THE IMPACT OF CLIMATE CHANGE ON TURKISH AGRICULTURE: AN ANALYSIS OF CROP YIELDS AND ACREAGE DECISIONS

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THE IMPACT OF CLIMATE CHANGE ON TURKISH AGRICULTURE: AN ANALYSIS OF CROP YIELDS AND ACREAGE DECISIONS

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DECLARATION OF ORIGINALITY

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ABSTRACT

The Impact of Climate Change on Turkish Agriculture:

An Analysis of Crop Yields and Acreage Decisions

This study construes the impact of climate change on crop (barley, corn, sunflower, wheat) acreage and yield by focusing on the Turkish districts between the period 2009-2017. After detecting spatial autocorrelation among districts with local Moran's I test, this study establishes implications of spatial autoregressive with spatially autocorrelated errors model (SARAR). Estimation results reveal that except for barley acreage model, overheating and over-precipitation are not harmful. In this context, the climate impact on crop production is moderate. Moreover, the study controls input and output prices. Empirical findings illustrate that even if price vector is not statistically significant for every crop model, when the analysis excludes the price vector, the effect of climate vector is overestimated. Results of this study indicate that climate variables have direct but limited effect on crop acreage and yield and that there are several reasons such as production decisions, agricultural policy and producers household characteristics which influence agricultural production.

ÖZET

İklim Değişikliğinin Türkiye Tarımına Etkisi:
Mahsül Verimi ve Ekili Alan Kararları Analizi

Bu çalışma iklim değişikliğinin arpa, ayçiçeği, buğday ve mısır ürünlerinin hasat ve verimlerine olan etkisini 2009-2017 yılları arasında Türkiye'deki ilçeler için değerlendirmiştir. Yerel Moran'ın I testi uygulanarak mekansal otokorelasyon tespit edildikten sonra, bu çalışma SARAR modelini kullanmayı tercih etmiştir. İstatiktiksel analiz sonuçlarına göre, arpa hasat modeli dışında, aşırı sıcaklık veya aşırı yağış ürünler için zararlı değildir. Genel itibarıyla, iklim değişikliğinin ürünler üzerindeki etkisi sınırlıdır. Ayrıca, bu çalışma fiyat vektörünü kullanarak girdi ve ürün fiyatlarını da kontrol etmeyi hedeflemiştir. Her bir ürün için fiyat vektörü istatistiksel olarak anlamlı olmasa da, modele konulmadığında, iklim vektörünün ürünlerin hasat ve verimi üzerindeki etkisi olduğundan fazla tahmin edilmiştir. Bu çalışmanın sonuçları, iklim değişkenlerinin mahsulün hasatı ve verimi üzerine doğrudan ama sınırlı bir etkisi olduğunu ve üretim kararları, tarım politikası ve üreticilerin hanehalkı özellikleri gibi tarımsal üretimi etkileyen birkaç nedenin daha olduğunu göstermektedir.

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CHAPTER 1

INTRODUCTION

International institutions underline the potential adverse effects of climate change on human life. One of the most fundamental impacts is the danger of depletion of food resources. In this regard, it is essential to underscore how agricultural production alters due to climate change. Although existing analyses are digging out this issue by focusing on different regions, we do not have enough information about the Turkish case. Hence, this study aims to compensate this information deficit by scrutinizing the impact of climate change on agricultural production in Turkey.

Many of the previous researches used field experiments or simulation approaches to evaluate the effects of the change in climate conditions on yields, land values, and profits (Callaway et al. 1982; Decker et al. 1986; Adams et al., 1988,1990; Adams 1989; Rind et al., 1990; Rosenzweig & Parry, 1994). These studies neglect the individual effects of reactions to the change in agricultural production, which leads to an overestimation of environmental impacts on the agricultural output (Mendelsohn et al. 1994).

Studies that emphasize the nexus of agricultural production and climate change continues with different regions around the world. Wang et al. (2016) analyze this nexus by focusing on Hunan Province, China. They, additionally, try to control technological factors (adoption rate of hybrid crops and chemical fertilizer input per unit area). The authors aim to sort out farmers' responses to the change in climate variables with the help of the advancements in technology. Zhang et al. (2017) attempt to propose alternative climate variables other than temperature and precipitation. They take into account humidity, wind speed, sunshine duration, and

evaporation and conclude that specifically humidity and wind speed have primary factors influencing crop growth. Thus, disregarding these variables leads to an over-prediction of the impact of climate change on agricultural production. As Miao et al. (2015) also find out, Acharya (2018) reached the same conclusion about the importance of input/output prices while scrutinizing the relationship between climate and crop yield in Nepal. This analysis also examines the role of education and concludes that the literacy rate has a significant effect on crop yields. Studies also aim to get rid of the overestimation problem by proposing alternative variables. Lu et al. (2018), in this context, have a fundamental contribution. They propose that crop yields response is differentiated between drylands and irrigated lands. They examine this issue in southern Alberta, Canada and concluded that an increase in precipitation in drylands has a positive effect and has a reverse effect on irrigated lands.

Tunde et al. (2011) analyze the Nigerian case for maize production. The results revealed that maize production is highly connected with rainfall amount whereas the effect of relative humidity, the number of rainy days or maximum and minimum temperature is weak. Hence, for this case, climate variables have a limited impact on crop production. Schlenker and Roberts (2009), and Miao et al. (2015) statistically proved that GDD has a non-linear effect on crop yield and temperature over a threshold may be harmful for agricultural production for the US case. Grange and Hand (1987) control humidity levels for horticultural crop production and they state that humidity level below and above a certain range may lead to harm crop production. Ali et al. (2017) analyze the effects of the fluctuations in climate variables on food security in Pakistan. According to results, maximum temperature and low rainfall level have a negative impact on crop production.

Moreover, recent studies elaborate on this issue by focusing on different regions. For instance, Benjamin and Gallic (2017) and Vaitkeviciute (2019) for Europe; Etwire et al. (2017) for Ghana; Edet et al. (2018) and Fonta et al. (2018) for Nigeria; Hossain et al. (2018) for Bangladesh; Lungarska and Chakir (2018) for France, and Trinh (2017) for Vietnam sort out the influence of climate change on agricultural production. This research emphasizes explicitly on Trinh (2017) analysis. Trinh (2017) takes into account household characteristics while analyzing the effect of climate change on agricultural production. In this regard, this research reveals that socioeconomic factors also have an influence.

In addition to analyzing the impacts of climate variables on corn and soybean yields in the United States with panel data, Miao's et al. (2015) investigate the effect of the change in prices on the yield. The reason why this study uses input/output prices is to measure the indirect effects on agricultural production. The climate variables in Miao et al. (2015) accounts for precipitation and temperature. They also control policy changes together with climate variables and prices. As a result, the study proposes that climate is not the only factor that changes agricultural production. Farmers' decisions based on price changes and agro-economic conditions also have a fundamental impact on agricultural production.

Analyses emphasizing the nexus of climate change and agricultural production except for experimental studies also differ methodologically. Computable General Equilibrium Models (CGE) is one of these methods. The main characteristic of this model is to comprehend how changes in climate variables influence the economic system as a whole. Rather than focusing on the agricultural sector alone, this model sorts out how climate conditions change economic sectors which

may alter individuals' income and consumption preferences indirectly. Since this model assumes that there is an interaction among sectors, calculating the impact of climate change on agriculture is not possible by disregarding other industries. However, this approach has some drawbacks. First, the model takes into account different dimensions of industries in a single one. This process cannot capture the differentiation of local agricultural productions; those have major impacts on the agricultural sector (Trinh, 2017). Wang et al. (2009) state that CGE models cannot assess the individual effects of adopting new production techniques or switching crops based on the impacts of climate change. Since this model treats the agricultural sector as a whole without considering its regional characteristics, it ignores the adaptation capacity of farmers to climatic variations by changing their farming techniques or by alternating between crops.

In addition to the CGE method, there are Partial Equilibrium Models one of which is the Crop Simulation Model. This model discusses the issue by analyzing how crop yields vary depending on the change in exogenous factors like inputs, nutrients or weather conditions. This method also assumes that farmers do not adopt new strategies for differentiation of these exogenous variables which is considered to be the drawback of this technique (Trinh, 2017). Torriani et al. (2007) in Switzerland, Kawasaki and Herath (2011) in Thailand, Kelbore (2012) in Ethiopia, and Dasgupta et al. (2014) in Bangladesh emphasize on the nexus of climate change and crop yields by using crop simulation models.

Another partial equilibrium analysis is the Ricardian Method. Mendelsohn et al. (1994) state that this approach enables us to comprehend the effects of climate change on land values and farm revenues. The main structure of this method

takes into account farmers' production decisions that try different input-output combinations depending on the change in exogenous variables, such as climate change, to maximize their revenues. Hence, this method will equalize the present and future values to the land value (Trinh, 2017). The fundamental advantage of this method is to eliminate the barriers mentioned previously. More precisely, this technique enables us to analyze how farmers adopt crop and planting decisions or agronomic practices based on climate impact.

Most of the recently conducted studies, therefore, apply the Ricardian models. By employing the Ricardian Technique, Mendelsohn et al. (1994) use cross-sectional data on climate, farmland prices, and control variable (economic and geophysical) for approximately 3000 counties in the United States to scrutinize the relationship between climate change and land prices. The key findings of this study are that there is a positive relation between precipitation and farm values whereas high temperatures reduce the value except for autumns. Additionally, the study proposes that global warming scenario based on the model has a low impact on US agricultural production. Cline (1996) criticizes this study because disregarding irrigation may lead to overestimation of the impact of precipitation on agricultural production. In other words, these critics underline that irrigation techniques can be the substitute for precipitation. Schlenker et al. (2005) and Kurukulasuriya et al. (2008) indicate that climate effects differentiation among the net revenues for drylands and irrigated lands.

Nevertheless, as Wang et al. (2009) underlines that the problem of data availability for testing the difference between dry/irrigated farming limits the vast implications. Data availability is not a problem for only dry/irrigated farming, but

also, it is an obstacle to determine land value. Mendelsohn et al. (1994), for instance, used land price as a dependent variable whereas especially in developing countries, data on land price is not available mostly (Wang et al. 2009). Analyses prefer to use net revenue because of easy access (Trinh, 2017). Additionally, as Miao et al. (2015) propose that the analysis of the effect of climate variables on agricultural production is possible by emphasizing on average yield per acre.

Therefore, the recent studies prefer to use the logarithmic form of dependent variables rather than practicing linear forms because the predictive power of the log-linear model is more uniform compared to the linear models (De Salvo et al. 2013, Trinh, 2017). Lastly, as Trinh (2017) underlined that another concern related to the previous analyses using the Ricardian technique is the limitation of the single-year cross-sectional analysis.

The benchmark model of this work is based on Miao's et al. (2015) frame. This study also prefers to use yield as a dependent variable. Using average yield per acre has two fundamental advantages. First, the data on agricultural cost and total sales may not be available for every city. Second, city-level price data may not be sufficient enough for studies that aim to reflect micro-scale differentiation within a specific region as this research will do. More precisely, this study will sort out how agricultural production in districts of Turkey reacts to the change in climate variables. Using city-level agricultural prices may lead to disregarding district-level differentiation. Since this study aims to measure the long-term impact of climate change on agricultural production of barley, wheat, corn, and sunflower; it will apply the Ricardian Technique with panel data analysis.

To sum up, the main focus of the recent analyses in the literature is to diversify the nexus of climate change and crop yields regionally and to sort out the real impact of climate variables on agricultural production by scrutinizing different methods and variables. In this context, while this study contributes to the literature by construing the Turkish case, it also aims to elaborate on the Miao's et al. (2015) model by adding new variables.

The rest of the study continues as follows; in chapter 2, the theoretical framework will be introduced. In chapter 3, empirical findings will be illustrated. In the final chapter, the results of the study will be discussed and a discussion for further research on this topic will be introduced.

CHAPTER 2

DATA AND METHODOLOGY

2.1 Data and variables

This analysis focuses on the relationship between climate variables and agricultural production in 928 districts in Turkey for the period 2009-2017.

This study obtains the district-level crops yield and acreage data and city-level output price data from the Crop Production Statistics Department and Agricultural Price Statistics Departments of TURKSTAT, respectively. The statistics of input prices are received from the Ministry of Agriculture and Forestry whereas our cost function consists of diesel and DAP fertilizer prices. The potential impact of the data scarcity will be discussed below. This study works on district-level climate variables. While monthly precipitation and monthly temperature deviations i.e. monthly max. and min. temperatures are received from the General Directorate of Meteorology Services of Turkey, and other climate variables are simulated [1].

In addition to crop yield and acreage, and input and output prices, the tables in Appendix A provide detailed information about the dataset. All prices are TL-denominated and all climate variables are in Celsius degree.

This analysis also uses heating degree days which refers to days in a year when the air temperature is higher than 30°C. Similarly, the cooling degree days are used for the days in a year when the air temperature is less than 10°C. Growing degree days (GDD) is the variable which defines the days in a year when the air temperature is between 10°C and 30°C.

[1] The simulated climate variables (annual total precipitation, annual heavy rainy day, annual rainy day, annual average sunbathing time, annual average heat, number of days when the air temperature is higher than 30°C and less than 10°C, annual total evaporation, annual average humidity) were provided by courtesy of M. Tufan Turp, based on their work in Turp et al. (2014), Öztürk et al. (2017) and An et al. (2018).

2.2 Empirical framework

This study has two basic benchmark models. Yield model, the first one, represented below:

$$Y_{ijt} = \beta_{i0} + \beta_{i1}\Omega_{ijt} + \beta_{i2}\varphi_{ijt} + \beta_{i3}\zeta_{ijt} + u_{ij} + e_{ijt} \quad (1)$$

Y_{ijt} is a district-specific average yield per acre; $i \in \{c, s, w, b\}$ where c is for corn, s is for sunflower, w is for wheat, and b is for barley in district j and in year t where β_{i0} is a constant, and $\beta_{i1}, \beta_{i2}, \beta_{i3}$ are estimated parameter vectors of prices, climate variables, and time trends respectively. The price vector Ω includes both input and output prices. The input price is represented by diesel fuel and fertilizer prices. The output prices are city-level received prices.

The climate vector φ consists of GDD (growing degree days) and its squared term, heating degree days, monthly mean precipitation and monthly deviation in temperature. Monthly precipitation and monthly temperature deviation are used to analyze the potential impact of timing and seasonal changes in climate variables on crop production. In order to catch the technological advancements and improvements in agronomic practices, time trend vector ζ with linear and quadratic forms of time trend is used.

With same specified vectors, the reduced-form of acreage model is as follows:

$$A_{ijt} = \gamma_{i0} + \gamma_{i1}\Omega_{ijt} + \gamma_{i2}\varphi_{ijt} + \gamma_{i3}\zeta_{ijt} + v_{ij} + \varepsilon_{ijt} \quad (2)$$

2.3 Model specification

Tobler's first law of geography (1970) underlines the fact that "everything is related to everything else, but near things are more related than distant things." Hence, climate conditions and other factors affecting district-level yield and acreage may have connection among different districts in a large proportion of regions. This is why this study digs out the potential spatial autocorrelation among districts. In this regard, Moran's I statistic is used to test whether there is a spatial connection among regions that this study focused on. Moran (1948), Cliff and Ord (1973), and Anselin (1995) propose that this analysis is a cross-product statistic between a variable and its spatial lag.

2.3.1 Moran's I Test

The benchmark formula[2] is given below;

$$I_i = \frac{x_i - \bar{X}}{S_i^2} \sum_{j=1, j\neq i}^{n} w_{i,j}(x_j - \bar{X}) \tag{3}$$

where for each i, x_i is an attribute, the mean of the corresponding feature is $\bar{X}$, the spatial weight between i and j is $w_{i,j}$, and:

$$S_i^2 = \frac{\sum_{j=1, j\neq i}^{n} w_{i,j}(x_j - \bar{X})^2}{n-1} \tag{4}$$

where the total number of features equates to n.

[2]https://pro.arcgis.com/en/pro-app/tool-reference/spatial-statistics/h-how-cluster-and-outlier-analysis-anselin-local-m.htm

The formulation of z_{I_i} score for the statistics is:

$$z_{I_i} = \frac{I_i - E[I_i]}{\sqrt{V[I_i]}} \tag{5}$$

with:

$$E[I_i] = -\frac{\sum_{j=1, j\neq i}^{n} w_{i,j}}{n-1} \tag{6}$$

$$V[I_i] = E[I_i] - E[I_i]^2 \tag{7}$$

Specifically, climate conditions, input and output prices have a relation within a large region, those may impact on district-level yield and crop acreage significantly (Miao et al., 2015). Rather than using global spatial autocorrelation which enables us to find out spatial pattern in a general basis, local Moran attaches importance to the spatial pattern on a local basis. Since this study interests in a district-level analysis which is one of the smallest scales in Turkey, local investigation of spatial autocorrelation may give more certain results.

In this context, 5 groups are used by Anselin (1995) in order to define similar and dissimilar clustering. Based on this classification, insignificant groups reveal districts do not have significant clustering, high-high group forms of clustering high values neighbors between each other and these are above the mean. Low-low group is the cluster consists of low values get together and these are below the mean. Other two groups are low-high and high-low and both of them are below the mean (see Appendix B).

Based on cluster maps and Moran scatter plots, all crop yield and acreage maps have spatial autocorrelation. More than 90% of clustering consists of high-high and low-low groups, more than 50% of clustering are from high-high groups. Additionally, 50% of clusters are insignificant, but, district-level connection map, which is independent of crop-based mapping, (see Appendix B) indicates that every district (there are 928 districts in total) have 5 neighbors in average approximately. Hence, all the indicators reveal that there is a spatial connection among districts which may impact on crop acreage and yields. That is, even if crop production cannot be capable of statistically significant clusters, the district map indicating their neighborhood relations reveals that they are spatially autocorrelated in terms of the climate factor at least.

2.3.2 SARAR Model

This study prefers to use spatial autocorrelation model which is also known as the spatial autoregressive with spatially autocorrelated errors (SARAR). While analyzing the interaction between spatial units, as Moran's I test revealed, there is a spatial autoregressive process in the error term (Elhorst, 2010).

Another option is the spatial lag model which is "typically considered as the formal specification for the equilibrium outcome of a spatial or social interaction process, in which the value of the dependent variable for one agent is jointly determined with that of the neighboring agents" (Anselin et al., 2006, p. 6). Spatial lag models are generally used when "the OLS diagnostics indicate the presence of a diffusion process or an instrumental variables specification incorporating instruments for the spatially lagged dependent variables" (Darmofal, 2015, 96).

Since the panel data diagnostic does not indicate endogeneity problem or diffusion process, this analysis disregards spatial lag models. Additionally, when we compare spatial error, which is also a model taking into account autocorrelation problem, and spatial autocorrelation models, Akaike's information criterion and Bayesian information criterion suggest that the latter one is more reliable. Also, panel data diagnostic based on the Hausman test indicates that all crop yield and acreage models are consistent under the fixed effects model. Hence, this study automatically eliminates spatial panel analysis with random effects.

Lastly, before concentrating on spatial analysis, the study scrutinizes the potential endogeneity problem as Miao et al. (2015) mentioned. In their model, Miao et al. (2015) found out that input and output prices are endogenous for which they used 2SLS after getting rid of the spatial autocorrelation issue. Nevertheless, input and output prices are endogenous in this analysis. One reason for this situation may be the reliability problem of the data. More precisely, district-level dataset indicating input prices for crop production in Turkey are not available. Thus, this study cannot create fertilizer price index as Miao et al. (2015) have. Instead, this study makes use of diesel prices and a fixed fertilizer for every crop. This choice may enable us to disregard the endogeneity problem. Another reason may be related to the regional scale of data availability. That is, since there is no district-level statistics for input and output prices, the analysis used city-level statistics for these variables. Furthermore, almost all regression results revealed that input and output prices are statistically insignificant. Hence, when the study takes into account all of these statistical facts, there is no need to use spatial IV panel regression.

Based on the above discussion, this study prefers to use spatial panel data models. A general specification of spatial panel model is given below (Lee et al. 2010);

$$y_t = \rho W y_t + X_t + \mu + \nu_t \tag{8}$$

$$\nu_t = \lambda M \nu_t + \varepsilon_{it} \tag{9}$$

with $\varepsilon_{it} \sim \mathcal{N}(0, \sigma^2)$ and M is the weight matrix for the spatial-autocorrelated error term which may or may not be equal to W. For this study, we used both matrices as the same.

W refers to nxn spatial weight matrix for the period $t = 1, \ldots, T$ where y_t is nx1 column vector of the dependent variable and X_t is the nxk matrix of independent variables. μ is a vector of parameters to be estimated in the fixed-effects variant. Parameter ρ denotes the spatial interaction effect which controls the connection between a region and its neighbors. Spatial interaction is also taken into account by specifying a spatial autoregressive process in error term ν_t with which λ captures this effect for the error term.

Lastly, it will be beneficial to elaborate on a spatial weight matrix explicitly in this part of the study. Each non-negative matrix, $W = (w_{ij} : i, j = 1, ..., n)$ is a possible spatial weight matrix to define spatial relations for n spatial units. Each spatial weight w_{ij} refers to a spatial influence of unit j on i. $w_{ii} = 0$ for all $i = 1, ..., n$. Hence, W has a zero diagonal (Cliff and Ord, 1969). As Miao et al. (2015) used, this study prefers to work on the symmetric form of k-nearest neighbor weights (See appendix C).

CHAPTER 3

FINDINGS

After setting the benchmark model and the statistical structure of the analysis, this part illustrates empirical findings. Each crop yield and acreage model consists of three different sub-models. The study defines model 1 as an illustration of Miao et al. (2015) specification on the Turkey case. Model 2 aims to expand the climate vector of the first one by adding new climate variables which may have direct effects on crop yield and acreage. The last model excludes price vector to test whether market prices have the power to change the effects of climate variables. All models and the results are presented in Appendix D.

One of the main variables of interest in this study is growing degree days (GDD) which is statistically significant for every regression except for the second model for sunflower acreage. GDD and its squared terms are both statistically meaningful for wheat, corn, and barley. As Miao et al. (2015) offers, GDD has a positive and its squared term has a negative relation with barley and corn yield, and wheat yield and acreage models. This indicates that GDD has a U-shape relation with these crops. Barley and corn acreage models have an inverse U-shaped whereas sunflower yield and acreage models are only connected with GDD negatively and GDD^2 is not statistically significant for these models.

This analysis also used heating degree days which refers to days when the air temperature is higher than 30°C. This variable enables us to understand the impact of extremely high temperature on crops. Even though the Miao's et al. (2015) findings stated that high temperature is harmful to crop acreages and yields, our study proposes that heating degree days are not harmful to crop models. Except for

sunflower, this variable is statistically significant for wheat and corn yield models and is not significant for acreage models. For the case of barley yield and acreage models, it is statistically significant for both.

This analysis also benefits from monthly precipitation and monthly temperature deviation. These climate variables enable us to control monthly reactions of crops to climate variations. Rather than using every month, the analysis prefers to choose months depending on planting and harvesting seasons of crops. Planting and harvesting seasons for wheat are from May to August and October-November, for sunflower are spring and summer terms, and September, for barley are spring term and from October to December, and for corn are winter term and from April to September (See Appendix A, Figure A1). We also used the monthly climate variables for planting and harvesting time of each crop to solve the problem of time inconsistency resulting from using yearly GDD in the model.

When we focus on wheat yield model, precipitation in June is the only variable which is statistically significant for the three models. Precipitation in October for model 3 and in November for model 2 and 3 are statistically important months. Monthly temperature deviation is not a significant factor for wheat yield model except in November for the models 2 and 3, but, the significance level is 10% for these two models. For the acreage models, May is the prominent month for precipitation in every model. In acreage models, temperature deviations have considerable effects, because farmers decide the acreage time depending on temperature deviation which has a direct effect on the last stage of the ripening period of wheat. For the case of sunflower, both monthly variables do not look like a significant impact on acreage and yield models in general. Precipitation in May

and July, and temperature deviation in March are statistically significant for both models. Corn models display the same pattern as the sunflower ones. Comparing to other crops, this study prefers to focus on broader monthly period, because corn production requires more precipitation. When we check out the results, precipitation in May and August for yield, and in August for acreage are statistically significant. In the context of temperature deviation, winter term is statistically significant for yield models. However, the connection between crop yield and temperature deviation is different than expected. That is, the results revealed that an increase in temperature deviation in the winter period pushes up corn yield whereas corn production needs a balanced temperature. When we scrutinize the barley crop and acreage models, even if temperature deviation and precipitation are not statistically significant in general for the yield models, especially monthly precipitation becomes statistically meaningful during the cold period. For the case of acreage models, summer term precipitation and temperature deviation are the main determinants of the amount of acreage. While precipitation and temperature deviation have a positive impact on the amount of early acreage, they become negative throughout the end of the summer.

After adapting Miao's et al. (2015) climate vectors on the Turkey case, this study also attempted to expand the vector by adding new climate variables introduced in the previous chapter (also see Appendix A). All of these variables are annual and we use them in model 2 with prices and model 3 without prices. Annual average heat, for instance, is one of the variables which may indicate the effect of an ongoing global warming trend on crop production for the Turkey case. Except for sunflower yield models, an increase in annual average heat shifts down crops yield. This variable is statistically significant in wheat and corn yield and acreage models, and

barley acreage models. Even though the study used monthly precipitation variables, we additionally prefer to control annual total precipitation, annual rainy day, and annual heavy rainy day, we expect that those enable us to capture annual fluctuations in precipitation. The results reveal that these factors are not statistically significant for sunflower yield and acreage models. Even if the annual heavy rainy day has a positive nexus of barley yield and acreage models, this variable has a negative impact on wheat acreage and yield. Annual rainy day has a positive connection with crop production mostly whereas crops do not react positively to an increase in annual total precipitation. Hence, the connection between crop production and annual rainy day, and annual total precipitation mean that crop production requires balanced precipitation, but the amount of precipitation above or below threshold levels leads to drop crop production.

This study also emphasizes on price vector for each crop model. Price vector is excluded in model 3 to examine how it changes the influence of climate variables in crop production. As mentioned previous parts, cost function consists of diesel and DAP fertilizer prices. DAP fertilizer is a composite product and consists of nitrogen and phosphorus. Its effect pushes up if DAP is used with other fertilizers [3]. Hence, using only DAP is not enough to create an effective cost function. Additionally, input and output prices are city-level, so, this may limit to understand the district-level variation. In this context, output prices are not statistically significant for corn and wheat models. Based on sunflower yield model, output price pushes up yield and it is statistically significant whereas it is not statistically significant even if the effect is the same. Barley is the only crop that output price is statistically significant for

[3] https://www.toros.com.tr/documents/TARIMSAL/%C3%9Cr%C3%BCnler/Bitki%20Besleme/Klasik%20G%C3%BCbre/Anlat%C4%B1m/DAP%20(Diamonyum%20Fosfat).pdf

both yield and acreage models. The impact of crop prices fluctuates even for the same dependent variable like wheat. For the case of corn, corn price has a negative relation between acreage and yield. Barley price pushes up yield whereas decreases acreage. While we check out the input prices, barley is the only crop that diesel and fertilizer has a statistically significant impact on yield and acreage, but the effect of DAP is quite small. DAP is the only cost parameter which is statistically significant for wheat yield and acreage models. Whereas its impact is quite small for the yield model, it has a positive effect on acreage. This positive relationship between the fertilizer and acreage means that farmers use less DAP and more other fertilizers that this study cannot control and this change in crop production may increase in crop acreage. Sunflower yield models revealed that diesel price is statistically significant and its effect is positive. This positive relation may cause an increase in using more technology. While technological improvements in agricultural production make fossil fuels necessary goods, it also improves total production and yield. Hence, even if diesel prices increase in, yield also shifts up for sunflower yield models. For corn production, diesel is statistically significant for yield model and its impact is the same with sunflower production, DAP is statistically meaningful for corn acreage models. Moreover, it is beneficial to construe the difference between the effects of climate variables on crop production in model 3 and the others. Especially focusing on GDD in model 3 and model 1 reveal that price vector makes some climate variable like GDD smooth. Except for sunflower, all yield models display the price effect.

Furthermore, explaining the relation between time trend and crop production is a fundamental task to comprehend how crop yield and acreage change. This study rarely prefers to use the quadratic form of a time trend. As Miao et al. (2015) states,

this analysis also uses the time trend to the capture change in agro-technology. Empirical findings state that there is a negative connection between wheat acreage and yield models and time trend. Understanding this relation requires to know household characteristics of wheat-producers because changes in agro-technology and its usage are also related to socio-economic characteristics of crop producers. For example, if wheat producers are low-income families, we do not expect that wheat producers adopt technological improvements. For corn models, time trend has a statistically meaningful impact on acreage and yield models and it is positive. Sunflower yield and acreage, and barley yield models have a statistically weak connection with time trend, but the trend variable is statistically significant for barley acreage models and it is positive except model 3.

Lastly, when we check out the mechanical structure of the models, R^2 is approximately 13% at most. In this context, especially sunflower acreage models look problematic. All sunflower acreage models can explain less than 1% of the variance of the dependent variable. For example, model 3 is 0.1%. Nevertheless, ρ and λ, which are indicators of spatial interaction for dependent variables and error terms as mentioned in the model specification section, estimation results illustrate that they are statistically significant for every model and this means that the spatial autoregressive with spatially autocorrelated errors model sets exactly to explain the empirical relationship between crop production and climate.

CHAPTER 4

DISCUSSION AND CONCLUSION

This study aimed to analyze the impact of climate variables on crop (barley, corn, sunflower, wheat) acreage and yield based on Miao et al. (2015) model by focusing on the Turkey case between the period 2009-2017. This district-level analysis benefited from spatial autoregressive with spatially autocorrelated errors model which enables us to capture spatial interaction among dependent variables and error terms by taking into account the Tobler's first law of geography (1970) which underlines the fact that districts have connections between each other. In this context, climate conditions within a region may impact crop production of other regions. Since this study focused on micro-scale analysis, districts are one of the smallest accommodation units in Turkey, the connection among regions expected to become more intense.

In this regard, this study illustrated local Moran's I test which spatial autocorrelation among regions for each crop separately. As illustrated in previous parts, the results indicate that crop production in most of the districts has a spatial interaction among each other. After illustrated spatial autocorrelation among districts, this study introduced the benchmark model which consists of climate, trend, and price vectors. The analysis obtained empirical results based on the structure constructed in the model specification part.

The analysis consisted of three models for each crop yield and acreage. Model 1 is the Miao's et al. (2015) implication for the Turkey case, model 2 expands the climate vector in the first one by adding new climate variables, and model 3 excludes price vector to test whether there is an overestimation issue for climate

variables. Based on the empirical results, sunflower crop and acreage models are the weakest ones. Except for model 1 and 2, R^2 is less than 1%. Price vector (diesel and sunflower price) is statistically significant. Output price has a positive effect on its supply and yield. The positive relation between input price and yield may indicate that sunflower production is a technology-dependent crop. Also, the exclusion of price vector does not create an overestimation problem in yield model whereas the GDD effect decreases in acreage models. Depending on the impact of climate vector estimation results, climate impact on sunflower crop and acreage is moderate.

Estimation results for corn production stated that output prices do not have an explanatory power and diesel price is statistically meaningful and it is positive for yield model. This positive relationship may be interpreted as corn is also a technology-dependent crop. The positive relationship with time trend variable also supports this interpretation. Exclusion of price vector leads to an overestimation of GDD for the yield models. However, the overestimation of climate variable is not high in model 2 comparing to the first one. Additional climate variables may compensate for the impact of exclusion of price vector on GDD. When we emphasize only climate vector, climate impact on corn yield is limited, but on corn acreage it is attention-grabbing. When we take into consideration time trend and price vector, climate impact on corn yield and acreage models is compensated.

Barley acreage and yield models also reveal the same results. Diesel price has a negative effect on supply naturally whereas the positive relation with yield reveals that technology is a significant factor for barley production. Exclusion of price vector leads to an overestimation problem of GDD for acreage and yield models. Climate effect can be negligible for yield model, however, the connection between barley

acreage and climate relationship is interesting. Almost every climate variable has a negative connection with barley acreage and they are statistically significant. In barley acreage model, the relation between barley price and supply has a negative relationship, but this connection destroys the fundamental economic rule of supply. The expected result requires a positive relationship because of the rule of supply. The potential explanation of this relation may be related to financial fluctuations and its impact on barley production. Even though this research topic is out of the boundaries of the analysis, a brief discussion may enable us to clarify the issue. More precisely, after 2009, global financial fluctuations and domestic political turmoil in Turkey make exchange rates vulnerable. Since Turkey imports technology, fossil fuels and fertilizers, these currency fluctuations may have a direct effect on crop production. In this context, an increase in output price may not compensate for an increase in the price of technology and fossil fuels, so, an increase in barley price cannot enough to shift up barley supply.

The fertilizer price is statistically significant input cost for wheat production. Even if its impact on wheat yield is pretty small, wheat acreages and diesel price have a positive relationship. Climate impact on wheat yield is pretty small, but wheat supply pushes up with an increase in climate variables. Additionally, when we compare model 1 and 3, the exclusion of price vector leads to an overestimation problem of climate variables, especially GDD. Annual average heat needs special attention. While it has a positive impact on wheat supply, yield per ton decreases. Global warming trend for wheat production in Turkey may not be harmful to wheat supply in the short run, but it is for sure that it deteriorates effective production efficiency.

The general conclusion based on empirical framework formed in this study is that in addition to climate factors, there are several reasons like production decisions, agricultural policy and producers' household characteristics which influence agricultural production. As illustrated in previous chapters, the price vector, for example, makes effects of climate factors smooth. Even if some climate variables directly change crop acreage and yield, the results of the empirical frame state that the impact of climate variables on crops yield is limited and it may sometimes be positive. For the case of crop acreage models, except barley acreage, which is affected negatively by climate warming and over precipitation, climate effect is moderate as the yield models. Although it is difficult to define an exact climate change effect on agriculture since our analysis only included a short period of time, the significant but moderate effect of climate variables on acreage and yield implies the more obvious results.

Lastly, it would be beneficial to open a discussion for further researches which analyze the impact of climate change on crop production in Turkey. Scrutinizing the way in which the effects of climate change on irrigated and dry farming differentiates may clarify this issue more. Even though TURKSTAT has a dataset for this research, the time scale is limited. Additionally, taking into account household characteristics of farmers like their monthly income, education level or the number of family members may enable us to consider the effect of an individual factor on this issue. Since production decision-making is a dynamic process, working on human reaction to climate fluctuations provides alternative research opportunities. Moreover, agricultural policies will be another control vector which affects production decision; hence, they influence the effect of climate change.

APPENDIX A

DETAILED INFORMATION ABOUT THE DATASET

Table A1. Data Labeling

Variable Name	Unit	Label
annual average heat	Celcius	-
annual average humidity	%	-
annual heavy rainy day	# of day	-
annual rainy day	# of day	-
annual total evaporation	mm	-
annual total precipitation	mm	-
annual average sunbathing time	total hours/days	-
barley acreage	decare	-
barley price	TL/decare	-
barley yield	kg/decare	-
corn acreage	decare	-
corn price	TL/decare	-
corn yield	kg/decare	-
DAP fertilizer price	TL/kg	-
diesel price	TL/liter	-
growing degree days	# of day	365-(Tmax. $>$ 30°C+Tmax. $<$ 10°C)
monthp1	mm	Monthly precipitation in Jan
monthp2	mm	Monthly precipitation in Feb
monthp3	mm	Monthly precipitation in March
monthp4	mm	Monthly precipitation in April
monthp5	mm	Monthly precipitation in May
monthp6	mm	Monthly precipitation in June
monthp7	mm	Monthly precipitation in July
monthp8	mm	Monthly precipitation in August
monthp9	mm	Monthly precipitation in Sep
monthp10	mm	Monthly precipitation in Oct
monthp11	mm	Monthly precipitation in Nov
monthp12	mm	Monthly precipitation in Dec
sunflower acreage	decare	-
sunflower price	TL/decare	-
sunflower yield	kg/decare	-
tempdev1	Celcius	Max Temp in Jan - Min Temp in Jan
tempdev2	Celcius	Max Temp in Feb - Min Temp in Feb
tempdev3	Celcius	Max Temp in March - Min Temp in March
tempdev4	Celcius	Max Temp in April - Min Temp in April
tempdev5	Celcius	Max Temp in May - Min Temp in May
tempdev6	Celcius	Max Temp in June - Min Temp in June
tempdev7	Celcius	Max Temp in July - Min Temp in July
tempdev8	Celcius	Max Temp in August - Min Temp in August
tempdev9	Celcius	Max Temp in Sep - Min Temp in Sep
tempdev10	Celcius	Max Temp in Oct - Min Temp in Oct
tempdev11	Celcius	Max Temp in Nov - Min Temp in Nov
tempdev12	Celcius	Max Temp in Dec - Min Temp in Dec
Tmax. $<$ 10°C	# of day	-
Tmax. $>$ 30°C	# of day	-
wheat acreage	decare	-
wheat price	TL/decare	-
wheat yield	kg/decare	-

Table A2. Summary Statistics of Dataset (928 districts, 8.352 observations, 2009-2017)

Variables	Mean	Std. Dev.	Min.	Max.
wheat acreage	97,930.85	134,322.10	5.00	1,337,799.00
wheat yield	222.09	116.99	13.03	1,350.00
wheat price	0.55	0.22	0.22	1.03
annual total precipitation (mm)	944.48	414.43	65.46	4,283.44
annual heavy rainy day	7.08	6.53	0.00	61.00
annual rainy day	102.00	30.51	10.00	223.00
annual average sunbathing time	150.73	70.89	70.99	311.17
annual average heat	12.82	3.56	3.15	21.84
Tmax. $<$ 10°C	81.37	43.53	0.00	216.00
Tmax. $>$ 30°C	73.29	42.77	0.00	187.00
annual total evaporation (mm)	642.98	307.03	54.76	3,033.53
annual average rel. humidity (%)	66.17	8.03	37.05	82.73
diesel price	3.77	0.65	2.43	4.83
DAP fertilizer price	1,201.58	354.89	537.15	1,835.39
growing degree days	210.35	45.50	113.00	365.00
corn acreage	9,593.58	28,555.76	1.00	507,579.00
corn yield	2,437.27	1,837.79	29.63	8,000.00
corn price	0.60	0.42	0.35	3.50
sunflower acreage	5,985.32	24,067.57	1.00	353,974.00
sunflower yield	64.17	102.39	14.40	528.54
sunflower price	0.88	0.87	0.31	3.44
barley acreage	38,414.79	66,543.76	1.00	757,510.00
barley yield	232.33	144.85	13.89	2,308.96
barley price	0.57	0.18	0.32	1.10

Crop	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Barley						H	H	H	H	P	P	P
Corn	P	P		H	H	H	H	H	H			P
Sunflower			P	P	P	H	H	H	H			
Wheat					H	H	H	H		P	P	

Figure A1. Crop calendar

P denotes peak planting time; H denotes peak harvest time [4]

[4] http://hayrabolutb.org.tr/media/ziraat/Misir-Tarimi.pdf
https://arastirma.tarimorman.gov.tr/ttae/Sayfalar/Detay.aspx?SayfaId=54
https://arastirma.tarimorman.gov.tr/ttae/Sayfalar/Detay.aspx?SayfaId=49
https://arastirma.tarimorman.gov.tr/etae/Belgeler/EgitimBrosur/125-ciftcibro.pdf
https://eziraatci.com/arpa-hangi-ayda-hasat-edilir.html
https://www.tarim.bayer.com.tr/tr/bilgi-tarlasi/bugdayin-tarladaki-yolculugu-hasat-ile-son-buluyor/

APPENDIX B

CLUSTER MAPS, MORAN SCATTER PLOTS AND DISTRICT LEVEL NEIGHBORHOOD RELATIONS MAP

Based on cluster maps and Moran scatter plots, all crop yield and acreage maps have spatial autocorrelation. More than 90% of clustering consists of high-high and low-low groups, more than 50% of clustering are from high-high groups. Additionally, 50% of clusters are insignificant, but, district-level connection map, which is independent of crop-based mapping, indicates that every district (there are 928 in total) have 5 neighbors in average approximately. Hence, all the indicators reveal that there is a spatial connection among districts which may impact on crop acreage and yields.

Figure B1. The map showing neighborhoods of districts

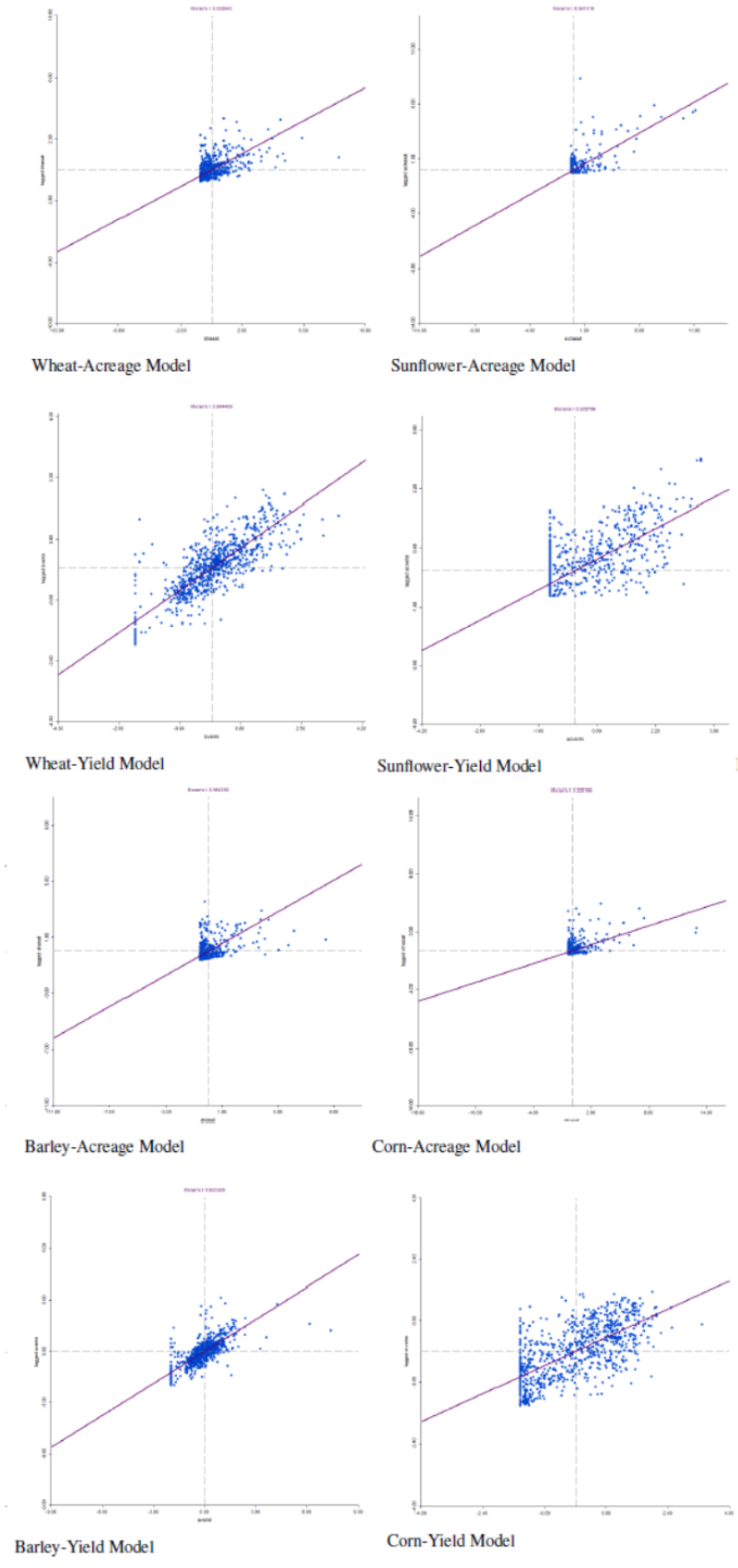
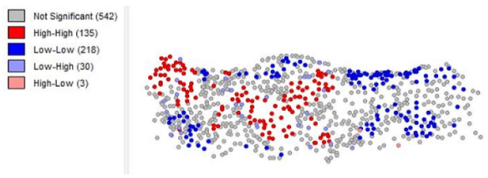
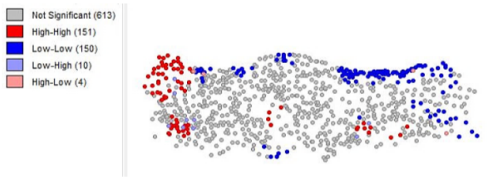


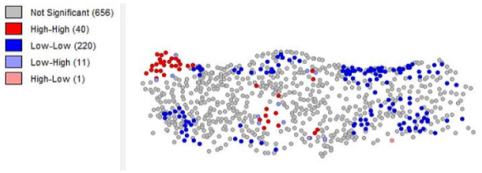
Figure B2. Local Moran's I Test scatter plots



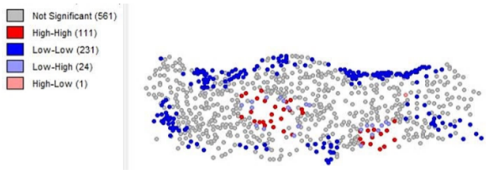
Sunflower-Yield Model



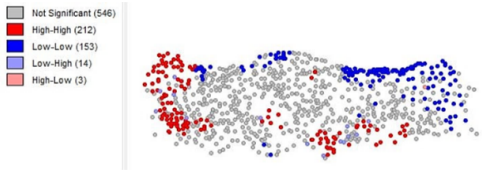
Barley-Yield Model



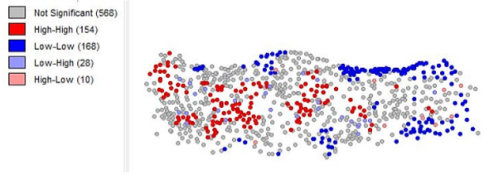
Sunflower-Acreage Model



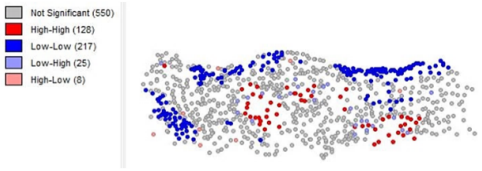
Barley-Acreage Model



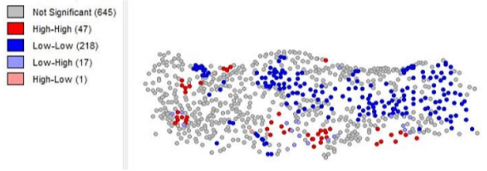
Wheat-Yield Model



Corn-Yield Model



Wheat-Acreage Model



Corn-Acreage Model

Figure B3. Local Moran's I Test cluster maps

APPENDIX C

K-NEAREST NEIGHBOR WEIGHTS

Let the geometric center distances of each spatial unit i to all units $j \neq i$ are lined as follows: $d_{ij(1)} \leq d_{ij(2)} \leq ... \leq d_{ij(n-1)}$. Thereafter for each $k = 1, ..., n-1$, the set $N_k(i) = \{j(1), j(2), ..., j(k)\}$ includes the k nearest units to i. For each given k the k-nearest neighbor weight matrix, W, has spatial weigh form as:

$$w_{ij} = \begin{cases} 1, & j \in N_k(i) \\ 0, & otherwise \end{cases} \qquad (Standard\ \ Form) \qquad (10)$$

The symmetrical version of the matrix where positive weights are assigned to all ij pairs for which at least one is within the k-nearest neighbors of the other:

$$w_{ij} = \begin{cases} 1, & j \in N_k(i)\ or\ i \in N_k(j) \\ 0, & otherwise \end{cases} \qquad (Symmetric\ \ Form) \qquad (11)$$

After creating the spatial weight matrix for 928 districts, we normalized the matrix based on rows. For $(w_{ij} : j \neq i)$ $[w_{ii} = 0]$, all spatial weights affecting spatial unit i are included in i^{th} row of W. Then, by normalizing each row of the (nonnegative) weights to have a unit sum, we get;

$$\sum_{j=1}^{n} \frac{w_{i,j}}{k} = 1, i = 1, ..., n \qquad (12)$$

APPENDIX D

EMPIRICAL FINDINGS FROM THREE MODELS: (1) WITH PRICE VECTOR, (2) WITH CLIMATE VARIABLES AND (3) WITHOUT PRICE VECTOR

Table D1. Determinants of Sunflower Yield and Acreage

	Sunflower Yield			Sunflower Acreage		
Variables	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
GDD	-0.0942***	-0.0737	-0.0875*	-11.80***	-14.31**	-15.74**
	(-0.0279)	(-0.0493)	(-0.0492)	(-4.082)	(-5.829)	(-6.199)
sunflower price	6.295***	6.126***		321.2	321.3	
	(-1.698)	(-1.7)		(-207.8)	(-205.8)	
annual total precipitation		-0.00406	-0.00443		0.957	0.936
		(-0.00461)	(-0.00454)		(-0.643)	(-0.639)
annual heavy rainy day		-0.0558	-0.0357		-41.9	-43.54
		(-0.229)	(-0.227)		(-29.88)	(-29.47)
annual rainy day		0.0561	0.0579		-12.71	-12.86
		(-0.059)	(-0.0589)		(-8.995)	(-8.9)
annual average sunbathing time		-0.00744	-0.0205**		2.712***	2.133**
		(-0.0102)	(-0.00922)		(-0.98)	(-0.993)
annual average heat		0.927	1.26		38.61	61.35
		(-1.077)	(-1.083)		(-124.5)	(-133.8)
Tmax. $>$ 30°C		-0.0179	-0.0699		-7.644	-9.551
		(-0.0819)	(-0.084)		(-8.206)	(-9.007)
annual total evaporation		-0.0172**	-0.0169**		0.0874	0.115
		(-0.00843)	(-0.00817)		(-0.357)	(-0.356)
annual average humidity		0.245	0.0282		-0.582	-3.87
		(-0.377)	(-0.372)		(-44.28)	(-43.39)
diesel price	3.061**	3.030**		-41.36	-114.4	
	(-1.342)	(-1.328)		(-212.6)	(-212.6)	
DAP fertilizer price	0.000384	0.000739		0.342*	0.33	
	(-0.00157)	(-0.00186)		(-0.18)	(-0.202)	
monthp3	0.026	0.0243	0.0156	0.0265	0.545	0.96
	(-0.0162)	(-0.0162)	(-0.014)	(-1.453)	(-1.512)	(-1.224)
monthp4	-0.0138	-0.00961	-0.00701	1.915	2.464	2.216
	(-0.013)	(-0.014)	(-0.0134)	(-1.602)	(-1.61)	(-1.374)
monthp5	-0.0356**	-0.0285*	-0.0306**	-4.318**	-5.291**	-5.388**
	(-0.0147)	(-0.0152)	(-0.0151)	(-2.028)	(-2.177)	(-2.149)
monthp6	0.0212	0.018	0.0188	-0.953	-0.239	0.262
	(-0.0145)	(-0.0154)	(-0.0158)	(-1.373)	(-1.445)	(-1.371)
monthp7	0.0249**	0.0319***	0.0292***	-3.423**	-3.008*	-3.028*
	(-0.0104)	(-0.0113)	(-0.0112)	(-1.538)	(-1.59)	(-1.601)
monthp8	0.0185	0.0153	0.0162	-2.452	-2.139	-2.411
	(-0.0183)	(-0.0187)	(-0.0178)	(-1.938)	(-1.966)	(-1.872)
monthp9	-0.00665	-0.00997	-0.00636	2.194	2.863*	2.984*
	(-0.00836)	(-0.0088)	(-0.00905)	(-1.637)	(-1.706)	(-1.659)
tempdev3	0.394*	0.438*	0.540**	59.59**	51.23*	47.53*
	(-0.232)	(-0.236)	(-0.228)	(-26.59)	(-27.08)	(-26.6)
tempdev4	0.0378	0.0149	-0.0356	-29.53	-25.28	-26.62
	(-0.181)	(-0.186)	(-0.186)	(-19.24)	(-19.86)	(-19.05)
tempdev5	-0.052	-0.0578	-0.176	-10.23	-7.447	-7.182
	(-0.137)	(-0.141)	(-0.137)	(-16.93)	(-16.47)	(-13.23)
tempdev6	-0.102	-0.0774	-0.065	3.908	3.595	-7.191
	(-0.216)	(-0.217)	(-0.208)	(-23.26)	(-23.85)	(-20.81)
tempdev7	-0.114	-0.0975	0.0142	5.067	3.272	10.17
	(-0.183)	(-0.193)	(-0.191)	(-16.46)	(-17.8)	(-18.08)
tempdev8	-0.0328	-0.0384	-0.0992	-22.67	-22.2	-21.86
	(-0.136)	(-0.14)	(-0.14)	(-21.27)	(-20.46)	(-20.45)
tempdev9	0.24	0.207	0.196	29.08	28.69	30.34
	(-0.152)	(-0.152)	(-0.145)	(-20.94)	(-20.34)	(-20.95)
trend	0.187	0.459	1.621***	-105,795***	5.266	33.58
	(-0.372)	(-0.556)	(-0.408)	(-37739)	(-71.12)	(-53.73)
$trend^2$				26.29***		
				(-9.37)		
ρ	0.484***	0.477***	0.498***	0.656***	0.653***	0.656***
	(-0.0598)	(-0.0612)	(-0.0587)	(-0.0562)	(-0.0566)	(-0.0556)
λ	-0.324***	-0.315***	-0.334***	-0.498***	-0.494***	-0.498***
	(-0.0841)	(-0.0859)	(-0.0834)	(-0.0983)	(-0.0988)	(-0.0978)
observations	8352	8352	8352	8352	8352	8352
R-squared	0.107	0.12	0.022	0.006	0.004	0.001
number of districts	928	928	928	928	928	928
AIC	85938.93	85932.77	85968.39	168408.2	168411.6	168417.3
BIC	86093.59	86143.67	86158.21	168541.8	168573.3	168571.9

Robust standard errors in brackets.
*** p<0.01, ** p<0.05, * p<0.1

Table D2. Determinants of Corn Yield and Acreage

	Corn Yield			Corn Acreage		
Variables	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
GDD	11.54***	19.33***	19.55***	-58.26***	-28.97**	-28.10**
	(-2.85)	(-3.86)	(-3.842)	(-20.55)	(-13.97)	(-13.92)
corn price	-11.5	-6.549		-259.5	-287.6	
	(-36.63)	(-36.8)		(-245.4)	(-239.5)	
annual total precipitation		-0.16	-0.156		-2.341**	-2.283**
		(-0.0991)	(-0.0988)		(-0.915)	(-0.921)
annual heavy rainy day		4.726	4.934		-42.92	-42.46
		(-4.664)	(-4.659)		(-37.08)	(-36.91)
annual rainy day		2.585*	2.632*		8.755	9.039
		(-1.427)	(-1.429)		(-15.38)	(-15.17)
annual average sunbathing time		-0.248	-0.457		-3.384	-0.94
		(-0.398)	(-0.396)		(-4.379)	(-5.144)
annual average heat		-227.3***	-230.1***		-1,926***	-1,920***
		(-43.71)	(-43.92)		(-696.7)	(-709.1)
Tmax. $>$ 30°C		11.39***	11.32***		7.373	6.819
		(-3.324)	(-3.322)		(-18.1)	(-18.26)
annual total evaporation		0.26	0.267*		6.543***	6.465***
		(-0.163)	(-0.162)		(-1.527)	(-1.556)
annual average humidity		-20.14**	-22.54**		-198.2	-199.3
		(-9.954)	(-9.767)		(-147.8)	(-147.2)
diesel price	152.2***	99.50**		440.1	-24.85	
	(-54.07)	(-49.99)		(-915.5)	(-803.6)	
DAP fertilizer price	-0.019	-0.0672		-0.859*	-1.414***	
	(-0.0523)	(-0.0564)		(-0.44)	(-0.431)	
monthp1	-0.0748	0.0855	0.0484	-3.461	-1.575	-1.874
	(-0.284)	(-0.29)	(-0.287)	(-3.898)	(-3.714)	(-3.668)
monthp2	0.214	0.0908	-0.0137	8.716**	7.511**	7.817**
	(-0.273)	(-0.274)	(-0.269)	(-4.008)	(-3.727)	(-3.75)
monthp4	-0.292	-0.511	-0.463	-1.788	-1.064	-1.234
	(-0.423)	(-0.423)	(-0.423)	(-4.73)	(-4.817)	(-4.944)
monthp5	-0.743*	-0.811**	-0.801*	-0.785	-2.006	-2.109
	(-0.401)	(-0.412)	(-0.411)	(-4.72)	(-4.713)	(-4.764)
monthp6	-0.044	-0.0843	-0.191	0.256	0.889	0.274
	(-0.351)	(-0.359)	(-0.361)	(-3.593)	(-3.712)	(-3.819)
monthp7	0.081	0.0304	0.0223	2.812	4.615	5.014
	(-0.364)	(-0.37)	(-0.369)	(-2.928)	(-3.06)	(-3.086)
monthp8	0.0147	0.14	0.209	-12.79***	-12.92***	-11.37***
	(-0.394)	(-0.404)	(-0.393)	(-4.532)	(-4.507)	(-4.41)
monthp9	0.413	0.424	0.402	2.304	3.762	3.675
	(-0.287)	(-0.284)	(-0.287)	(-2.38)	(-2.481)	(-2.391)
monthp12	-0.743***	-0.489**	-0.435*	-1.992	0.267	0.296
	(-0.236)	(-0.244)	(-0.243)	(-3.089)	(-3.123)	(-3.073)
tempdev1	5.796*	6.312**	5.537*	-18.95	-6.705	-4.074
	(-3.086)	(-3.19)	(-3.018)	(-37.72)	(-40.13)	(-41.73)
tempdev2	-7.686*	-6.873*	-6.770*	-37.03	-26.55	-30.45
	(-3.948)	(-3.944)	(-3.874)	(-46.13)	(-47.61)	(-48.72)
tempdev4	-4.186	-3.201	-2.903	42.53	45.75	45.62
	(-4.196)	(-4.259)	(-4.248)	(-47.84)	(-49.14)	(-49.17)
tempdev5	2.735	2.898	2.296	-61.28*	-46.03	-43.44
	(-2.733)	(-2.763)	(-2.748)	(-34.31)	(-34.6)	(-34.06)
tempdev6	0.566	-0.672	0.138	66.14	63.38	65.34
	(-5.038)	(-5.052)	(-5.037)	(-50.18)	(-50.03)	(-49.5)
tempdev7	6.689	6.744	6.765	60.77*	57.9	57.22
	(-4.758)	(-4.773)	(-4.764)	(-36.52)	(-37.28)	(-37.31)
tempdev8	-2.219	-2.174	-2.426	-22.33	-26.08	-27.67
	(-2.978)	(-3.039)	(-3.019)	(-24.02)	(-23.17)	(-23.27)
tempdev9	-7.743***	-5.918*	-6.059**	-14.49	-9.567	-10.26
	(-3.001)	(-3.047)	(-3.046)	(-27.34)	(-27.58)	(-27.26)
tempdev12	8.350**	6.766**	7.490**	65.19**	30.9	31.55
	(-3.334)	(-3.441)	(-3.421)	(-32.33)	(-31.37)	(-31.98)
GDD^2	-0.0394***	-0.0428***	-0.0429***	0.0689*		
	(-0.0084)	(-0.00774)	(-0.00771)	(-0.0375)		
trend	43.92**	61.72**	79.73***	555.5**	652.5**	457.3**
	(-18.82)	(-25.05)	(-19.75)	(-252.1)	(-273.8)	(-208.4)
ρ	-0.528***	-0.526***	-0.534***	-0.549***	-0.560***	-0.563***
	(-0.0745)	(-0.073)	(-0.071)	(-0.191)	(-0.185)	(-0.184)
λ	0.580***	0.580***	0.586***	0.716***	0.722***	0.724***
	(-0.0487)	(-0.0481)	(-0.0461)	(-0.0823)	(-0.0801)	(-0.0792)
observations	8352	8352	8352	8352	8352	8352
R-squared	0.062	0.044	0.044	0.003	0.031	0.031
number of districts	928	928	928	928	928	928
AIC	132897.6	132840.4	132837.9	172575.7	172524.2	172523.5
BIC	133080.4	133079.5	133055.9	172737.4	172728.1	172713.3

Robust standard errors in brackets.
*** p<0.01, ** p<0.05, * p<0.1

Table D3. Determinants of Wheat Yield and Acreage

Variables	Wheat Yield			Wheat Acreage		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
GDD	0.424***	0.690***	0.673***	310.9***	308.3***	327.3***
	(-0.124)	(-0.145)	(-0.143)	(-77.74)	(-81.27)	(-80.38)
wheat price	-5.106	2.783		-5515	-6873	
	(-5.708)	(-6.069)		(-4504)	(-4470)	
annual total precipitation		-0.00149			-3.3	-3.506
		(-0.00526)			(-3.075)	(-3.062)
annual heavy rainy day		-0.335			-263.4*	-245.4*
		(-0.249)			(-141)	(-139.7)
annual rainy day		0.121*	0.0381		23.19	16.43
		(-0.0624)	(-0.046)		(-40.15)	(-40.05)
annual average sunbathing time		-0.0228**	-0.0230**		-14.75	-2.328
		(-0.0112)	(-0.0102)		(-11.7)	(-10.21)
annual average heat		-6.225***	-6.378***		2,169*	2,317*
		(-1.19)	(-1.204)		(-1250)	(-1259)
Tmax. $>$ 30°C		0.397***	0.397***		-14.49	-5.046
		(-0.115)	(-0.114)		(-47.78)	(-48.66)
annual total evaporation		0.0118*	0.0116*		0.956	0.45
		(-0.00622)	(-0.00616)		(-4.843)	(-4.753)
annual average humidity		-0.676*	-0.495		695.2*	735.1**
		(-0.35)	(-0.336)		(-356.5)	(-344.9)
diesel price	-1.159	-0.0361		-363.5	792.9	
	(-1.205)	(-1.181)		(-1022)	(-1143)	
DAP fertilizer price	0.00660***	0.00389*		6.199***	5.161***	
	(-0.00201)	(-0.00206)		(-1.466)	(-1.572)	
monthp5	-0.0167	-0.0196	-0.0168	27.05**	29.59**	28.39**
	(-0.0135)	(-0.0142)	(-0.0143)	(-11.77)	(-11.9)	(-12.16)
monthp6	-0.0261*	-0.0301**	-0.0259*	5.9	0.509	1.57
	(-0.0138)	(-0.0139)	(-0.0137)	(-10)	(-10.86)	(-10.84)
monthp7	0.00934	0.00544	-0.00368	3.831	12.36*	13.59**
	(-0.0116)	(-0.0123)	(-0.0127)	(-6.803)	(-7.034)	(-6.716)
monthp8	-0.0201	-0.0231	-0.0263*	1.567	-0.113	-4.4
	(-0.0151)	(-0.0153)	(-0.0149)	(-10.14)	(-10.01)	(-9.837)
monthp10	-0.0136	-0.0178	-0.0238**			
	(-0.0108)	(-0.0112)	(-0.0101)			
monthp11	0.0135	0.0299**	0.0274**			
	(-0.0121)	(-0.0123)	(-0.0121)			
tempdev5	-0.216	-0.2	-0.222	360.6**	376.7**	394.0***
	(-0.184)	(-0.186)	(-0.169)	(-150.9)	(-153)	(-143.9)
tempdev6	-0.0189	0.047	-0.0819	-453.0***	-420.8***	-462.9***
	(-0.155)	(-0.166)	(-0.156)	(-128.4)	(-126)	(-123.7)
tempdev7	-0.054	0.0143	0.0913	-98.77	-98.19	-83.44
	(-0.166)	(-0.178)	(-0.172)	(-122.3)	(-118.2)	(-118.7)
tempdev8	0.0822	0.0764	0.121	279.3***	242.8***	257.9***
	(-0.138)	(-0.146)	(-0.145)	(-87.47)	(-80.91)	(-82.57)
tempdev10	-0.0821	-0.280*	-0.298*			
	(-0.138)	(-0.164)	(-0.155)			
tempdev11	0.0798	0.161	0.142			
	(-0.153)	(-0.161)	(-0.159)			
GDD^2	-0.00106***	-0.00131***	-0.00127***	-0.534***	-0.607***	-0.634***
	(-0.000295)	(-0.000279)	(-0.000274)	(-0.153)	(-0.16)	(-0.16)
trend	-32.24	-975.1***	-853.8**	-942,098**	-1.136e+06**	-883.2**
	(-291.8)	(-366.5)	(-372.3)	(-370846)	(-454694)	(-422.2)
$trend^2$	0.0081	0.243***	0.212**	233.6**	282.0**	
	(-0.0725)	(-0.0911)	(-0.0925)	(-92.08)	(-113)	
ρ	0.774***	0.758***	0.761***	-0.434***	-0.456***	-0.457***
	(-0.0172)	(-0.0182)	(-0.0178)	(-0.0882)	(-0.088)	(-0.0893)
λ	-0.698***	-0.678***	-0.680***	0.445***	0.464***	0.466***
	(-0.0404)	(-0.0428)	(-0.0424)	(-0.0601)	(-0.0616)	(-0.0624)
observations	8352	8352	8352	8352	8352	8352
R-squared	0.137	0.019	0.015	0.099	0.083	0.06
number of districts	928	928	928	928	928	928
AIC	89073.68	89024.28	89028.81	190402.5	190384.2	190754.3
BIC	89228.34	89235.19	89204.56	190493.9	190524.8	190602.7

Robust standard errors in brackets.
*** p<0.01, ** p<0.05, * p<0.1

Table D4. Determinants of Barley Yield and Acreage

	Barley Yield			Barley Acreage		
Variables	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
GDD	0.780***	2.043***	2.039***	-343.4***	-295.2***	-325.2***
	(-0.164)	(-0.379)	(-0.378)	(-56.44)	(-56.21)	(-55.5)
barley price	20.08***	25.25*		-5,268***	-7,118***	
	(-6.879)	(-13.01)		(-1512)	(-1615)	
annual total precipitation		-0.0365***	-0.0367***		-3.433**	-2.846**
		(-0.0124)	(-0.0124)		(-1.355)	(-1.316)
annual heavy rainy day		1.423***	1.448***		339.0***	307.8***
		(-0.477)	(-0.474)		(-69.64)	(-66.65)
annual rainy day		0.0903	0.0823		13.88	17.21
		(-0.139)	(-0.139)		(-19.94)	(-20.53)
annual average sunbathing time		0.00895	-0.0992		-30.80***	-3.937
		(-0.0732)	(-0.0657)		(-6.852)	(-6.251)
annual average heat		-2.433	-3.967		-4,121***	-4,083***
		(-6.769)	(-6.827)		(-840.4)	(-915)
Tmax. $>$ 30°C		0.721**	0.723**		106.3***	94.40***
		(-0.32)	(-0.317)		(-29.97)	(-29.84)
annual total evaporation		-0.00403	-0.000277		10.78***	10.10***
		(-0.0128)	(-0.013)		(-2.381)	(-2.57)
annual average humidity		1.189	0.785		-853.4***	-809.5***
		(-1.317)	(-1.309)		(-205)	(-217.7)
diesel price	4.951**	28.85***		-3,712***	-4,228***	
	(-2.072)	(-7.867)		(-628.4)	(-809.7)	
DAP fertilizer price	0.00781**	0.00691		-6.276***	-7.412***	
	(-0.00365)	(-0.00667)		(-1.122)	(-1.284)	
monthp6	-0.0191	-0.072	-0.0734	14.90***	16.05***	18.59***
	(-0.0212)	(-0.06)	(-0.0597)	(-5.527)	(-5.992)	(-6.25)
monthp7	0.0296	0.0653*	0.0522	-7.599*	-14.69***	-9.018**
	(-0.0196)	(-0.0357)	(-0.0347)	(-4.014)	(-4.225)	(-4.098)
monthp8	-0.0621**	-0.0739*	-0.0721*	-14.85**	-17.62***	-14.52**
	(-0.025)	(-0.042)	(-0.0423)	(-6.303)	(-6.375)	(-6.32)
monthp9		0.038				
		(-0.0418)				
monthp10	0.00192	0.105**	0.0306	2.287	-3.284	0.2
	(-0.0174)	(-0.048)	(-0.041)	(-4.923)	(-5.194)	(-5.342)
monthp11	0.0470**	-0.135**	0.107**	0.614	9.299*	11.63**
	(-0.0204)	(-0.0555)	(-0.0474)	(-4.873)	(-5.424)	(-5.707)
monthp12	-0.0440**	-0.154	-0.133**	1.457	3.035	2.068
	(-0.0184)	(-0.504)	(-0.0547)	(-2.792)	(-3.195)	(-3.293)
tempdev6	0.246	-0.233	-0.0892	220.5***	198.9***	175.1***
	(-0.261)	(-0.417)	(-0.506)	(-63.37)	(-61.6)	(-59.44)
tempdev7	-0.361	-0.428	-0.256	3.845	26.96	27.06
	(-0.252)	(-0.279)	(-0.415)	(-61.31)	(-59.75)	(-59.67)
tempdev8	-0.422	0.0454	-0.449	-210.8***	-177.3***	-164.0***
	(-0.294)	(-0.688)	(-0.275)	(-48.07)	(-45.81)	(-42.47)
tempdev9		0.231				
		(-0.279)				
tempdev10	-0.414	-0.878**	0.0981	-28.38	-107.1*	-140.2**
	(-0.435)	(-0.39)	(-0.676)	(-54.71)	(-58.21)	(-56.78)
tempdev11	0.446*		0.184	-145.4	-114.4	-97.08
	(-0.258)		(-0.276)	(-90.75)	(-89.47)	(-87.18)
tempdev12	-0.266		-0.830**	212.7***	224.7***	202.0***
	(-0.299)		(-0.388)	(-71.17)	(-71)	(-70.73)
GDD^2	-0.00201***	-0.00380***	-0.00376***	0.612***	0.596***	0.638***
	(-0.000406)	(-0.000795)	(-0.000792)	(-0.0927)	(-0.0895)	(-0.0859)
trend	-0.828	3.568	13.35***	1.151e+06***	2,049***	-462.5*
	(-0.602)	(-3.616)	(-3.252)	(-238176)	(-400.6)	(-252.1)
trend^2				-285.6***		
				(-59.12)		
ρ	0.753***	-0.690***	-0.697***	-0.376***	-0.412***	-0.483***
	(-0.0471)	(-0.0832)	(-0.0807)	(-0.105)	(-0.107)	(-0.104)
λ	-0.690***	0.762***	0.768***	0.389***	0.412***	0.487***
	(-0.0803)	(-0.0468)	(-0.0443)	(-0.0768)	(-0.0782)	(-0.0723)
observations	8352	8352	8352	8352	8352	8352
R-squared	0.101	0.091	0.074	0.128	0.09	0.086
number of districts	928	928	928	928	928	928
AIC	96301.35	96298.12	96305.51	182208	182106.8	182188.9
BIC	96441.96	96502	96488.3	182327.5	182261.5	182336.5

Robust standard errors in brackets.
*** p<0.01, ** p<0.05, * p<0.1

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