield.

Table 4-36: ARDL(4,3,3,3) Results with PMG, MG, DFE Estimators for Cluster-1 Countries

Dependent variable: lnYield	PMG		MG		DFE	
Crop: maize	Coef	Std error	Coef	Std error	Coef	Std error
Long run coefficients						
lnArea	0.0383	0.1349	0.7851	3.1612	0.1851	0.1994
Temperature	-1.0140***	0.1052	-2.3902*	1.395	0.0886	0.1694
Precipitation	0.0053***	0.0005	-0.0011	0.00972	0.0030***	0.0011
Error correction coefficient	-0.2492	0.2569	-0.7032	0.5645	-0.5849***	0.1107
Short run coefficients						
Δ Yield(-1)	-0.1937	0.3129	-0.1345	0.3154	-0.1576	0.104
Δ Yield(-2)	-0.7424**	0.346	-0.6225	0.4414	0.1069	0.095
Δ Yield(-3)	-0.1963	0.2512	-0.3466	0.4256	0.0124	0.0766
Δ Area	0.3158	0.1963	0.1918	0.735	0.0826	0.1283
Δ Area(-1)	-0.0721*	0.2919	0.0398	1.026	0.1006	0.1246
Δ Area(-2)	0.2651	0.2034	0.0677	0.9283	-0.01	0.1125
Δ Temp	-0.4493	0.3056	0.456	0.5672	0.0142	0.0932
Δ Temp(-1)	-0.2289	0.1978	0.2202	0.372	0.0798	0.0806
Δ Temp-2)	-0.2364	0.1505	-0.109	0.1757	-0.0236	0.0598
Δ Prep	-0.0019	0.0015	-0.0025	0.0045	-0.0004	0.0006
Δ Prep(-1)	-0.0013	0.0009	-0.0016	0.0026	0.0001	0.0005
Δ Prep(-2)	-0.001	0.0008	-0.0011	0.001	-0.0001	0.0003
C	-2.6652	3.0108	27.4886	28.5514	3.3024*	1.8725
Hausman Test	0.9987(0.9984)					
Observations	154		154		154	
Number of countries	7		7		7	

Note: The table reports the results for the pooled mean group (PMG), mean group (MG) and dynamic fixed effect estimators. The dependent variable is yield. The asterisks ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. The Hausman test is the statistic for the null hypothesis that the slope is homogeneous across countries ($\beta_i=\beta$) under the null hypothesis that, the PMG estimator is better than the MG estimator. PMG estimate outputs are both obtained by using E-Views-9 and Stata-13 software programs in order to check the accuracy of the results. For MG and DFE estimates; Stata-13 routine xtpmg is used.

Table 4-36 portrays the estimation of long and short run parameters connecting climatic variables and area with agricultural yield by PMG, MG and DFE approaches. According to results of Hausman test, we can say that null hypothesis of homogeneity restriction on the variables in the long run is strongly significant which shows that PMG estimate is more preferable to MG estimator. Based on PMG approach; temperature and precipitation have negative and positive significant impact on yield, respectively. Regarding the long run coefficients and error correction coefficient PMG estimates tend to be close to DFE estimate. Furthermore, the estimated values of the error correction coefficient is varying between -0.24 and -0.70 based on the three estimator types. Nevertheless, the error correction coefficient obtained from DFE estimator is significant. Besides, majority of the short run coefficients are not significant according to all estimators, in general. There is no significant impact of precipitation and temperature on maize yield for Cluster-1 countries in the short term.

4.2.3.2 Maize for Cluster-2 Countries

Cluster-2 countries are Bosnia and Herzegovina, Croatia, France, Greece Israel, Italy, Lebanon, Serbia and Montenegro, Spain and Slovenia.

In order to determine the order of integration of the series, unit root test are applied. Table 4-37 and Table 4-38 report the results of the four first generation panel unit root tests. We can infer that all series are stationary at level so they are I(0). Then, cross sectional dependence tests are applied. According to results portrayed in Table 4-39, null hypothesis of no cross-sectional dependence is rejected. Therefore due to presence of cross-sectional dependence problem, we need to employ Pesaran (2007)'s CADF unit root test. Table 4-40 displays the results of the test which indicate that series of area and temperature are stationary at the level. However, precipitation and yield become stationary when their first differences are taken; so they are I(1). As a result, we can conclude that series have mixed order of integration.

Table 4-37: Unit Root Results (Level) for Maize for Cluster-2 Countries

Intercept	lnyield	Lnarea	Temp	Prep
Levin-Lin-Chu	-4.5767	-16.5894[a]	-8.2124[a]	-10.9920[a]
Im, Pesaran and Shin W-stat	-5.0095[a]	-6.6530[a]	-8.0234[a]	-10.9820[a]
ADF - Fisher Chi-square	65.8425[a]	288.6600[a]	97.3696[a]	136.0480[a]
PP - Fisher Chi-square	66.6787[a]	41.5410[a]	111.9640[a]	197.2830[a]
Intercept and trend	lnyield	lnarea	Temp	Prep
Levin-Lin-Chu	-4.4221[a]	-2.2081[b]	-7.4906[a]	-9.2864[a]
Im, Pesaran and Shin W-stat	-3.7342[a]	-2.3000[b]	-7.4475[a]	-9.0031[a]
ADF - Fisher Chi-square	49.3449[a]	35.4201[b]	84.9505[a]	103.1020[a]
PP - Fisher Chi-square	58.8497[a]	28.5477[c]	107.5320[a]	180.8730[a]

Note: a, b and c denote significance at the 1%, 5% and 10% level, respectively. For Levin-Lin-Chu unit root test, null hypothesis is that there exists unit root (assumes common unit root process). For Im, Pesaran and Shin W-stat, ADF - Fisher Chi-square and PP - Fisher Chi-square unit root tests, null hypothesis is that there exists unit root unit root (assumes individual unit root process). Automatic lag length is selected based on AIC. EViews-9 software program is used.

Table 4-38: Unit Root Results (First Difference) for Maize for Cluster-2 Countries

Intercept	lnyield	lnarea	Temp	Prep
Levin-Lin-Chu	-12.4816[a]	-9.6175[a]	-12.1200[a]	-7.1664[a]
Im, Pesaran and Shin W-stat	-12.4494[a]	-10.4540[a]	-13.0738[a]	-10.7610[a]
ADF - Fisher Chi-square	153.2560[a]	128.4470[a]	164.6510[a]	137.5620[a]
PP - Fisher Chi-square	416.3150[a]	151.8530[a]	746.9560[a]	1304.8900[a]
Intercept and trend	lnyield	lnarea	Temp	Prep
Levin-Lin-Chu	-8.7096[a]	-8.0681[a]	-9.7527[a]	-4.6138[a]
Im, Pesaran and Shin W-stat	-9.5022[a]	-8.8733[a]	-10.8401[a]	-8.9214[a]
ADF - Fisher Chi-square	109.2640[a]	100.8550[a]	125.3890[a]	105.9220[a]
PP - Fisher Chi-square	562.1940[a]	138.5280[a]	1025.8900[a]	922.4640[a]

Note: a, b and c denote significance at the 1%, 5% and 10% level, respectively. For Levin-Lin-Chu unit root test, null hypothesis is that there exists unit root (assumes common unit root process). For Im, Pesaran and Shin W-stat, ADF - Fisher Chi-square and PP - Fisher Chi-square unit root tests, null hypothesis is that there exists unit root unit root (assumes individual unit root process). Automatic lag length is selected based on AIC. EViews-9 software program is used.

Table 4-39: Residual Cross-Section Dependence Test for Maize for Cluster-2 Countries

Test	**Statistic**
Breusch-Pagan LM	1377274***
Pesaran scaled LM	8720234***
Bias-corrected scaled LM	8482139***
Pesaran CD	9310823***

Note: The asterisks ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Null hypothesis is that there exists no cross-section dependence (correlation) in residuals. EViews-9 software program is used.

Table 4-40: Pesaran (2007) CADF Unit Root Test for Maize for Cluster-2 Countries

Variables	Pesaran Z[t-bar]	
(lag=3)	level	first difference
lnyield	1.656	-0.542[c]
lnarea	-1.879[b]	-1.098
temp	-1.376[c]	-3.206[a]
prep	-0.011	-0.394[c]

Note: a, b and c denote significance at the 1%, 5% and 10% level, respectively. Following Hoechle (2007) We choose the ideal lag length by using Newey and West's (1994) plug-in method at $(4*(T/100)^{(2/9)}$ =~3). Stata routine "pescadf" is used.

Before employing PMG, MG and DFE estimators, it is necessary to determine the lag orders of the variables. We perform the lag selection according to Akaike Information Criterion (AIC) setting 4 as the maximum lag unit. According to results presented in Table 4-41, we choose ARDL(4,3,3,3) model according to AIC.

Table 4-41: Model Selection Criteria Table for Maize for Cluster-2 Countries

Model	LogL	AIC*	BIC	HQ	Specification
12	271.720989	**-1.430233**	1.106394	-0.401740	**ARDL(4, 3, 3, 3)**
9	253.740836	-1.341565	1.017675	-0.384994	ARDL(3, 3, 3, 3)
8	216.887669	-1.265419	0.561662	-0.524616	ARDL(3, 2, 2, 2)
11	225.822038	-1.253578	0.750889	-0.440853	ARDL(4, 2, 2, 2)
1	161.662863	-1.207365	**-0.267217**	**-0.826175**	**ARDL(1, 1, 1, 1)**
4	170.729253	-1.196992	-0.079457	-0.743879	ARDL(2, 1, 1, 1)
2	187.856649	-1.165074	0.307234	-0.568116	ARDL(1, 2, 2, 2)
7	177.843997	-1.164933	0.129988	-0.639898	ARDL(3, 1, 1, 1)
10	180.748288	-1.086092	0.386216	-0.489135	ARDL(4, 1, 1, 1)
6	220.690553	-1.085451	1.096403	-0.200803	ARDL(2, 3, 3, 3)
3	195.200783	-0.913342	1.091125	-0.100617	ARDL(1, 3, 3, 3)
5	164.105769	-0.790064	0.859630	-0.121184	ARDL(2, 2, 2, 2)

Note: AIC, SBC, HQ represent Akaike Information Criterion, Schwarz Bayesian Criterion, Hannan-Quinn Criterion, respectively. Dependent variable is lnyield.

Table 4-41 reveals the results of PMG, MG and DFE estimation and Hausman test for Cluster-2 countries for the crop maize cultivated. Long run coefficients of temperature (-0.4041) and precipitation (0.0147) are significantly negative and positive, for PMG approach. We can infer that while increase in temperature affects maize yield negatively, increase in precipitation influences it positively for Cluster-2 countries. Precipitation is very important for maize crop in growing season in order to produce in high amounts. This fact confirms our findings related to impact of precipitation. According to results of Hausman test, homogeneity restriction imposed on the long-run coefficients is not significant. It confirms the consistency and efficiency of PMG estimators. Error coefficient term obtained from PMG estimator is almost 0.18 meaning that only 18 % of the imbalances will become removed in the next year. However, error coefficient term is not statistically significant based on estimator PMG. Besides, most of the short run coefficients are not significant according to all estimators which imply that there is no significant impact of temperature and precipitation on maize yield for Cluster-2 countries in the short run.

Table 4-42: ARDL(4,3,3,3) Results with PMG, MG, DFE Estimators for Cluster-2 Countries

Dependant variable: lnYield Crop: Maize	PMG		MG		DFE	
	Coef	**Std error**	**Coef**	**Std error**	**Coef**	**Std error**
Long run coefficients						
lnArea	-0.4281	0.3441	3.8713	4.2371	-0.6819***	0.1408
Temperature	-0.4041***	0.1404	0.4975	0.6925	-0.0893	0.0667
Precipitation	0.0147***	0.0029	0.0019	0.0020	0.0001	0.0003
Error correction coefficient	-0.1774	0.1948	-0.2225	0.6123	-0.7288***	0.1322
Short run coefficients						
Δ Yield(-1)	-1.1681**	0.5415	-1.1567*	0.6078	-0.1322	0.1178
Δ Yield(-2)	-0.6680*	0.34786	-0.7469	0.4811	-0.1410	0.1001
Δ Yield(-3)	-0.1121	0.0988	-0.2320	0.2558	-0.0208	0.0768
Δ Area	-0.2612	0.4978	0.5350	0.6105	-0.0181	0.1277
Δ Area(-1)	-0.7893*	0.4205	-0.2878	0.7352	-0.0611	0.1145
Δ Area(-2)	-0.3168	0.5250	-0.6145	0.8314	-0.1904*	0.1034
Δ Temp	0.0483	0.0933	0.3081***	0.1189	0.0241	0.0375
Δ Temp(-1)	-0.1023	0.0760	0.0909	0.0932	0.0037	0.0312
Δ Temp-2)	-0.1292	0.1378	-0.0756	0.1476	0.0171	0.0238
Δ Prep	0.0030	0.0030	0.0029	0.0031	0.0003	0.0002
Δ Prep(-1)	0.0022	0.0024	0.0023	0.0024	0.0002	0.0002
Δ Prep(-2)	0.0011	0.0012	0.0011	0.0012	0.0000	0.0001
C	-1.3345	1.5221	18.6189	15.5045	15.0533***	2.9475
Hausman Test	0.9299 (0.9998)					
Observations	220		220		220	
Number of countries	10		10		10	

Note: The table reports the results for the pooled mean group (PMG), mean group (MG) and dynamic fixed effect estimators. The dependent variable is yield. The asterisks ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. The Hausman test is the statistic for the null hypothesis that the slope is homogeneous across countries (β_i=β) under the null hypothesis that, the PMG estimator is better than the MG estimator. PMG estimate outputs are both obtained by using E-Views-9 and Stata-13 software programs in order to check the accuracy of the results. For MG and DFE estimates; Stata-13 routine xtpmg is used.

4.2.3.3 Maize for All Countries

In this section, unit root and cross sectional dependence test results are reported for all Mediterranean countries where maize is cultivated. Table 4-43 reveals the results of unit root tests which suggest that all variables are stationary so they are I(0) f based on first generation panel unit root tests. Then, cross sectional dependence tests are applied and according to test results displayed in Table 4-44, there exists cross sectional dependence among variables. Therefore, we employ Pesaran (2007) CADF unit root test to the first differenced series in order to determine the order of integration. Based on results, given in Table 4-45, except for the temperature, all series are stationary when they are first differenced. However, series of temperature is (I0). Hence, series have a mixed order of integration, I(0) and I(1).

Table 4-43: Unit Root Results (Level) for Maize for All Countries

Intercept	lnyield	lnarea	Temp	Prep
Levin-Lin-Chu	-3.3043[a]	-14.9762[a]	-10.5224[a]	-13.6428[a]
Im, Pesaran and Shin W-stat	-4.6476[a]	-4.3955[a]	-9.7018[a]	-12.6702[a]
ADF - Fisher Chi-square	92.9459[a]	303.3260[a]	153.3420[a]	209.1630[a]
PP - Fisher Chi-square	94.2124[a]	70.3359[a]	179.1730[a]	281.3110[a]
Intercept and trend	lnyield	lnarea	Temp	Prep
Levin-Lin-Chu	-4.9092[a]	-2.4433[a]	-10.4100[a]	-11.7476[a]
Im, Pesaran and Shin W-stat	-4.3029[a]	-3.2358[a]	-9.5523[a]	-11.1664[a]
ADF - Fisher Chi-square	78.9577[a]	66.0106[a]	144.0240[a]	167.0560[a]
PP - Fisher Chi-square	87.9172[a]	68.5892[a]	180.4750[a]	269.5540[a]

Note: a, b and c denote significance at the 1%, 5% and 10% level, respectively. For Levin-Lin-Chu unit root test, null hypothesis is that there exists unit root (assumes common unit root process). For Im, Pesaran and Shin W-stat, ADF - Fisher Chi-square and PP - Fisher Chi-square unit root tests, null hypothesis is that there exists unit root unit root (assumes individual unit root process). Automatic lag length is selected based on AIC. EViews-9 software program is used.

Table 4-44: Residual Cross-Section Dependence Test for Maize for All Countries

Test	**Statistic**
Breusch-Pagan LM	4690838***
Pesaran scaled LM	1916540***
Bias-corrected scaled LM	1876063***
Pesaran CD	1697430***

Note: The asterisks ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Null hypothesis is that there exists no cross-section dependence (correlation) in residuals. EViews-9 software program is used.

Table 4-45: Pesaran, (2007) CADF Unit Root Test for Maize for All Countries

Variables	Pesaran Z[t-bar]	
(lag=3)	level	first difference
lnyield	2.087	-1.504[c]
lnarea	-0.409	-3.208[a]
temp	-4.167[a]	-4.680[a]
prep	1.093	-0.922[c]

Note: a, b and c denote significance at the 1%, 5% and 10% level, respectively. Following Hoechle (2007), we choose the ideal lag length by using Newey and West's (1994) plug-in method at (4*(T/100)^$^{(2/9)}$ =~3). Stata routine "pescadf" is used.

Before conducting PMG, MG and DFE estimators, we perform the lag selection based on AIC to determine the model. Table 4-46 reveals the results of appropriate model selection according to three criteria. Based on AIC, the most proper model can be written in the form of the ARDL(4,3,3,3) model.

Table 4-46: Model Selection Criteria Table for Wheat for Cluster-1 Countries

Model	LogL	AIC*	BIC	HQ	Specification
12	483.169883	**-1.582810**	1.349818	-0.409950	**ARDL(4, 3, 3, 3)**
9	425.127758	-1.314561	1.411201	-0.224434	ARDL(3, 3, 3, 3)
8	336.602027	-1.069294	1.035870	-0.227366	ARDL(3, 2, 2, 2)
7	285.321803	-1.067463	0.417104	-0.473733	ARDL(3, 1, 1, 1)
1	251.009555	-1.065422	**0.005413**	**-0.637158**	**ARDL(1, 1, 1, 1)**
11	351.961283	-1.058570	1.253459	-0.133910	ARDL(4, 2, 2, 2)
4	266.958320	-1.058551	0.219150	-0.547554	ARDL(2, 1, 1, 1)
10	293.993188	-1.013027	0.678405	-0.336565	ARDL(4, 1, 1, 1)
5	308.881911	-0.999228	0.899070	-0.240033	ARDL(2, 2, 2, 2)
6	359.734833	-0.998267	1.520629	0.009127	ARDL(2, 3, 3, 3)
2	288.812702	-0.979168	0.712264	-0.302706	ARDL(1, 2, 2, 2)
3	317.325152	-0.832191	1.479839	0.092470	ARDL(1, 3, 3, 3)

Note: AIC, SBC, HQ represent Akaike Information Criterion, Schwarz Bayesian Criterion, Hannan-Quinn Criterion respectively. Dependent variable is lnyield.

Table 4-47: ARDL(4,3,3,3) Results with PMG, MG, DFE Estimators for All Countries

Dependent variable: lnYield Crop: maize	PMG		MG		DFE	
	Coef	Std error	Coef	Std error	Coef	Std error
Long run coefficients						
lnArea	-1.0358***	0.0483	2.5894	2.7623	-0.0636	0.1503
Temperature	-1.7497***	0.0903	-0.6916	0.7651	-0.0074	0.0929
Precipitation	0.0072***	0.0002	0.0007	0.0040	0.0008	0.0005
Error correction coefficient	-0.3131	0.2326	-0.4205	0.4204	-0.5227***	0.0675
Short run coefficients						
Δ Yield(-1)	-0.4040***	0.1546	-0.7358*	0.3917	-0.1966***	0.0673
Δ Yield(-2)	-0.5180***	0.1730	-0.6957**	0.3270	-0.0259	0.0645
Δ Yield(-3)	-0.2663***	0.0963	-0.2792	0.2233	-0.0611	0.0523
Δ Area	-0.0351	0.3637	0.3937	0.4566	-0.0146	0.0823
Δ Area(-1)	0.1538	0.4065	-0.1529	0.5857	0.0405	0.0808
Δ Area(-2)	-0.2528	0.4120	-0.3336	0.6073	-0.0717	0.0754
Δ Temp	0.2522	0.2323	0.3690	0.2339	-0.0095	0.0418
Δ Temp(-1)	0.1730	0.1342	0.1441*	0.1566	0.0061	0.0358
Δ Temp-2)	0.0300	0.0467	-0.0894	0.1095	0.0011	0.0267
Δ Prep	-0.0023	0.0016	0.0007	0.0026	0.0001	0.0002
Δ Prep(-1)	-0.0015	0.0010	0.0007	0.0018	0.0002	0.0002
Δ Prep(-2)	-0.0009**	0.0004	0.0002	0.0009	0.0000	0.0001
C	14.7506	11.4946	22.2711	14.3738	5.9614***	1.2404
Hausman Test	0.21 (0.9757)					
Observations	374		374		374	
Number of countries	17		17		17	

Note: The table reports the results for the pooled mean group (PMG), mean group (MG) and dynamic fixed effect estimators. The dependent variable is yield. The asterisks ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. The Hausman test is the statistic for the null hypothesis that the slope is homogeneous across countries ($\beta_i=\beta$) under the null hypothesis that, the PMG estimator is better than the MG estimator. PMG estimate outputs are both obtained by using E-Views-9 and Stata-13 software programs in order to check the accuracy of the results. For MG and DFE estimates; Stata-13 routine xtpmg is used.

Table 4-47 reports the results of PMG, MG and DFE estimators with Hausman test for all countries for the crop maize cultivated. According to results of Hausman test, we can conclude that PMG estimate is preferable to MG estimate. The results show that while temperature and area harvested have negative impact on yield, precipitation has positive effect on yield in the long run according to PMG estimator. We can interpret results like saying “1 °C increase in temperature” as mentioned in Data and Methodology part of the dissertation. That is to say, an increase in temperature and precipitation by 1 °C and by 1 mm rainfall, separately leads to decrease in 1.7% in yield and increase in 0.01% in yield, respectively when the other factors are held constant. In addition, as stated in the maize yield of Cluster-2 countries, water is more important agent for maize to produce higher amount of it when compared to wheat and potato. Once again, our findings about impact of precipitation on yield are in line with this fact. Another point is that standard errors of long run coefficients obtained from PMG estimators are smaller than the other estimator. Moreover, error correction coefficient is -0.3131 which is indication of existence of long run stable relationship according to PMG estimator. However, it is not statistically significant like long run coefficients obtained from MG and DFE estimators. Short run coefficients related to yield are significant at 1% significance level. However, short run coefficients of temperature and precipitation are not significant. There is no significant impact of temperature and precipitation on maize yield in the short run.

To sum up, the impact of temperature and precipitation have negative and positive impact on maize yield, respectively, based on PMG estimator. By clustering countries, we prefer to determine the impact of climate change on two clusters having different characteristics in terms of agricultural vulnerability. Hence, we can measure the possible different impacts of climatic variables on maize yield. Based on model results we conclude that the effect of climate change on maize yield are the same for two cluster groups and all countries.

4.2.4 Potato

4.2.4.1 Potato for Cluster-1 Countries

Cluster -1 is composed of eight countries which are Albania, Algeria, Egypt, Libya, Morocco, Syria, Tunisia and Turkey according to results reported in Chapter-3

In the first step, panel unit root tests are applied. The panel unit root tests of all series are tested both in levels and in first differences in Table 4-48 and Table 4-49. It can be inferred that for the series of area and temperature with intercept, the unit root hypothesis cannot be rejected when the variables are taken in levels. Nevertheless, when the first differences are used, the hypothesis of unit root non-stationary is rejected at the 1% level of significance. Besides, series of precipitation and yield are stationary at their level.

Table 4-48: Unit Root Results (Level) for Potato for Cluster-1 Countries

Intercept	lnyield	lnarea	Temp	Prep
Levin-Lin-Chu	-2.7256[a]	-0.1114	-8.5261[a]	-8.2383[a]
Im, Pesaran and Shin W-stat	-1.4732[c]	0.4107	-7.2919	-7.9985[a]
ADF - Fisher Chi-square	32.6441[a]	17.4119	79.5109	86.7217[a]
PP - Fisher Chi-square	36.2568[a]	18.5732	133.7970	89.6707[a]
Intercept and trend	lnyield	lnarea	Temp	Prep
Levin-Lin-Chu	-3.7846[a]	-2.9778[a]	-9.4587[a]	-6.0869[a]
Im, Pesaran and Shin W-stat	-4.6257[a]	-1.7487[b]	-7.9848[a]	-7.0531[a]
ADF - Fisher Chi-square	50.7173[a]	23.3250	81.1070[a]	72.5185[a]
PP - Fisher Chi-square	56.6863[a]	28.5783[b]	120.7150[a]	75.7961[a]

Note: a, b and c denote significance at the 1%, 5% and 10% level, respectively. For Levin-Lin-Chu unit root test, null hypothesis is that there exists unit root (assumes common unit root process). For Im, Pesaran and Shin W-stat, ADF - Fisher Chi-square and PP - Fisher Chi-square unit root tests, null hypothesis is that there exists unit root unit root (assumes individual unit root process). Automatic lag length is selected based on AIC. EViews-9 software program is used.

Table 4-49: Unit Root Results (First Difference) for Potato for Cluster-2 Countries

Intercept	lnyield	lnarea	Temp	Prep
Levin-Lin-Chu	-14.4762[a]	9.5833[a]	-13.2724[a]	-7.2759[a]
Im, Pesaran and Shin W-stat	-14.4095[a]	-10.0855[a]	-14.0327[a]	-10.0926[a]
ADF - Fisher Chi-square	160.1120[a]	110.2040[a]	156.4930[a]	113.4360[a]
PP - Fisher Chi-square	342.6140[a]	179.2360[a]	406.7250[a]	659.3780[a]
Intercept and trend	lnyield	lnarea	Temp	Prep
Levin-Lin-Chu	-9.9528[a]	-5.2909[a]	-10.8094[a]	-7.2577[a]
Im, Pesaran and Shin W-stat	-11.1593[a]	-9.1575[a]	-12.1020[a]	-9.3682[a]
ADF - Fisher Chi-square	113.6610[a]	92.6941[a]	121.8430[a]	97.2240[a]
PP - Fisher Chi-square	327.5050[a]	173.5940[a]	496.3960[a]	552.0900[a]

Note: a, b and c denote significance at the 1%, 5% and 10% level, respectively. For Levin-Lin-Chu unit root test, null hypothesis is that there exists unit root (assumes common unit root process). For Im, Pesaran and Shin W-stat, ADF - Fisher Chi-square and PP - Fisher Chi-square unit root tests, null hypothesis is that there exists unit root unit root (assumes individual unit root process). Automatic lag length is selected based on AIC. EViews-9 software program is used.

Results of cross sectional dependence tests are reported in Table 4-50. According to results, we can conclude that cross-sectional dependence exists among variables. Therefore, we conduct the Pesaran (2007) CADF unit root test. Based on results displayed in Table 4-51, most of variables become stationary when their first differences are taken, except for temperature which is stationary at level. Thus, series have a mixed order of integration, I(0) and I(1).

Table 4-50: Residual Cross-Section Dependence Test for Potato for Cluster-1 Countries

Test	**Statistic**
Breusch-Pagan LM	1103231***
Pesaran scaled LM	9931841***
Bias-corrected scaled LM	9741365***
Pesaran CD	8112865***

Note: The asterisks ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Null hypothesis is that there exists no cross-section dependence (correlation) in residuals. EViews-9 software program is used.

Table 4-51: Pesaran (2007) CADF Unit Root Test for Cluster-1 Countries

Potato (Cluster-1)	Pesaran Z[t-bar]	
	level	first difference
lnyield	-0.513	-1.954[b]
lnarea	-0.359	-1.266[c]
temp	-4.167[a]	-3.013[a]
prep	-0.170	-1.284[c]

Note: a, b and c denote significance at the 1%, 5% and 10% level, respectively. Following Hoechle (2007), we choose the ideal lag length by using Newey and West's (1994) plug-in method at $(4*(T/100)^{(2/9)}=\sim 3)$. Stata routine "pescadf" is used.

Before applying PMG, MG and DFE approaches, as done for the other crops, we conduct the lag selection based on AIC to determine the model. Table 4-52 displays the results of proper model selection according to three criteria. Based on AIC, the most appropriate model can be written in the form of the ARDL(4,3,3,3) model.

Table 4-52: Model Selection Criteria Table for Potato for Cluster-1 Countries

Model	LogL	AIC*	BIC	HQ	Specification
12	330.736177	**-2.996336**	-0.624610	-2.032600	**ARDL(4, 3, 3, 3)**
9	306.742390	-2.774200	-0.567464	-1.877507	ARDL(3, 3, 3, 3)
6	293.970448	-2.707923	-0.666176	-1.878272	ARDL(2, 3, 3, 3)
11	280.094140	-2.626307	-0.749550	-1.863699	ARDL(4, 2, 2, 2)
5	259.723692	-2.565607	-1.018829	-1.937084	ARDL(2, 2, 2, 2)
8	267.561358	-2.563352	-0.851585	-1.867787	ARDL(3, 2, 2, 2)
3	270.255751	-2.489663	-0.612906	-1.727055	ARDL(1, 3, 3, 3)
1	220.225038	-2.461459	**-1.574640**	**-2.101106**	**ARDL(1, 1, 1, 1)**
7	230.392654	-2.380454	-1.163655	-1.886015	ARDL(3, 1, 1, 1)
4	222.203916	-2.377832	-1.326023	-1.950436	ARDL(2, 1, 1, 1)
2	235.728764	-2.343455	-0.961667	-1.781974	ARDL(1, 2, 2, 2)
10	234.293864	-2.323526	-0.941738	-1.762045	ARDL(4, 1, 1, 1)

Note: AIC, SBC, HQ represent Akaike Information Criterion, Schwarz Bayesian Criterion, Hannan-Quinn Criterion, respectively. Dependent variable is yield.

After determining the proper model, we employ panel ARDL method for PMG, MG and DFE estimators to determine the link between the yield and climatic variables with area harvested. Table 4-53 reports the results of the models for three estimators along with the Hausman test. The coefficient of temperature and precipitation are 0.6978 and 0.0023, respectively. They indicate that precipitation and temperature has positive and significant impact in the long run and no effect in the short run on yield according to PMG estimator for Cluster-1 countries. The reason behind this may be that the impact of temperature and precipitation can offset each other. The Hausman test failed to reject the null hypothesis of homogeneity of the long-run parameters revealing that the PMG estimate is preferable to the MG estimate. In this regard, standard errors of the long run coefficients obtained from PMG estimator are the smallest among all estimators. Furthermore, PMG and DFE both estimate the speeds of adjustment about 17% which means that adjustment is slow, with 17% occurring within one year. However, estimate of PMG is not significant.

Table 4-53: ARDL(4,3,3,3) Results with PMG, MG, DFE Estimators for Cluster-1 Countries

Dependant variable: lnYield Crop: potato	PMG		MG		DFE	
	Coef	**Std error**	**Coef**	**Std error**	**Coef**	**Std error**
Long run coefficients						
lnArea	-0.3956***	0.0751	-0.6064	0.6953	-0.3569	0.3173
Temperature	0.6978***	0.0210	0.7477	0.4903	0.1024	0.1988
Precipitation	0.0023***	0.0001	0.0002	0.0010	0.0030**	0.0013
Error correction coefficient	-0.1697	0.1488	0.6838	2.5619	-0.1636***	0.0613
Short run coefficients						
Δ Yield(-1)	-0.7169***	0.2224	-1.3848	1.7256	-0.4476*	0.0824
Δ Yield(-2)	-0.3858	0.3531	-0.1131	0.6985	-0.1004	0.0845
Δ Yield(-3)	-0.3310*	0.2006	-0.4631	0.5336	0.0755	0.0733
Δ Area	-0.3278	0.2875	-0.1966	0.3862	-0.2050***	0.0736
Δ Area(-1)	-0.3128	0.1597	-0.5167	0.2890	-0.1123*	0.0656
Δ Area(-2)	-0.0018	0.0928	-0.1552*	0.3321	-0.0866	0.0611
Δ Temp	-0.0112	0.0752	0.0873	0.4291	0.0293	0.0319
Δ Temp(-1)	-0.0076	0.0429	0.0018	0.2826	0.0446*	0.0264
Δ Temp-2)	0.0170	0.0432	-0.0188	0.1390	0.0370**	0.0184
Δ Prep	-0.0001	0.0004	0.0015	0.0017	-0.0003**	0.0002
Δ Prep(-1)	-0.0004	0.0004	0.0012	0.0015	-0.0002**	0.0001
Δ Prep(-2)	0.0001	0.0002	0.0008	0.0009	0.0000	0.0001
C	1.1627	0.9204	-15.7182	29.5365	0.8954	0.7594
Hausman Test	0.91 (0.8223)					
Observations	176		176		176	
Number of countries	8		8		8	

Note: The table reports the results for the pooled mean group (PMG), mean group (MG) and dynamic fixed effect estimators. The dependent variable is yield. The asterisks ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. The Hausman test is the statistic for the null hypothesis that the slope is homogeneous across countries (β_i=β) under the null hypothesis that, the PMG estimator is better than the MG estimator. PMG estimate outputs are both obtained by using E-Views-9 and Stata-13 software programs in order to check the accuracy of the results. For MG and DFE estimates; Stata-13 routine xtpmg is used.

4.2.4.2 Potato for Cluster-2 Countries

Cluster-2 countries are Bosnia and Herzegovina, Croatia, Cyprus, France, Greece, Israel, Italy, Lebanon, Serbia and Montenegro, Spain and Slovenia.

Results of first generation panel unit root tests (Levin-Lin-Chu, Im-Pesaran-Shin, the Fisher-type tests of using ADF and PP tests), cross section dependence test and Pesaran (2007) CADF test are given in this section for the Cluster-2 countries.

Table 4-54 and Table 4-55 present the unit root results of variables at their level and first differences, respectively. Series of yield, temperature and precipitation are stationary at level based on all first generation unit root tests. However, based on Im, Pesaran and Shin W-stat and ADF - Fisher Chi-square, for series of area, null hypothesis of presence of unit root is failed to reject indicating that series is not stationary at level. However, when it is first differenced, it becomes stationary; that is to say, it is I(1). To sum up, series have mixed order of integration.

Table 4-54: Unit Root Results (Level) for Potato for Cluster-2 Countries

Intercept	lnyield	Lnarea	Temp	Prep
Levin-Lin-Chu	-3.8040[a]	-1.4281[c]	-8.9056[a]	-10.4880[a]
Im, Pesaran and Shin W-stat	-2.2516[b]	1.1113	-8.3107[a]	-11.1260[a]
ADF - Fisher Chi-square	36.5960[b]	21.9197	106.2940[a]	145.3930[a]
PP - Fisher Chi-square	52.9891	45.8117[a]	124.7680[a]	217.0200[a]
Intercept and trend	lnyield	lnarea	Temp	Prep
Levin-Lin-Chu	-5.5064[a]	-4.3817[a]	-8.6577[a]	-8.0634[a]
Im. Pesaran and Shin W-stat	-3.9631[a]	-4.0584[a]	-8.1092[a]	-8.8952[a]
ADF - Fisher Chi-square	64.1228[a]	57.5331[a]	95.5436[a]	108.5010[a]
PP - Fisher Chi-square	79.6316[a]	42.7593[a]	115.1560[a]	201.3070[a]

Note: a, b and c denote significance at the 1%, 5% and 10% level, respectively. For Levin-Lin-Chu unit root test, null hypothesis is that there exists unit root (assumes common unit root process). For Im, Pesaran and Shin W-stat, ADF - Fisher Chi-square and PP - Fisher Chi-square unit root tests, null hypothesis is that there exists unit root unit root (assumes individual unit root process). Automatic lag length is selected based on AIC. EViews-9 software program is used.

Table 4-55: Unit Root Results (First Difference) for Potato for Cluster-2 Countries

Trend	lnyield	lnarea	Temp	Prep
Levin-Lin-Chu	-14.0336[a]	-12.1356[a]	-15.2945[a]	-9.2079[a]
Im, Pesaran and Shin W-stat	-12.9607[a]	-11.6997[a]	-15.4543[a]	-13.0750[a]
ADF - Fisher Chi-square	179.4210[a]	154.8590[a]	203.4400[a]	174.4940[a]
PP - Fisher Chi-square	725.5290[a]	457.7690[a]	655.9660[a]	1528.5400[a]
Intercept and trend	lnyield	lnarea	Temp	Prep
Levin-Lin-Chu	-7.7525[a]	-7.7968[a]	-12.2345[a]	-6.6026[a]
Im. Pesaran and Shin W-stat	-10.0234[a]	-9.1275[a]	-12.7147[a]	-11.0180[a]
ADF - Fisher Chi-square	126.1900[a]	113.6500[a]	151.9690[a]	136.0230[a]
PP - Fisher Chi-square	517.9960[a]	440.7380[a]	918.2760[a]	1013.0500[a]

Note: a, b and c denote significance at the 1%, 5% and 10% level, respectively. For Levin-Lin-Chu unit root test, null hypothesis is that there exists unit root (assumes common unit root process). For Im, Pesaran and Shin W-stat, ADF - Fisher Chi-square and PP - Fisher Chi-square unit root tests, null hypothesis is that there exists unit root unit root (assumes individual unit root process). Automatic lag length is selected based on AIC. EViews-9 software program is used.

Table 4-56 portrays the results of cross-sectional dependence tests. Null hypothesis of no cross-section dependence is strongly rejected. Therefore, there exists cross-sectional dependence in series. In this regard, we perform Pesaran (2007) unit root test. According to results given in Table 4-57, for the series of area and precipitation, the test does not reject the null hypothesis of a unit root. However, when they are first differenced, they become stationary. Thus, they are, I(1). Series of temperature and yield are stationary at level. As a result, it is inferred that variables do not exhibit the same order of integration. They have mixed order of integration based on Pesaran (2007) CADF test results.

Table 4-56: Residual Cross-Section Dependence Test for Potato for Cluster-2 Countries

Test	Statistic
Breusch-Pagan LM	1722136***
Pesaran scaled LM	1012707***
Bias-corrected scaled LM	9865161***
Pesaran CD	7551717***

Note: The asterisks ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Null hypothesis is that there exists no cross-section dependence (correlation) in residuals. EViews-9 software program is used.

Table 4-57: Pesaran (2007) CADF Unit Root Test for Potato for Cluster-2 Countries

Variables	Pesaran Z[t-bar]	
	level	first difference
lnyield	-1.308c	-2.813^{a}
lnarea	1.098	-2.372^{a}
temp	-1.787^{b}	-3.079^{a}
prep	0.287	-4.440^{a}

Note: a, b and c denote significance at the 1%, 5% and 10% level, respectively. Following Hoechle (2007) we choose the ideal lag length by using Newey and West's (1994) plug in method at $(4*(T/100)\text{^}^{(2/9)} = \sim 3)$. Stata routine "pescadf" is used.

Before conducting PMG, MG and DFE estimators, we perform the lag selection based on AIC to determine the model Table 4-58 indicates the results of appropriate model selection according to three criteria. Based on AIC, the most appropriate model can be written in the form of the ARDL(3,3,3,3) model.

Table 4-58: Model Selection Criteria Table for Potato for Cluster-2 Countries

Model	LogL	AIC*	BIC	HQ	Specification
9	316.691192	**-1.724153**	0.700528	-0.742723	**ARDL(3, 3, 3, 3)**
12	311.450331	-1.560104	1.047259	-0.504730	ARDL(4, 3, 3, 3)
6	277.287109	-1.437244	0.804757	-0.529756	ARDL(2, 3, 3, 3)
5	237.598278	-1.369680	0.324276	-0.684023	ARDL(2, 2, 2, 2)
8	239.996135	-1.282789	0.593848	-0.523189	ARDL(3, 2, 2, 2)
2	216.463824	-1.267311	0.243963	-0.655598	ARDL(1, 2, 2, 2)
11	246.653337	-1.238923	0.820396	-0.405379	ARDL(4, 2, 2, 2)
4	190.543218	-1.227709	-0.081798	-0.763882	ARDL(2, 1, 1, 1)
1	178.851260	-1.220720	**-0.257490**	**-0.830836**	**ARDL(1, 1, 1, 1)**
7	199.052153	-1.202547	0.126046	-0.664777	ARDL(3, 1, 1, 1)
10	202.372751	-1.124977	0.386297	-0.513264	ARDL(4, 1, 1, 1)
3	232.012764	-1.091038	0.968281	-0.257494	ARDL(1, 3, 3, 3)

Note: AIC, SBC, HQ represent Akaike Information Criterion, Schwarz Bayesian Criterion, Hannan-Quinn Criterion, respectively. Dependent variable is lnyield.

Table 4-59: ARDL(3,3,3,3) Results with PMG, MG, DFE Estimators for Cluster-2 Countries

Dependant variable: lnYield Crop: Potato	PMG		MG		DFE	
	Coef	**Std error**	**Coef**	**Std error**	**Coef**	**Std error**
Long run coefficients						
lnArea	-0.0679	0.1182	-0.6071*	0.3606	-0.2384***	0.0587
Temperature	1.0149***	0.2229	0.0900	0.1783	-0.0053	0.0579
Precipitation	-0.0010***	0.0004	0.0007	0.0010	0.0006	0.0004
Error correction coefficient	-0.1602*	0.2064	-1.0803**	0.5022	-0.5946***	0.1068
Short run coefficients						
Δ Yield(-1)	-0.3903	0.4140	0.0992	0.5809	-0.3245***	0.0951
Δ Yield(-2)	-0.0320	0.2822	-0.0926	0.3574	-0.3053***	0.0777
Δ Area	0.5464	0.5555	0.3830	0.8056	-0.1083	0.0868
Δ Area(-1)	-0.1355	0.5720	0.0505	0.5534	-0.1123	0.0862
Δ Area(-2)	-0.2783	0.5061	-0.2929	0.3351	-0.2247***	0.0798
Δ Temp	-0.1612	0.1546	-0.0756	0.1798	-0.0083	0.0295
Δ Temp(-1)	-0.1160	0.0993	-0.1080	0.1049	-0.0206	0.0245
Δ Temp-2)	-0.0144	0.0584	-0.0179	0.0590	0.0040	0.0181
Δ Prep	0.0002	0.0002	0.0006	0.0005	-0.0002	0.0002
Δ Prep(-1)	0.0001	0.0002	0.0005	0.0004	-0.0001	0.0001
Δ Prep(-2)	0.0003*	0.0002	0.0005*	0.0003	0.0000	0.0001
C	0.0762	0.2603	7.2227	19.5711	8.5322***	1.6720
Hausman Test	1.409 (0.917)					
Observations	242		242		242	
Number of countries	11		11		11	

Note: The table reports the results for the pooled mean group (PMG), mean group (MG) and dynamic fixed effect estimators. The dependent variable is yield. The asterisks ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. The Hausman test is the statistic for the null hypothesis that the slope is homogeneous across countries (β_i=β) under the null hypothesis that, the PMG estimator is better than the MG estimator. PMG estimate outputs are both obtained by using E-Views-9 and Stata-13 software programs in order to check the accuracy of the results. For MG and DFE estimates; Stata-13 routine xtpmg is used.

The results of the PMG, MG and DFE estimators with Hausman test are presented in Table 4-59. While temperature has positive and significant effect, precipitation has negative and significant impact on yield according to PMG estimator. It reveals that increase in precipitation affected negatively the potato crop. Its impact on yield is different from the other crops like maize and wheat. The reason may be that high frequency of the precipitation is important for growing of potato crop. The irregular rainfall can influence it adversely. In addition, negative and significant value of speed adjustment term (-0.1602) ensures the cointegration relationship among the variables under consideration. In fact, adjustment speed is low since it is completed six periods later. According to Hausman test, null hypothesis of homogeneous slope across countries is not rejected. Therefore, test results again clearly favor the PMG over MG. Moreover, we can conclude that short run coefficients obtained from PMG estimator are not statistically significant. We can conclude that temperature and precipitation have no significant impact on potato yield for Cluster-2 countries in the short run. Besides; based on DFE estimator, increase in area harvested leads to reduction in yield. It has a negative and significant effect on yield. Error correction term obtained from DFE estimator is negative and significant which is in line with PMG estimator. However, estimation of adjustment speed according to DFE is higher than PMG.

4.2.4.3 Potato for All Mediterranean Countries

In this section, unit root and cross sectional dependence test results are reported for all Mediterranean countries where potato is cultivated. Table 4-60 reveals the results of unit root tests which suggest that series of yield, temperature and precipitation are (I0). However, null hypothesis of presence of unit root can not be rejected for series of area according to Im, Pesaran and Shin and ADF - Fisher Chi-square unit root tests. When first difference of the series is taken, it becomes stationary so it is judged to be I(1) as reported in Table 4-60.

Table 4-60: Unit Root Results (First Difference) for Potato for All Countries

Trend	lnyield	lnarea	Temp	Prep
Levin-Lin-Chu	-19.7680[a]	-15.1219[a]	-20.2329[a]	-11.6987[a]
Im, Pesaran and Shin W-stat	-19.1516[a]	-15.4427[a]	-20.8623[a]	-16.5018[a]
ADF - Fisher Chi-square	339.5330[a]	265.0630[a]	359.9330[a]	287.9300[a]
PP - Fisher Chi-square	1068.1400[a]	637.0050[a]	1062.6900[a]	2187.9200[a]
Intercept and trend	lnyield	lnarea	Temp	Prep
Levin-Lin-Chu	-12.7016[a]	-9.6929[a]	-16.0349[a]	-9.6908[a]
Im, Pesaran and Shin W-stat	-14.8255[a]	-12.8656[a]	-17.5195[a]	-14.4603[a]
ADF - Fisher Chi-square	239.8510[a]	206.3440[a]	273.8110[a]	233.2470[a]
PP - Fisher Chi-square	845.5010[a]	614.3320[a]	1414.6700[a]	1565.1400[a]

Note: a, b and c denote significance at the 1%, 5% and 10% level, respectively. For Levin-Lin-Chu unit root test, null hypothesis is that there exists unit root (assumes common unit root process). For Im, Pesaran and Shin W-stat, ADF - Fisher Chi-square and PP - Fisher Chi-square unit root tests, null hypothesis is that there exists unit root unit root (assumes individual unit root process). Automatic lag length is selected based on AIC. EViews-9 software program is used.

Table 4-61 reveals the cross sectional dependence tests conducted and based on test results, null hypothesis of presence of no cross-section dependence are strongly rejected. Thus, there exists cross sectional dependence among variables and we employ Pesaran (2007) CADF unit root test in order to determine the order of integration. Based on results, reported in Table 4-62, series of yield and temperature are stationary at their level which is in line with the results of first generation panel unit root tests. However, series of area and precipitation are not stationary at level. When their first difference is taken, they become stationary; so they are (I1). Hence, series have a mixed order of integration, I(0) and I(1).

Table 4-61: Residual Cross-Section Dependence Test for Potato for All Countries

Test	**Statistic**
Breusch-Pagan LM	6711520***
Pesaran scaled LM	2601772***
Bias-corrected scaled LM	2556534***
Pesaran CD	1921012***

Note: The asterisks ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Null hypothesis is that there exists no cross-section dependence (correlation) in residuals. EViews-9 software program is used.

Table 4-62: Pesaran (2007) CADF Unit Root Test for Cluster-1 Countries

Variables	Pesaran Z[t-bar]	
(lag=3)	level	first difference
Lnyield	-1.760[b]	-1.873[b]
Lnarea	1.615	-2.970[a]
Temp	-3.678[a]	-6.130[a]
Prep	0.881	-6.602[a]

Note: a, b and c denote significance at the 1%, 5% and 10% level, respectively. Following Hoechle (2007), we choose the ideal lag length by using Newey and West's (1994) plug-in method at (4*(T/100)^(2/9) =~3). Stata routine "pescadf" is used.

Panel ARDL model results with different estimators for the crop potato cultivated in all Mediterranean countries are employed. Before conducting these approaches, we perform the lag selection based on AIC to determine the model. Table 4-63 displays the results of proper model selection according to three criteria. Based on AIC, the most appropriate model can be written in the form of the ARDL(4,3,3,3) model.

Table 4-63: Model Selection Criteria Table for Potato for All Countries

Model	LogL	AIC*	BIC	HQ	Specification
12	599.059908	**-1.930175**	1.086094	-0.728576	**ARDL(4, 3, 3, 3)**
9	578.731908	-1.922409	0.880815	-0.805681	ARDL(3, 3, 3, 3)
6	548.100703	-1.854390	0.735789	-0.822534	ARDL(2, 3, 3, 3)
8	500.603436	-1.798851	0.365239	-0.936737	ARDL(3, 2, 2, 2)
11	516.778822	-1.782332	0.594802	-0.835347	ARDL(4, 2, 2, 2)
5	472.669546	-1.746606	0.204439	-0.969363	ARDL(2, 2, 2, 2)
2	453.430531	-1.745208	-0.007209	-1.052837	ARDL(1, 2, 2, 2)
3	507.655075	-1.728977	0.648157	-0.781992	ARDL(1, 3, 3, 3)
1	388.054630	-1.696226	**-0.597362**	**-1.258469**	**ARDL(1, 1, 1, 1)**
7	407.561396	-1.588078	-0.063124	-0.980578	ARDL(3, 1, 1, 1)
4	382.290351	-1.551406	-0.239497	-1.028777	ARDL(2, 1, 1, 1)
10	414.747249	-1.518990	0.219009	-0.826619	ARDL(4, 1, 1, 1)

Note: AIC, SBC, HQ represent Akaike Information Criterion, Schwarz Bayesian Criterion, Hannan-Quinn Criterion, respectively. Dependent variable is lnyield.

Table 4-64 displays the results of PMG, MG and DFE estimation and Hausman test for Mediterranean Countries for the crop potato cultivated. Long run coefficients of temperature and precipitation are positive based on all estimators but, they are both statistically significant at %1 significance level according to PMG estimator. We can conclude that temperature and precipitation have a positive effect on the potato cultivated in Mediterranean countries. Hausman test results indicated that homogeneity restriction imposed on the long-run coefficients cannot be rejected. Thus, we can conclude that, PMG gives more consistent and efficient estimate than MG. Furthermore, all estimation methods are in agreement in that the error correction term is negative and significant with almost similar size. In fact, speed of adjustment is lower for DFE estimate than PMG approach which confirms that movement from PMG to DFE estimate decreases the speed of convergence (from 0.26 to 0.10 in Table 4-64) because of the downward bias in dynamic heterogeneous panel data. In addition, as indicated in Table 4-64, imposing the long-run homogeneity restrictions leads to reduction in standard errors of both error correction coefficient and long-run coefficients of the variables under consideration. Besides, almost all short run coefficients of temperature and precipitation are not significant like the previous models. It reveals that there is no significant impact of them on potato yield.

To sum up, clustering of the countries based on agricultural vulnerability index provides us with to measure the impact of climate change on potato yield separately for two clustered groups having distinct characteristics such as different climatic conditions and agricultural infrastructure. The impact of temperature on potato yield is positive for all models. In addition, based on results of all countries model, increase in temperature and precipitation both have positive impact on potato yield for all models. However, when clustered groups are taken into account, the impact of precipitation is negative and it is different from the other models. Therefore, making cluster analysis enable us to determine the heterogeneous impacts of climate change on potato yield peculiar to each clustered groups.

Table 4-64: ARDL(4,3,3,3) Results with PMG, MG, DFE Estimators for All Countries

Dependant variable: lnYield Crop: potato	PMG		MG		DFE	
	Coef	**Std error**	**Coef**	**Std error**	**Coef**	**Std error**
Long run coefficients						
lnArea	0.6871***	0.0486	-0.6424*	0.3547	-0.0570	0.1090
Temperature	0.3691***	0.0536	0.4771*	0.2615	0.1002	0.0938
Precipitation	0.0022***	0.0002	0.0009	0.0008	0.0014**	0.0006
Error correction coefficient	-0.2691*	0.0547	0.0509	1.1143	-0.1012***	0.0598
Short run coefficients						
Δ Yield(-1)	-0.5828***	0.1365	-1.1149	0.8266	-0.4393***	0.0679
Δ Yield(-2)	-0.1717	0.1156	-0.5651	0.4491	-0.2588***	0.0669
Δ Yield(-3)	-0.0679	0.0761	-0.4164	0.2888	0.08550*	0.0545
Δ Area	-0.0015	0.2644	0.1288	0.6495	-0.2365***	0.0600
Δ Area(-1)	-0.2674	0.2264	-0.8247*	0.4403	-0.1608***	0.0576
Δ Area(-2)	-0.2568*	0.1577	-0.9837**	0.5114	-0.2012***	0.0543
Δ Temp	0.0135	0.0203	0.1517	0.2063	-0.0206	0.0234
Δ Temp(-1)	-0.0264	0.0194	0.0440	0.1428	-0.0220	0.0197
Δ Temp-2)	-0.0096	0.0214	-0.0092	0.0692	0.0054	0.0143
Δ Prep	0.0001	0.0001	0.0009	0.0009	-0.0002*	0.0001
Δ Prep(-1)	-0.0001	0.0001	0.0007*	0.0008	-0.0002*	0.0001
Δ Prep(-2)	0.0002**	0.0001	0.0006	0.0004	0.0000	0.0001
C	-0.1516	0.1288	-12.9887	19.8256	2.8444***	0.8570
Hausman Test	0.08 (0.9943)					
Observations	418		418		418	
Number of countries	19		19		19	

Note: The table reports the results for the pooled mean group (PMG), mean group (MG) and dynamic fixed effect estimators. The dependent variable is yield. The asterisks ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. The Hausman test is the statistic for the null hypothesis that the slope is homogeneous across countries ($\beta_i=\beta$) under the null hypothesis that, the PMG estimator is better than the MG estimator. PMG estimate outputs are both obtained by using E-Views-9 and Stata-13 software programs in order to check the accuracy of the results. For MG and DFE estimates; Stata-13 routine xtpmg is used.

4.2.5 Econometric Analysis for Turkey

In this part, econometric analysis results based on MG estimator for wheat, maize and potato are presented for Turkey. Since MG estimator is used, short and long run coefficients differs for each country for each crop. Therefore, slope coefficients for short and long term, error correction coefficient and intercept are peculiar to Turkey.

4.2.5.1 Wheat for Turkey

Turkey is in Cluster-1 countries based on clustering analysis. Table 4-65 reports the results of MG estimation for Turkey for the crop wheat. The coefficients of temperature (-0.4352) and precipitation variables (0.0072) are significantly negative and positive, respectively. It reveals that while temperature has a significant negative effect on yield, precipitation has positive impact on yield in the long run. The reason behind this may be that wheat is cultivated in regions where the temperature is high and rainfall amount is small. Therefore wheat production is highly sensitive to climatic variables. Further, error correction term (-0.6921) confirms the existence of stable long-run relationship. The speed of adjustment about 38% which means that adjustment is fast, with almost 69% occurring within one year. In addition, short run coefficients for precipitation are significant. However, since impacts of climate change on crop yield are emerged in the long term, we generally focus on the long run results of temperature and precipitation which are more reliable.

Table 4-65: ARDL(3,3,3,3) Results with MG Estimators for Wheat for Turkey

Dependant variable: lnYield Crop: wheat	MG	
	Coef	Std error
Long run coefficients		
lnArea	-4.3184	3.8110
Temperature	-0.4352*	0.5749
Precipitation	0.0072*	0.0081
Error correction coefficient	-0.6921*	0.7808
Short run coefficients		
Δ Yield(-1)	0.2724	0.5205
Δ Yield(-2)	0.4689	0.2853
Δ Area	4.2181***	1.0945
Δ Area(-1)	3.9990***	1.4776
Δ Area(-2)	4.2737***	1.5348
Δ Temp	0.1612**	0.0741
Δ Temp(-1)	-0.0550	0.0465
Δ Temp-2)	-0.0143	0.0478
Δ Prep	0.0032*	0.0013
Δ Prep(-1)	0.0016*	0.0009
Δ Prep(-2)	0.0011*	0.0006
C	61.359**	25.057

Note: The table reports the results for the mean group (MG) estimator. The dependent variable is yield. The asterisks ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Stata-13 routine xtpmg is used.

4.2.5.2 Maize for Turkey

Table 4-66 reports the results of MG estimation for Turkey for the crop maize. Long run coefficients of temperature (-2.8837) and precipitation (0.0143) are significantly negative and positive, for PMG approach. We can infer that while increase in temperature affects maize yield negatively, increase in precipitation influences it positively for Turkey. Our findings are in line with the results of Cluster-1 countries which also include Turkey. In Turkey, precipitation is very important for maize crop in growing season in order to produce in high amounts. This fact confirms our findings related to impact of precipitation. What is more, error correction coefficient is -0.1803 which is negative and significant. It indicates the existence of long run stable relationship. Furthermore, in general, short run coefficients are not significant as it is expected since impacts of climate change can be more reliably measured in the long term rather than the short term.

Table 4-66: ARDL(4,3,3,3) Results with MG Estimators for Turkey

Dependant variable: lnYield Crop: maize	MG	
	Coef	Std error
Long run coefficients		
lnArea	18.3430**	8.7578
Temperature	-2.8837*	1.6700
Precipitation	0.0143	0.0100
Error correction coefficient	-0.1803**	0.0900
Short run coefficients		
Δ Yield(-1)	0.3692	0.2313
Δ Yield(-2)	0.9856*	0.5355
Δ Yield(-3)	-0.7999*	0.4473
Δ Area	-2.6042*	1.4688
Δ Area(-1)	-3.8512**	1.4563
Δ Area(-2)	-3.2770**	1.3608
Δ Temp	0.23618*	0.1173
Δ Temp(-1)	0.28277	0.1293
Δ Temp(-2)	-0.0126	0.0516
Δ Prep	0.0006	0.0010
Δ Prep(-1)	0.0011	0.0009
Δ Prep(-2)	-0.0019*	0.0007
C	-38.784*	17.737

Note: The table reports the results for the mean group (MG) estimator. The dependent variable is yield. The asterisks ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Stata-13 routine xtpmg is used.

4.2.5.3 Potato for Turkey

Table 4-67 presents the results of MG estimation for Turkey for the potato crop. The coefficient of temperature and precipitation are 0.1870 and 0.0007, respectively. They indicate that temperature has positive and significant effect in the long term. Our findings are in line with the results of Cluster-1 countries in which Turkey is included. In addition short term coefficients for temperature and precipitation are also statistically significant. In the short term, impact of climate change can be determined for the potato crop. We can conclude that increasing temperature and precipitation leads to apparent rise in potato yield even in the short term. Direction of the long and short term impacts of two climatic parameters on potato yield is same and positive for Turkey.

Table 4-67: ARDL(4,3,3,3) Results with MG Estimators for Turkey

Dependant variable: lnYield Crop: potato	MG	
	Coef	Std error
Long run coefficients		
lnArea	-0.1560***	0.0077
Temperature	0.1870***	0.0039
Precipitation	0.0007***	0.0000
Error correction coefficient	18.229**	7.7331
Short run coefficients		
Δ Yield(-1)	-12.9573**	5.2649
Δ Yield(-2)	-3.5121**	1.5702
Δ Yield(-3)	-3.6273**	1.5575
Δ Area	-2.2450**	0.9602
Δ Area(-1)	-1.9800**	0.8664
Δ Area(-2)	-2.1624**	0.9548
Δ Temp	3.0352**	1.2407
Δ Temp(-1)	1.8424**	0.7456
Δ Temp(-2)	0.6832**	0.2847
Δ Prep	0.0130**	0.0053
Δ Prep(-1)	0.0117**	0.0046
Δ Prep(-2)	0.0067***	0.0025
C	-219.862**	94.556

Note: The table reports the results for the mean group (MG) estimator. The dependent variable is yield. The asterisks ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Stata-13 routine xtpmg is used.

CHAPTER 5

DISCUSSIONS AND RECOMMENDATIONS

Climate change has become a global threat for human beings. Its impacts on oceans, ecosystems, water resources, agriculture; briefly, on all dynamics of the earth system have been unequivocally and clearly detected and measured by scientists in last decades. According to IPPC (2014) report, human effect on the climate of the earth is obvious and anthropogenic greenhouse gases emissions are the highest in human history. This challenge has a widespread influence on human and natural systems. Therefore, considerable attention should be given to climate change and its effects.

Agriculture is one of the main sectors which is heavily susceptible to climate change. It is the major source of food and is strongly dependent on weather conditions. Climate change influences agriculture through different ways such as precipitation pattern, sowing & harvesting time and water availability. Blanc (2012) stated that, in order to recover from adverse impact of climate change on food security, it is required to develop adaptation mechanisms which enable farmers to avoid some of the adverse impacts of climate change.

Impacts of climate change on agriculture differ from region to region or country to country since every region or country have its own characteristics like climatic and structural features. Based on IPCC (2007 WG1), Mediterranean Basin is one of the region that will be mostly influenced by climate change. While the annual number of rainfall days will likely decline, severity of the summer droughts is expected to rise in Mediterranean Region (IPCC, 2007 WG1). Therefore, climate change researches linked to agriculture that are done for this region is very important to determine the past, present and future impacts; take the essential precautions and develop sustainable adaptive strategies.

This study attempts to determine the impact of climate change on agriculture in Mediterranean countries by employing statistical and econometric tools. In the first part of the study, vulnerability analysis is conducted for 50 countries including Mediterranean countries and major cereal producer countries in the world to determine the situation of the Mediterranean countries by employing PCA and cluster analysis. In the study, climatic, economic, environmental and social variables related to three components of the vulnerability are used. The methodology and selected variables makes a contribution to intellectual merit of the study. In the second part of the dissertation, an econometric model is developed for clustered countries created in the first part of the study for three mostly cultivated crops in Mediterranean Basin, wheat, maize and potato, by using panel ARDL technique. Yield, area harvested and gridded climatic data are used.

In the first part, agricultural vulnerability index is developed and countries are clustered based on index scores. The results suggest five groups ranking from most vulnerable to less vulnerable. In Group 1 and Group 2, there are not any Mediterranean countries. China is the only country in Group 1 and Group 2 involves India, USA, Philippines, Ethiopia and Cambodia. Algeria is in Group 3 as a North African Mediterranean country and is the most vulnerable country among the Mediterranean countries due to its low adaptive capacity and high sensitivity to climate change. These make great contribution to its high index score. The other North African countries with Syria, Albania and Turkey are among Group 4 countries. They are vulnerable to climate change in medium level when compared to Group 1 and Group 2 countries. Our findings are in line with the results of another globally scaled study done by Krishnamurthy, et al. (2014). In addition, Group 5 involves Southern European countries. Common feature of Group 3 and Group 4 countries is their geographical proximity, that is to say, they are all located in lower latitudes when compared to Group 5 countries except for Albania. Besides, adaptive capacity in terms of agriculture is higher for Group 5 countries than the Group 3 and Group 4 countries.

One benefit of the index will be to group countries by their vulnerabilities and proceed with the rest of the analyses based on the groupings. In previous related studies as stated in Chapter 2, indexes have been developed mostly by equally weighting all variables, which makes the index as an arithmetic mean of equally weighted indicators. What ignored by this approach is that correlated indicators may overestimate the index. One solution for this problem is to employ Principle Component Analysis approach (PCA). PCA will assign a unique weight for each indicator that is not necessarily equal to each other. Thus, main advantage of the conducting PCA is that it eliminates the double counting effect among the indicators. It provides unbiased measure of the agricultural vulnerability index. In fact, during the stages of the analysis, theoretically, some of the indicators are excluded due to collinearity issues. Therefore, there is an objective selection and weighting of the related indicators for each component of the vulnerability. To sum up, the indicators selected and methodologies used with the applied region are the unique features of this study.

North African countries have limited water resources and their economies are mostly dependent on agriculture. Moreover, biophysical and socioeconomic conditions, government effectiveness, access to infrastructure as well as the state of technology in the region are the primary factors behind the high vulnerability of the region to climate change (Scott, 2008). All these factors make North African countries more vulnerable in agriculture. In addition, as stated above, only one European country, Albania, falls into Group 4 including almost all North African countries. The major reason behind is that, deficiency in adaptive capacity measures such as rural population’s improved water source and improved sanitation facilities makes Albania more vulnerable to climate change. Another finding is that almost all European countries fall into Group 5. Due to their high adaptive capacity levels, they are less vulnerable. However, it should be noted that some of the European countries such as France and Italy are exposed to heavy climate events in the last decades. In fact, our analysis revealed that they both have the highest exposure component value among the all Mediterranean countries. On the other hand, as mentioned above, having high adaptive capacity offsets the adverse effect of climatic shocks for France and Italy.

Therefore, these two countries are good examples for understanding clearly the absolute importance of having high adaptive capacity measures in spite of their high exposure to climate change. To sum up, the countries located on the same geographical region and experiencing the same climate related stimuli may have different degree of vulnerability since their adaptive capacity levels coping with the adverse effects of climate change vary from country to country.

According to results of vulnerability and cluster analysis, we can conclude that there is geographical separation among the Mediterranean countries based on results of index scores. While North African countries with Syria, Albania and Turkey are falling into one cluster, Southern European countries are in other group. Another important finding is that, generally, water resources and adaptive capacity levels are the major determinants for the agricultural vulnerability to climate change in Mediterranean countries.

In the second part of the dissertation, comprehensive econometric analysis is practiced for Mediterranean countries based on the clusters developed in the first part of the study for the crops: wheat, maize and potato, as seen in Table 4-11. In this part, panel ARDL method with PMG, MG and DFE estimators is employed. We compare the results of three estimators with each other. Hausman test is employed in order to decide between the PMG and MG estimators. In all nine models, test results indicate that PMG is more preferable to MG. Moreover, according to view stated by Hsiao et al. (1999), MG estimator is probably to be inefficient for small cross sections or short time series. What is more, Pesaran and Zhao (1999) stated that error correction coefficient obtained by MG estimate can be subject to a downward lagged dependent variable bias. By regarding all these views with Hausman test results, we prefer to more focus on PMG results rather than MG. On the other hand, we also take into account results of DFE estimators. However, DFE models are exposed to a simultaneous equation bias from the endogeneity between the error term and the lagged dependent variable; that is to say, simultaneous equation bias should be minimal in order to obtain reliable results as stated in Baltagi, et al. (2000). Therefore, we consider that PMG results are more reliable than DFE results.

This study combines the climate change and agriculture by using panel ARDL method. When the literature is examined, it is seen that panel ARDL method is mostly used for energy economics and macroeconomics. This is most likely to be the first study that takes into account climate change and agriculture by using PMG, MG and DFE estimators. Furthermore, one of the important features of this study is that gridded latitude and longitude data are used and only relevant weather data related to area where crop is grown are taken into account.

For each crop, based on PMG, MG and DFE estimators, there is no definite significant impact of temperature and rainfall in the short run since impact of climate change on agriculture can not be more specifically determined in the short term. There should be a long time period in order to measure the impacts. In this regard, we obtain significant impacts of temperature and/or precipitation on each crop yields in the long run. Furthermore, Table 5-1 reveals the summary for long term results of PMG and DFE estimators for each crop. In general, the impact of rainfall and temperature on three crops are in the same direction for both methods and it is seen that temperature has greater impact on yields than the precipitation. While assessing the impact of one variable on yield, we hold other variables constant in the model.

More specifically, according to PMG results for Cluster-1 and Cluster-2 countries, an increase in temperature by 1% (other factors are held constant) leads to decline in 0.3% and increase in 1.1% in wheat yield, respectively. Since the evapotranspiration is higher in North African countries, increase in temperature restricts the growth of the wheat crop. Furthermore, there is direct proportion between the yield and precipitation. An increase in precipitation by 1% causes an increase in wheat yield by at the same proportion, by 1%.

For all models estimated by PMG, the rise in temperature has negative impact on maize yield. An increase in temperature by 1% leads to 0.36% and 0.67% decline in yield for Cluster-1 and Cluster-2 countries, respectively. As well, precipitation has a positive impact on maize yield according to both PMG and DFE estimators. Maize is always cultivated in sufficient rainfall areas since it produces larger yields than the other crops when rainfall is adequate (FAO, 1997). Audsley et al. (2006) and Moriondo et al. (2006) confirm our findings, since they also found out that significant decreases in yield are expected for maize in Southern Europe in the future due to decline in precipitation and increase in temperature.

Table 5-1: Comparison for Long Term Results of PMG and DFE Estimator for Three Crops

		PMG Estimator		**DFE Estimator**	
Crop	Model	Change in yield due to temperature (°C) rise by 1%	Change in yield due to precipitation (mm) rise by 1%	Change in yield due to temperature rise by (°C) 1%	Change in yield due to precipitation (mm) rise by 1%
Wheat	**Cluster 1**	0.30% ↓	1.00%↑	1.20%↑	1.00%↑
	Cluster 2	1.10% ↑	1.00%↑	1.13%↑	1.00%↑
	All	0.99%↓	1.00%↑	1.15%↑	1.00%↑
Maize	**Cluster 1**	0.36%↓	1.01%↑	1.09%↑	1.00%↑
	Cluster 2	0.67%↓	1.02%↑	0.92%↓	1.00%↑
	All	0.17%↓	1.01%↑	0.99%↓	1.00%↑
Potato	**Cluster 1**	2.01%↑	1.00%↑	1.12%↑	1.00%↑
	Cluster 2	2.76%↑	1.00%↓	0.99%↓	1.00%↑
	All	1.45%↑	1.00%↑	1.11%↑	1.00%↑

For potato yield, temperature has positive impact in the long run. In Cluster-1, an increase by 1% in temperature causes the rise in yield by about 2% and 2.8% for Cluster-1 and Cluster-2 countries according to PMG estimator. Precipitation has also positive impact on potato yield for all models based on DFE and PMG estimator except for Cluster-2.

To sum up, temperature and precipitation have different impacts in the long run on each crop under consideration. Especially, crop yields in Cluster-1 including North African countries are positively affected by precipitation. Our finding is in line with Schilling et al., (2012) which stated that North Africa almost completely rely on rainfall as the main water source for agriculture and dependence on rainfall determines the impact of climate change on agricultural productivity.

For Turkey, the impact of temperature and precipitation on three crop yields are in line with the Cluster-1 countries, that is to say, the direction of the climatic effects for Turkey are same with the Cluster-1 countries which also involves Turkey. For example, the impact of temperature on wheat yield is negative for both Cluster-1 countries and Turkey.

It is possible to make some recommendations for future studies by considering this study. The index can be recalculated for the countries where the impact of climate change is expected to become high in the future. For instance, according to climate scenarios, the number of climate related events such as droughts and floods with their impacts like mortality and economic losses can be identified. These new outputs can be used to calculate the new value of the index. In addition, the econometric analysis can be utilized for different types of crops and projected values of temperature and precipitation from climate scenarios of general circulation models can be used to forecast the future yield for crops. Further, variance of the temperature for each crop can also be taken into account for the econometric model.

To sum up, it is thought that the outcomes of locally scaled future studies, taking into account the development of this index, will ensure the applicability of composite agricultural vulnerability indicators to guide policy decision-making in the related sector of the countries. The results obtained from this assessment can be a helpful guide for policy makers dealing with this job to determine proper and reliable strategies as well as to implement appropriate regulations to decrease vulnerability in agriculture.

CHAPTER 6

CONCLUSION

Agriculture and food security are important fundamental aspects need to be seriously addressed for any country in the world. Due to climate change, it is expected that they will become more crucial issues affecting sustainable livelihood and welfare of the countries in the future. It is expected that, human induced climate change will be primary determinant of future agriculture in Mediterranean region which imposes further force on scarce water resources and people's livelihoods (Iglesias et al., 2011). Therefore, coping with or recovering from the adverse impacts of climate change on agriculture should be at the top of main agenda of the policy makers. In other words, strengthening the social and economic infrastructure in a region that exposed to climate variations is an obligatory to increase adaptive capacity. Besides, it is crucially important that farmers should be informed and warned about the possible impacts of climate change that exacerbates the yield loss, so that they can take the necessary precautions. In this scope, policymakers should decide on proper policies by regarding the studies and mechanisms that measure and monitor the effects of climate change.

This study suggests an agricultural vulnerability index to assess the susceptibility of agriculture to climate change at country level and measures the impact of climate change on major crops of Mediterranean region by a statistical crop model. One of the important findings of the vulnerability analysis is that North African Mediterranean countries are more vulnerable to climate change in terms of agriculture than South European countries due to lack of water resources and insufficient adaptive capacity measures. On the other side, South European countries such as France and Italy have much more exposed to climate related stimuli events such as droughts and floods than North African countries. However, since they have high adaptive capacity to climate change like improved infrastructure and high government effectiveness measures, these issues offset the adverse impact of the climatic shocks they exposed. Therefore, those countries are seen as less vulnerable to climate change.

Another result concluded from this study is that temperature has greater impact on wheat, maize and potato than precipitation. That is to say, the temperature can be considered as the limiting climatic factor on yield according to econometric model results. An increase in temperature and reduction in precipitation leads to significant decline in maize yield in Mediterranean countries when the other factors are held constant. Furthermore, precipitation has a positive impact on all Mediterranean countries and an increase in precipitation leads to rise in wheat yield. More specifically, for Cluster-1 and Cluster-2 countries, an increase in temperature by 1% causes to decrease in 0.3% and rise in 1.1% in wheat yield, respectively based on PMG results. Furthermore, there is direct proportion between the wheat yield and precipitation. An increase in precipitation by 1% causes an increase in wheat yield at the same proportion, by about 1%. In addition, according to PMG estimator, an increase in temperature by 1% leads to 0.36% and 0.67% decline in maize yield for Cluster-1 and Cluster-2 countries, respectively. For potato yield, temperature has positive effect in the long run. In Cluster-1, an increase by 1% in temperature leads to rise in yield by about 2% and 2.8% for Cluster-1 and Cluster-2 countries, respectively according to PMG estimator. Precipitation has also positive impact on potato yield for all models based on PMG estimator except for Cluster-2.

For Turkey, an increase in temperature and precipitation by 1% leads to almost 0.65% decrease and 1.00% increase in wheat yield, almost 0.05% decline and 1% increase in maize yield and finally about 1.20% increase and 1.00% rise in potato yield, respectively. Thus, the impact of rainfall and temperature on three crop yields are same both for Cluster-1 countries and Turkey.

There is no definite significant effect of temperature and precipitation in the short run for wheat, maize and potato yield based on PMG, MG and DFE estimators since the effect of climate change on agriculture can not be more specifically determined in the short term. There should be a long time period in order to measure the impacts. That is to say, in order to observe any increasing or decreasing trend, it must be focused on the long run impact since the climate change is related to long term alterations in weather phenomena. In this regard, we generally obtain significant effects of temperature and/or precipitation on each crop yields in the long run.

It could be concluded that, it is essential to understand all dimensions of climate change and food security in order to make a holistic analysis about the impact of climate change on food security. In this regard, the results obtained from this assessment will become a helpful guide for policy makers to determine proper and reliable strategies and implement appropriate regulations so as to reduce vulnerability of climate change to agriculture.

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APPENDICES

Table A-1: Correlation Matrix for Indicators Determining the Sensitivity Component of Vulnerability

	Average precipitation in depth (mm per year)	Cereal production (metric tons)	Cereal yield (kg per hectare)	Crop production index (2004-2006 = 100)	Fertilizer consumption (kg per hectare of arable land)	Food Production index	Forest area (% of land area)	Land under cereal production (hectares)	Agriculture. value added (% of GDP)
Average precipitation in depth (mm per year)	1.000								
Cereal production (metric tons)	0-.054	1.000							
Cereal yield (kg per hectare)	-0.297	0.253	1.000						
Crop production index (2004-2006 = 100)	-0.272	0.154	-0.116	1.000					
Fertilizer consumption (kilograms per hectare of arable land)	0.104	-0.411	-0.613	0.152	1.000				
Food Production index	-0.313	0.177	-0.157	0.933	0.129	1.000			
Forest area (% of land area)	0.577	-0.097	-0.318	-0.036	0.063	-0.068	1.000		
Land under cereal production (hectares)	-0.035	0.927	0.059	0.203	-0.242	0.234	-.0071	1.000	
Agriculture. value added (% of GDP)	-0.352	-0.003	-0.244	0.593	0.169	0.661	0.017	0.064	1.000

Table A-2: KMO and Bartlett's Test for Sensitivity Component of Vulnerability

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.586
Bartlett's Test of Sphericity	Approx. Chi-Square	299.942
	df	36
	Sig.	0.000

Table A-3: Correlation Matrix for Indicators Determining the Adaptive Capacity Component of Vulnerability

	Access to electricity, rural	GDP per capita	Improved water source, rural	Life expectancy at birth, total (years)	Rural population	Literacy rate, adult total	Government effectiveness	Health expenditure, total (% of GDP)	Internet users (per 100 people)	Improved sanitation facilities, rural
Access to electricity, rural	1.000									
GDP per capita	0.393	1.000								
Improved water source, rural	0.683	0.471	1.000							
Life expectancy at birth, total (years)	0.664	0.654	0.673	1.000						
Rural population	0.610	0.654	0.491	0.635	1.000					
Literacy rate, adult total	0.679	0.437	0.693	0.599	0.516	1.000				
Government effectiveness	0.495	0.793	0.590	0.647	0.603	0.503	1.000			
Health expenditure total (% of GDP)	0.420	0.732	0.508	0.540	0.596	0.465	0.718	1.000		
Internet users (per 100 people)	0.637	0.779	0.640	0.678	0.684	0.617	0.824	0.791	1.000	
Improved sanitation facilities, rural	0.660	0.566	0.706	0.726	0.574	0.693	0.511	0.511	0.662	1.000

Note: Improved water source, rural and improved sanitation facilities, rural refers to % of rural population with access. Literacy rate, adult total refers to % of people ages 15 and above. Rural population and access to electricity, rural are in % of total population. GDP per capita is in current US$.

Table A-4: KMO and Bartlett's Test for Adaptive Capacity Component of Vulnerability

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.	0.911

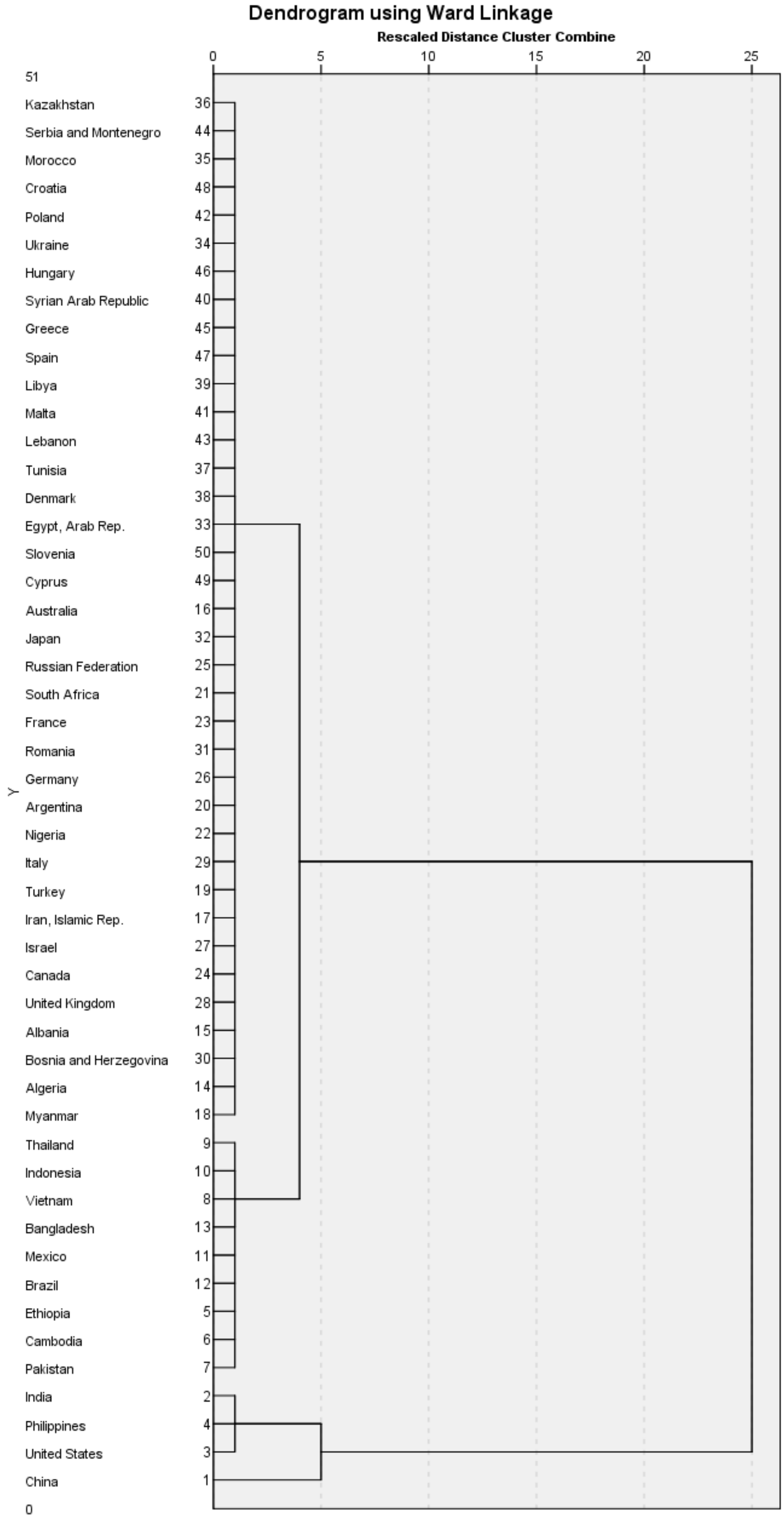

Figure A-1: Dendogram for Clustering of Countries Based on Exposure Component

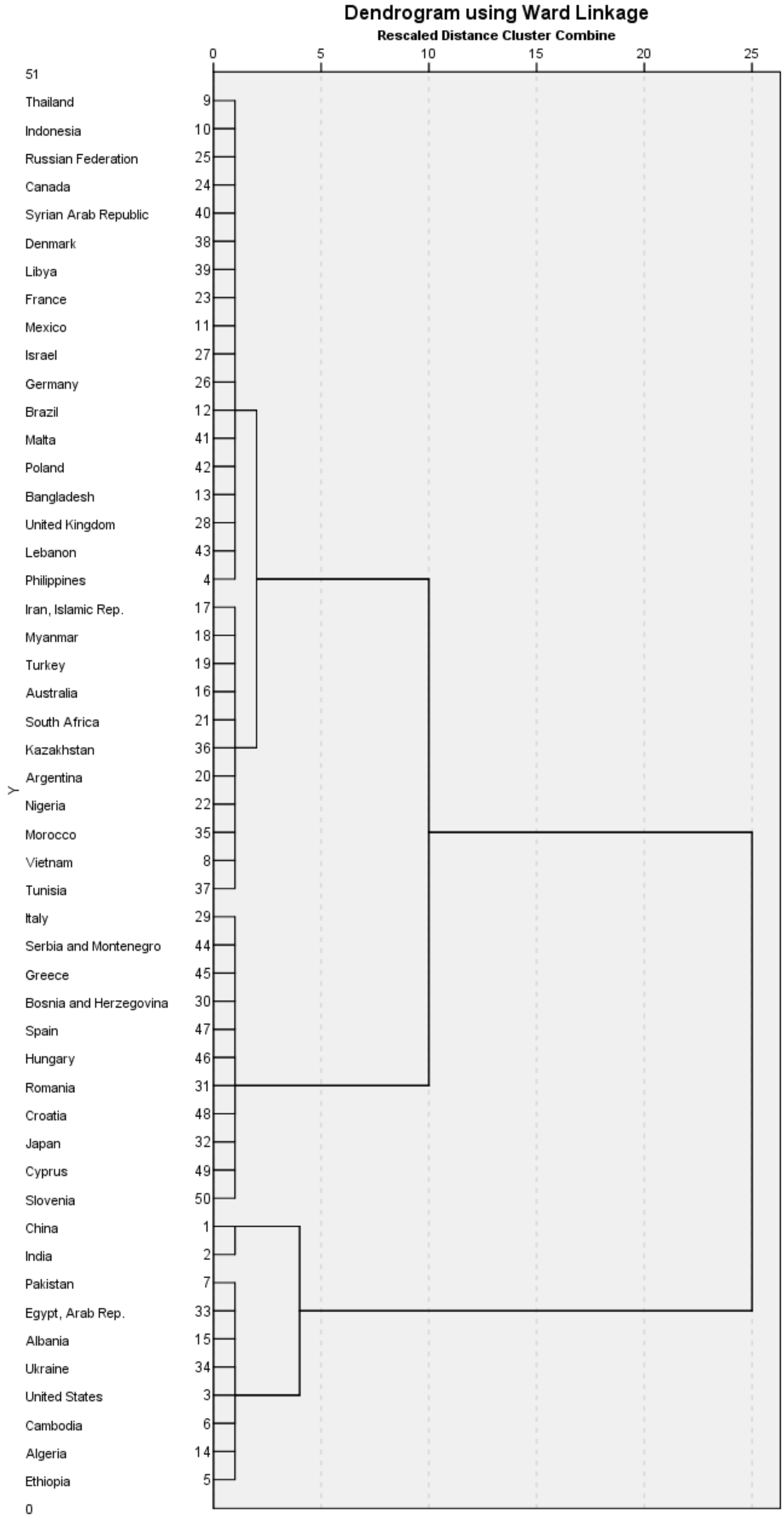

Figure A-2: Dendogram for Clustering of Countries Based on Sensitivity Component

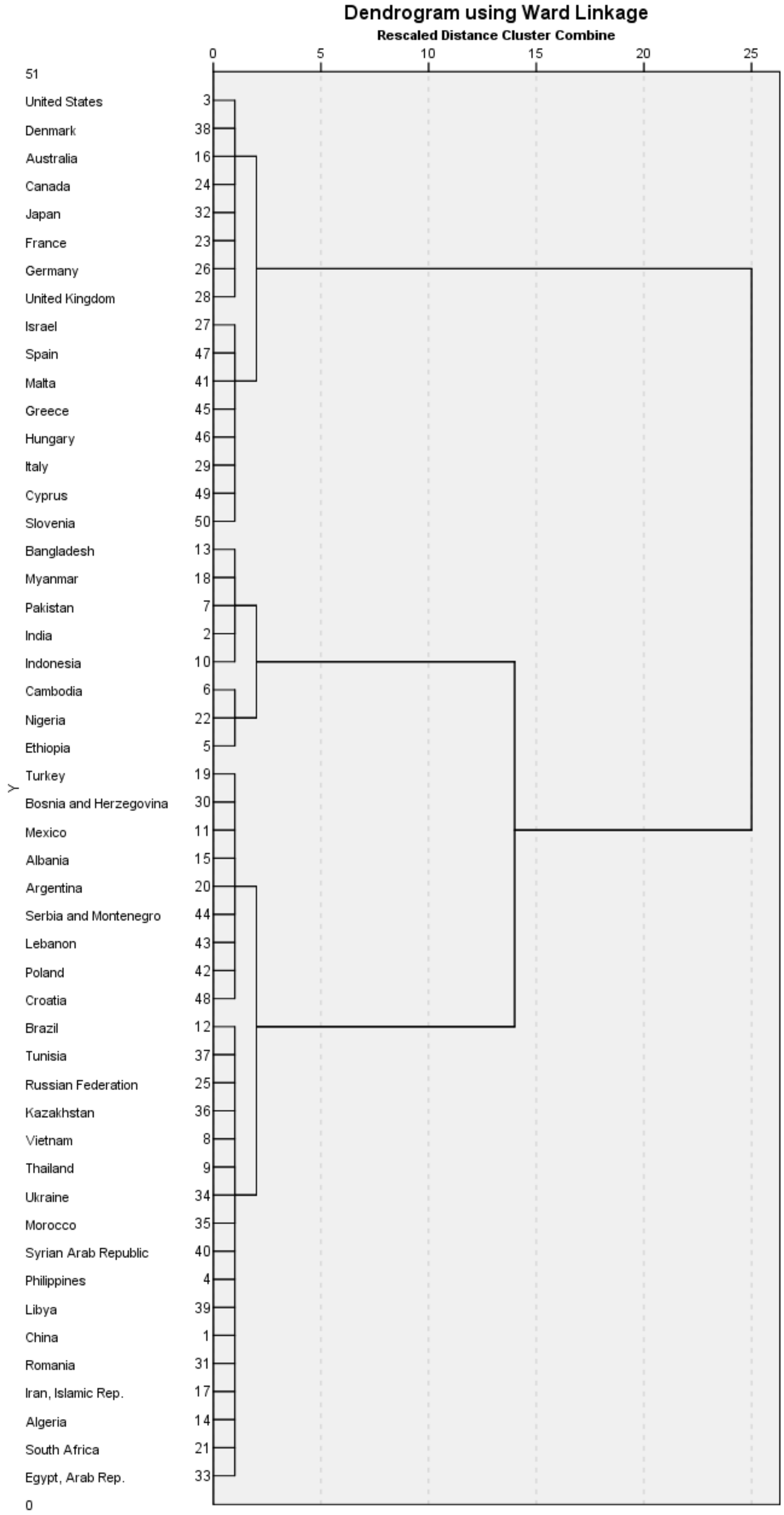

Figure A-3: Dendogram for Clustering of Countries Based on Adaptive Capacity Component

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PUBLICATIONS

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