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Abstract

Global combat with climate change is central to policymaking. However, recent discussions underline the rising disparity of the impact of climate change for countries with different topographic conditions. Motivated by the rising importance of local differences in climatic developments, this paper aims to investigate the impact of climate change on the spatial distribution of the agriculture sector in Turkey. Using provincial data between 2004 and 2019, our findings show that climate change has a pervasive impact on the regional distribution of agricultural activities. We find out that the impact of climate change on agricultural outcomes is mainly visible through rising temperatures. Those regions with accelerating average temperature are realizing falling agricultural value-added and employment. Moreover, our findings show that the same areas also experience higher food and overall price increases. Our local variability analyses reveal the non-monotonic relationships and suggest that the negative impact of climate change is more observable in for the eastern regions. Our findings demonstrate that climate change is another factor that contributing to the west-east regional development disparities in Turkey. These results are robust to different model specifications and endogeneity of climate change.

JEL Classifications: O10, R11, R12

Key words: agriculture, climate change, spatial heterogeneity, Turkey

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1 Introduction

Adverse effects of climate change have already brought sizable economic costs to countries. Variability in crop yields, loss of capital and land due to sea-level rise, capital damages due to extreme weather events, rising health expenditures associated with rising diseases and heat stress are the most visible effects of climate change (Dellink et al., 2019; Michetti and Pinar, 2019). As concerns increase on the side effects of changing climatic conditions, countries now face a trade-off between economic growth and its environmental consequences. Inevitably, lack of adaptation to climate change has been a global challenge (Adams, 1989; Adams et al., 1998), yet developing and less developed countries are observed to be more vulnerable and less resilient (Mendelsohn, 2008). Collier et al. (2008) argue that the impact of climate change will vary for less developed and developing countries with relatively more agricultural dependency. Drier, hotter weather conditions and increases in the frequency of extreme weather events will give rise to arid agricultural areas and falling crop yields in these geographies that heavily rely on agriculture . Among different territories (see Smit and Cai (1996) for Asia, Collier et al. (2008) for Africa, Du et al. (2017) for Europe and the United States among many others), the Middle East and North Africa (MENA) have specific importance. Evidence from MENA regions validates the inability of the region to cope with global warming and climate change (Waha et al., 2017; Solomon and Tausch, 2020). Moreover, heavy reliance on the agriculture sector in MENA countries exposes them to higher vulnerability than many areas (Sowers et al., 2011).

While the awareness of the importance of climate change is increasing, discussions rely on the the economic impact of climate change at the country level (Mendelsohn et al., 2006; Kahn et al., 2019). However, climatic developments may vary within countries with different topographic conditions (Schierhorn et al., 2020). Moreover, the impact of climate change can be variable across sectors (Dellink et al., 2019). For countries with spatial instabilities and local differences in production, further discussion will be essential to understand how the sectoral effects of climate change influence local and national economies. Originating from these recent discussions, this paper aims to investigate the impact of climate change on the spatial distribution of the agriculture sector in Turkey. Turkish economy is characterized by sizable topographic and regional disparities (Dogruel and Dogruel, 2003; Gezici and Hewings, 2004; Karahasan, 2020). Moreover, the geographical characteristics of regions create immense isolation for the non-urban and agricultural areas in Turkey. While these regions also suffer from the rapid transformation in Turkey (Dogruel and Dogruel, 2006), there is limited discussion about how these regions that count heavily on agriculture are influenced by the rising global warming and climate change. Moreover, while the impact of climate change on agriculture in Turkey has been discussed at the country level (Chandio et al., 2020) and regional level (Sen et al., 2012; Dudu and Çakmak, 2018), to our knowledge, there is no attempt to consider how climate change and agricultural development are spatially integrated.

We believe our setup will contribute to the knowledge of climate change's adverse effects in several pillars. First, most of the scholarly literature investigates the impact of climate change at the country level without considering the regional dimension. Although there are attempts to evaluate the effects of climate change at the sectoral and regional level the time-invariant local differences and the spatio-temporal dimension of local development are mostly neglected. However, it is rather difficult to fully understand the evolution of climate change's adverse effects on our planet without considering how micro aspects of climate change start to influence our daily life from very local to national economies. Second, regional studies within the environmental economics literature overlooked the impact of spatial dimension. In our setup, we consider spatial dimension by examining spatial dependence and heterogeneity. While the former enables us to consider the actual impact area of climate change, the latter helps in understanding the spatial dissimilarities in the impact of climate change on local agricultural development. In particular, this paper contributes to the environmental economics literature and to the development economics literature since understanding the spatial differences of the climate change's impact would enable us to examine spatial development differences. Furthermore, defining the natural borders of climate change's influence will help in understanding the spillovers of local policy implementations to mitigate the adverse effects of climate change. Henceforth, analyses considering the spatial heterogeneity will guide in constructing different local policies based on the regional priorities. The analyses considering the spatial heterogeneity will be instrumental in understanding that the "one size fits all" approach will be ineffective in combatting global warming in countries with substantial local differences. Finally, the investigation of Turkey is an important dimension of our paper. Turkey is one of the most spatially unequal countries among the developing countries , which led to an extensive investigation of regional disparities (Rey and Janikas, 2005). Prior literature already has a consensus on the regional problems of Turkey such as human capital development, income distribution and poverty, industrial development . (see e.g. Gezici et al. (2017); Karahasan and Bilgel (2020); Duman and Duman (2020) among many others.). However, the impact of climate change on rural development has not been central yet. Therefore, we argue that examining the effects of climate change in Turkey which has sizable spatial differences, acts as an essential benchmark for the construction of local and smart policies to mitigate the adverse effects of climate change on the disadvantageous rural areas that rely on agriculture .

The remainder of the paper is organized as follows. Section 2 provides a literature review about climate change and the agricultural sector in Turkey. Section 3 gives the details of the dataset and the methodology, section 4 provides the empirical results for baseline models and the robustness analyses and finally, section 5 concludes and provides policy recommendations.

2 Literature

Climate change led to an increase in global temperatures and occurrence of extreme events across the world (see e.g., IPCC (2013); Coumou and Robinson (2013); Cid et al. (2016); O'Neill et al. (2017) among many others). This led to increased adaptation practices worldwide concernign climate change (Conway and Mustelin, 2014; Turhan, 2016; Turhan et al., 2016). As a results, climate change adaptations are receiving significant attention on the policy front and impose major implications for food security and agricultural production (see e.g., Haile (2005); Easterling et al. (2007); Liverman and Kapadia (2010); Vermeulen et al. (2012); Ray et al. (2019) among many others). For instance, Ray et al. (2019) show varying effects of climate change on different crop yields across the world due to changes in temperature and precipitation during the growing seasons of these crops. Similarly, Ray et al. (2015) show that variations in temperature, precipitation, or their interaction explain 32-39 percent of the variation in crop yields globally. Among many others, Lobell et al. (2011) for a set of countries, Brisson et al. (2010) for France, Collier et al. (2008) and Roudier et al. (2011) for Africa, Tack et al. (2015) for the United States, Hochman et al. (2017) for Australia, Chandio et al. (2020) for Turkey also highlight the importance of climatic conditions for agricultural output.

Global climate change trends have also been detected in Turkey. Toros (2012) show that there has been a significant increase in both annual maximum and minimum temperature records between 1961 and 2008. In the same lines, Abbasnia and Toros (2018) find an increasing trend in warm-spell duration and the numbers of summer days, tropical nights, warm nights and increasing trends in annual precipitation in the Marmara region of Turkey between 1961 and 2008. Tayanç et al. (2009) show varying spatial effects of climate change across Turkish provinces where they found significant warming in southern and southeastern parts of the country and an increase or decrease in precipitation levels in different parts of Turkey.

The changes in precipitation and temperature levels due to climate change led to changes in crop yields and agriculture growth seasons in Turkey. For instance, Ozkan and Akcaoz (2002) demonstrate that wheat, maize and cotton production in southern Turkey between 1975 and 1999 was affected by the temperature in the harvesting period. On the other hand, Toros et al. (2019) construct four temperature indices for 15 coastal weather stations during 1961 and 2016 in Turkey and show that there has been a change in minimum and maximum temperature in coastal areas over the last decade, leading to agricultural growth season length in the southern coastal region to be relatively higher than that of the northern coastal region. In a recent paper, Chandio et al. (2020) demonstrate that the average increase in temperature levels in Turkey led to decreased cereal yields where the effect of precipitation was not significant (see also Sen et al. (2012), Dumrul and Kilicaslan (2017)). Some other studies in this area use global Computable General Equilibrium (CGE) models to estimate the climate change impacts on crop production and estimate that the negative consequences of climate change would be observed in the long-term (see e.g., Özdoğan (2011), Dudu and Çakmak (2018), Ouraich et al. (2019)).

The negative consequences of climate change on agriculture production not only led to increased food prices across the globe (e.g., Arndt et al. (2012), Bradbear and Friel (2013), Bandara and Cai (2014)) but also led to vulnerable employment in the agriculture sector (see e.g., Mueller et al. (2020)). In a related paper, Turhan et al. (2015) examine the effects of climate change on the seasonal workers' vulnerability in Turkey and find that political discourse is related to the commodities and workers but not the core vulnerabilities due to climate change.

Even though there are studies that examined the implications of climate change on the agricultural sector in Turkey, most of these studies were at a country level (e.g., Dumrul and Kilicaslan (2017), Chandio et al. (2020)) or consists of smaller geographical scales (e.g., Toros et al. (2019) for southern and northern parts of Turkey; Ozkan and Akcaoz (2002) for southern Turkey), or based on descriptive statistics (see e.g., Ozcan and Strauss (2016)). Given that climate change effects in Turkey vary spatially (see e.g., Selek et al. (2018); Tayanç et al. (2009), Toros et al. (2019)), this study aims to fill the research gap by examining the spatial effects of climate change on agricultural production, food prices and agricultural employment with the use of spatial methods taking into account the spatial dependence and heterogeneity.

Based on the above literature, we provide three hypotheses to be tested in this paper. To understand the extent of climate change, we will use the annual trends and deviations in temperature and precipitation at the regional level. We define three channels, which we believe are instrumental in understanding the adverse effects of climate change. The first channel is the agricultural output, which is expected to be negatively influenced by climate change (Collier et al., 2008; Roudier et al., 2011).

Hypothesis 1 (H1): Climate change will harm agricultural value added at the local level as rising temperatures and volatile precipitation will worsen crop yields.

The second channel is over the regional labor markets. We expect to observe falling employment in agriculture due to falling output of the sector and possible migration resulting from worsening climatic conditions (Mueller et al., 2020).

Hypothesis 2 (H2): For regions that that heavily rely on agriculture, the slow-down of agricultural production due to the adverse effects of climate change will decrease agricultural employment.

The third channel is related to prices, as falling agricultural output is expected to increase the food and overall prices. The overall rising prices would then hamper the standard of living of the citizens across all regions, yet the effect would be realized more in regions that are affected by climate change.

Hypothesis 3 (H3): Worsening climate conditions will decrease agricultural output and will negatively influence agricultural supply and lead to increased food and overall prices (Arndt et al., 2012; Bradbear and Friel, 2013; Bandara and Cai, 2014).

To test the above-stated hypotheses, we will first offer the data set employed in this study and then provide the spatial methodologies for the empirical analysis in the following sections.

3 Research Methodology

3.1 Data and Exploratory Analyses

Four main indicators are used to measure the impact of climate change : (i) Average annualized temperature (in Celsius degree), (ii) Average annualized precipitation (in millimeters), (iii) Standardized index for temperature, (iv) Standardized index for precipitation. Monthly data for temperature and precipitation is collected from the Meteorological Directorate of the Ministry of Forestry and Agriculture (MD, 2020) and covers the 1980-2020 period for the NUTS III regions (81 provinces). Due to data availability on agricultural production our empirical analyses covers only the post-2000 period. However, to give a better insight into the evolution of climatic conditions, we provide some descriptive figures for a longer time dimension.

To control for annual temperature and precipitation trends, we annualize the variables by taking their averages. Additionally, following (McKee et al., 1993; Sen et al., 2012), we define the Standardized Index (SI) for both average temperature and precipitation. This index is commonly used as a measure of drought, which can also be a crucial dimension to measure climate change in Turkey.[1] Equation 1 is the SI where X_i is the temperature and precipitation respectively at the regional level, $\bar{X}$ is the historical mean of the related variable (temperature and precipitation), and finally σ is the standard deviation.[2] Note that a negative (positive) value for SI refers to the start of drought based on precipitation (temperature) at the local level.

$$SI = \frac{(X_i - \bar{X})}{\sigma} \tag{1}$$

Figure 1 shows the increase in the average temperature during the 1980-2020 period. This trend can also be observed from the evolution of SI for temperature. Meanwhile, the average precipitation is relatively more volatile compared to the average temperature pattern. Once again, the SI for precipitation mimics the volatile path of the average precipitation. On the other hand, cross-sectional variation of average temperature shows declining patterns suggesting decreasing climatic differences between Turkish provinces. Combined results (i.e. mean and coefficient of variation, CoV) signal the severity of the climate change at a broader regional aggregation. The SI for temperature, shows a smooth and stable trend throughout the sample period. Meanwhile, variations in both precipitation and the SI for precipitation during the sample period exhibit a volatile pattern.

Next, we give a snapshot picture of the change in temperature and precipitation for the beginning and ending years of the sample period. Figure 2 shows the differences in average temperature between the 1980-2020 period. Almost 44 percent of the provinces (36 out of 81) realize an absolute increase in average temperature by more than 2^oC throughout the sample period. This pattern can also be seen from Figure 4 which suggests the rising drought risk (measured by temperature) for the same set of regions. On the other hand, Figures 3 and 5 indicate that around 70 percent (57 out of 81) provinces realize a decrease in the average precipitation during the sample period. Thus, these regions are faced with a higher risk in terms of drought and climate change.

We consider four indicators to examine the regional evolution of the agriculture sector: (i) Agricultural value-added, for which the data is available at NUTS III level for the 2004-2019 period (Turkstat, 2019), (ii) Employment in the agriculture sector (% of regional employment), for which the data is available

[1] For other alternative measures of drought-based indicators see Keyantash and Dracup (2002).

[2] While constructing the SI we prefer to use the 1980-2020 averages. We also replicate our analyses by using historical means at a longer time dimension. The long-term historical data on climatic conditions is simply a historical average for individual provinces. However, the time dimension of the historical series depends on the number and availability of meteorological stations in the regions. This results in an inconsistency for the time interval of the historical series at the province level. Therefore, results for the historical analyses are not provided, however available from the authors upon request.

for the 2004-2019 period at NUTS II level (Turkstat, 2020a), (iii) Regional price levels for the overall consumer price index (CPI) and its sub-components (including food prices), for which the data is also available at NUTS II level for the 2004-2019 period for the whole index and 2005-2019 for the sub-components (Turkstat, 2020b). We also use population density to control the impact of urbanization at the NUTS III level (Turkstat, 2020c). We expect that controlling for urbanization levels is essential to control for the transition from traditional to modern industrial production and will be inversely related to local agricultural development.[3] Based on the data availability, we merge the climatic variables with the available regional agriculture sector indicators and form a panel for the 2004-2019 period at the NUTS III level. In addition, we match the NUTS II variables with related NUTS III regions where necessary. It should be kept in mind that there will be less cross-sectional variability for the variables at the NUTS II level. On the other hand, recent evidence also validates that regional disparities among the NUTS II regions act as one of the most important source of regional disparities in Turkey (Karahasan, 2020). Therefore, we expect that matching the NUTS II level variables with their NUTS III level counterparts will have a negligible effect on the empirical approach of the paper. Descriptive statistics of the variables for the initial and last years of the sample are given in Table 1.

A vital dimension of regional studies is the spatiality of the variables. As we argued before, our empirical setup will also consider the spatial dimension. Therefore, we first examine the spatial auto-correlation and discuss the extent of spatial spillovers. Moran's I (Equation 2) is the spatial auto-correlation indicator, where n is the number of cross-sections, s is the summation of all the elements w_{ij} of the weight matrix W of provinces i and j (Anselin, 1996). Our results show that all variables under concern are spatially auto-correlated (Table 1), which confirms the existence of spatial externalities and the need for considering the spatial dimension in econometric analyses (Anselin, 2010).[4]

$$I = \frac{n}{s} \frac{\sum_i w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum (x_i - \bar{x})^2} \tag{2}$$

Another central element of spatial analyses is spatial heterogeneity, which creates different spatial regimes for the regional climate conditions. Local Indicator of Spatial Association ($LISA$) given in Equation 3 decomposes the global measure into four spatial regimes; High-High (H-H), Low-Low (L-L), High-

[3]Note that, we do not use share and/or value-added of industrial and or service-based production as control variables as we believe this will provoke specification problems such as multi-collinearity and endogeneity. For instance a correlation coefficient between industrial value-added and urbanization varies around 0.7 during the sample period. Similarly, a correlation coefficient between services and urbanization is around 0.6. Finally, correlation between industrial and service based production varies around 0.97. Therefore, we prefer to use urbanization as the main control to understand structural change.

[4]Our global and local spatial analyses are from a contiguity weight matrix. We also replicate the same set of analyses by an inverse distance weight matrix. Results are unchanged and available upon request.

Low (H-L), Low-High (L-H) (Anselin, 1995). H-H and L-L refer to a grouping of regions with similar climatic conditions. In terms of temperature (precipitation) H-H refers to worsening (improving) climatic conditions. In the meantime, H-L and L-H are outlier regions. H-L refers to spatially dissimilar areas with worsening (improving) local climatic conditions for temperature (precipitation). L-H outlier represents spatially nonidentical behavior of regions with improving (worsening) local climatic conditions for temperature (precipitation). This second spatial analysis will form the background of the need for considering spatial heterogeneity in spatial models (Fotheringham et al., 2002).

$$I_i = (x_i - \bar{x}) \sum_j w_{ij}(x_j - \bar{x}) \tag{3}$$

We plot the $LISA$ maps in Figure 6 for the sample averages only for the climatic indicators. These spatially descriptive findings show that southern and western regions realize a higher average temperature compared to inner and northern regions. That said, results with the SI for temperature indicates that the number of regions realizing temperature rise compared to their historical means is relatively higher. Meanwhile, inner regions realize lower precipitation compared to coastal regions. However, findings with the SI for precipitation variable shows that the southern regions suffer more from the low precipitation levels.

3.2 Non-Spatial and Spatial Panel Data Analyses

Our benchmark panel models follow a fixed effect specification without controlling for spatial auto-correlation. However, estimating non-spatial models by using spatially dependent variables can give biased estimates and provide inaccurate information on the actual mechanisms (Anselin, 1996, 2010). While fixed effect panel data models control time-invariant heterogeneities, they disregard the spatial dependencies containing information about the regional borders of causal links. However, a handful of papers that controlled for the spatial auto-correlation indicate that spatial spillovers can be central in examining the regional dimension of climate change (e.g., Chen et al. (2016); Nicita et al. (2020); Zouabi (2021)). Therefore, we augment our benchmark models by incorporating spatial dependence via a generalized panel spatial fixed-effects model.

$$y_t = \mu_i + \beta k_t + \rho W y_t + \gamma X_t + W X_t \theta + u_t \tag{4}$$

y_t is a $n \times 1$ column vector of agricultural development variable for each year t, $t = 1, \dots, T$; k is the related climate change indicator; X_t is a matrix consists of the regional control variables, μ_i is the regional fixed-effect, $u_t = \lambda W u_t + \epsilon_t$ is the error term, W is a contiguity weight matrix, and ρ, θ and λ define the spatial effects.[5] When $\rho = \theta = 0$, a spatial error model (SEM) is applicable, that considers common spillover of shocks and omitted variables. When $\theta = \lambda = 0$, we obtain the spatial lag model (SAR) that considers externalities of the outcome variable. Finally, if $\lambda = 0$, the spatial Durbin model (SDM) works, which allows for global spillovers in observables (Anselin, 2010; Elhorst, 2010; Kelejian and Prucha, 2010). In case $\rho = \theta = \lambda = 0$, our specification can be simplified to a non-spatial panel fixed-effect model.

3.3 Identification Strategy

The impact of climate change on regional agricultural development is at the center of this research. However, our empirical benchmark specifications disregard the possibility that climate change can be endogenous. The structural change arguments in developing countries posits the transition from agricultural towards industrial and service-based production. Naturally, falling agricultural activities that trigger non-agricultural industrial economic activities can generate indirect mechanisms that put pressure on the environmental developments. This will be more central for less developed and developing countries, which neglect environmental issues for rapid and aggressive economic growth. This reverse causality and the omitted variables bias can create an endogeneity problem.

To cope with this endogeneity problem, we apply an instrumental variable approach following Bartik (1991). Equation 5 is the shift-share instrument, which is linked with the fact that national climate change is exogenous to the climate change in provinces. To construct the instrumental variable ($k_{iv,i}$), we use the climatic indicators (k_b) for our base year and focus on the deviation from the year of interest (t) in our sample (2004-2019). $k_{i,b}$ is the climatic indicator within region i in the base year. K_b and K_t are the national climate change variables in the base year (b) and year of interest (t) respectively. Determination of the base year requires the identification of exogenous climatic conditions. Therefore, we use the climatic variables starting from the year 1980 as base the year in constructing shift-share instruments.

$$k_{iv,i,t} = k_{i,b}(1 + \frac{K_t - K_b}{K_b}) \tag{5}$$

[5] Similar to our strategy for the spatial auto-correlation analyses, we replicate all spatial econometric analyses by using an inverse distance weight matrix. These results are virtually unchanged, are available upon request.

3.4 Multi-scale Geographically Weighted Regression Analyses

An important dimension of regional analyses is spatial heterogeneity, which stems from the existence of different spatial regimes (Anselin, 1995). These spatial regimes are the core reason for observing spatial differences in the proposed causal mechanisms. Traditional spatial models fail to consider this spatial variability of the causal links. Fotheringham et al. (2002); Bivand (2017) propose to use local models to cope with this spatial heterogeneity problem. For m number regions this concern translates into the spatial heterogeneity of the coefficient parameters: $\hat{\beta}_i = (\hat{\beta}_{i0}, \hat{\beta}_{i1}......\hat{\beta}_{im})$. A possible solution to this spatial variability problem is the Geographically Weighted Regression (GWR) approach as given in Equation 6. x_{ij} is the j^{th} variable, $\beta_j(u_i v_i)$ is the j^{th} coefficient, k_i is the variable controlling for climate change. $(u_i v_i)$ represents the coordinates (location) of the region i. Calibration is central to the GWR estimation. The idea is to weight each observation based on the proximity to a given region i. Various discrete distance weight matrices can be preferred in spatial models; however, as argued in Fotheringham et al. (2002), GWR models construct the weighting scheme by a Gaussian or bi-square decay function based on fixed and adaptive kernels. Optimal bandwidth is selected based on Cross-Validation Score and Akaike Information Criterion (AIC).

$$y_i = \phi(u_i v_i) k_j + \sum_{j=0}^{m} \beta_j(u_i, v_i) x_{ij} + \epsilon_i \tag{6}$$

GWR model relies on a fixed (common) bandwidth and restricts the spatial variability among the variables at the same spatial scale. In contrast, recent developments in spatial heterogeneity analyses relax this restriction. Multi-scale GWR (MGWR) extends the bandwidth construction by enabling individual bandwidth selection for each variable and spatially varying relations (Fotheringham et al., 2017). MGWR model captures the spatial heterogeneity for spatial processes more accurately, by minimizing over-fitting, mitigating concurvity and reducing parameter estimates biases (Wolf et al., 2018; Yu et al., 2019; Wu et al., 2019). MWGR can be defined as in Equation 7.

$$y_i = \phi(u_i v_i) k_j + \sum_{j=0}^{m} \beta_{bwj}(u_i, v_i) x_{ij} + \epsilon_i \tag{7}$$

The crucial difference is the inclusion of bwj that depicts the bandwidth used during the calibration of the j^{th} relationship. The calibration of MGWR is different compared to the GWR model. As each pair of relations rely on varying different bandwidth, the GWR estimator is no longer applicable. Instead, a back-fitting algorithm is offered to obtain the MWGR estimator (Fotheringham et al., 2017; Wolf et al., 2018). In our final augmented setup, we will estimate MGWR models and examine the spatial variability of coefficient estimates.

4 Empirical Analyses

4.1 Benchmark Analyses

Our results from the benchmark panel fixed effect models are provided in Tables 2 and 3. These preliminary findings indicate that rising average temperature and SI for temperature negatively influence local agricultural development. Those regions with rising average temperature and rising variation from the historical averages have lower agricultural value-added and employment. Additionally, our preliminary findings show that regions with rising average temperatures and deviation from historical averages suffer from increasing price levels. We expect that the agricultural component of the consumer price index has a sizable influence at the country level. However, our results confirm that in regions where climatic conditions negatively influence agricultural production, price levels accelerate more than the others. This result is consistent both for the changes in the overall consumer and food prices. Interestingly precipitation and SI for precipitation variables are mostly insignificant in these baseline models. The only exception is the models for the food prices, where decreasing precipitation levels seem to have adverse effects on the food prices.

It is noteworthy to underline that our benchmark results are robust to the inclusion of the regional differences in population density. Moreover, note that population density controls for the extent of urbanization and the rising transformation from traditional agricultural to modern industry and service-based production. Therefore, it is fair to argue that our preliminary results do not depart from the structural transformation in Turkey. Instead, our initial findings confirm the validity of the three main hypotheses of the paper once the climate conditions of regions are measured over the spatio-temporal pattern of the temperature.

A related dimension of the baseline analyses is the spatial dependence, which could arise from agriculture and climate conditions. To incorporate a spatial battery, we estimate three different variants of a spatial fixed effect panel model (SAR, SEM and SDM). These results are provided when the agricultural value-added, employment, inflation and food inflation variables are used as dependent variables in Tables 4, 5, 6 and 7 respectively. Our results from the spatial panel models are mostly in line with the baseline results. Average temperature and the SI for temperature are significant in most cases. The climate change's influence over average temperature and SI for temperature is significant for the SAR and SEM specifications in most cases. The only exceptions are the models estimated for the overall and food inflation, where only the SAR model points out the significant influence of average temperature and SI for temperature. Overall, the LR test for spatial and non-spatial model comparison indicates that spatial models can not be simplified into non-spatial models. Moreover, based on Wald Test results SAR and SEM models are superior compared to SDM. Additionally, for all SAR and SEM specifications, spatial spillovers over the dependent and omitted variables are significant.

Overall evaluation of the benchmark models indicates interesting findings. First of all, the impact of climate on local agricultural development is visible primarily through rising average temperature. The long-run variation of the temperature from a historical mean and the average rise in the annual temperature points out worsening regional conditions for agricultural development. These results are robust to controlling the structural change (via population density) and the local spatial networks (via spatial dependence).

4.2 Robustness Analyses

This sub-section provides three set of analyses to test the robustness of the benchmark specifications. First, we focus on the identification issue and control for the possible endogeneity of climate change. Next, we offer a set of alternative specifications by using a different dependent variable and controlling for the possible interaction between climatic variables. Finally, we examine the spatial heterogeneity issue for a set of selected climatic variables.

4.2.1 Identification

An important threat to the identification is the possibility that climate change is endogenous. We perform a set of instrumental variables (IV) analyses by constructing a shift-share instrument to deal with the endogeneity problem. We also use the quadratic forms of the instruments in our analyses. Our combined findings are summarized in Table 8. Results from 2SLS models validate the initial set of findings. Rising temperature negatively influences agricultural value-added, employment, and price levels (overall and food). Meanwhile, falling precipitation's influence is visible on agricultural value-added and food prices. As the SI index is constructed via historical data (deviation from the long-run averages) and our shift-share setup calls for historical data, we do not replicate the IV analyses using the SI variables.

Next, we focus on the diagnostic of the IV estimations. First-stage F Statistics confirms that the preferred instrument is valid. This has been supported mainly by the Anderson-Rubin Wald Test, which confirms that excluded instruments are highly correlated with climatic indicators (except for Model 4). The endogeneity test has the null hypothesis that climate change is exogenous. Except for Models 2, 5 and 7, the related climate change variable is endogenous. Note that we implement the IV strategy for all models as it is still a safeguard to control for the endogeneity when the variable of interest can be exogenous. Under-identification test reports the Kleibergen-Paap rk Lagrange multiplier (LM) statistic with the null hypothesis of under-identification. Our results validate that none of the models suffer from under-identification. In the meantime, weak identification test critical values for 10% and 15% maximal instrumental variables (IV) size are 19.93 and 11.59, respectively (Stock and Yogo, 2005), suggesting the absence of a weak identification problem as well. Finally, The Hansen J-statistic has a null hypothesis that the instruments are uncorrelated with the error term and correctly excluded from the equation. Our results validate that none of the models suffer from such a problem.

4.2.2 Alternative Specifications

In our benchmark analyses, we consider four specific indicators to assess the impact of climate change on agricultural development. An additional dimension could be agricultural productivity. To consider this additional dimension, we compute the per hectare agricultural output at the provincial level. We estimate the benchmark models for three different spatial specifications (SAR, SEM and SDM fixed effects models).[6]

Results are provided in Table 9. Temperature and SI for temperature are positively associated with agricultural productivity. These results are robust to the spatial specifications. Similar to the first set of spatial analyses, we end up with no significant impact on the spatial dependency of the climate change variable (in the SDM). Overall, our findings for agricultural productivity contradicts our prior expectations. However, it should be noted that our results are global in the sense that it shows the average impact of the rising temperature on agricultural productivity. It could be possible that rising average temperature might create an ecosystem for certain agriculturally poor localities to benefit from hybrid forms of agricultural development. However, our global models do not enable us to assess the possible local instabilities. We

[6]Note that, we also estimate the non-spatial variants of the benchmark models and end up with similar results. These results are available upon request.

will introduce the spatial instability and heterogeneity issue in the following sub-section as an additional robustness check. Furthermore, Ergüner et al. (2019) also found that the rising temperature levels led to a lengthening of the growing season across the country. Therefore, an overall increase in the growing season may also lead to increased agricultural productivity.

Another important dimension which we have not covered so far is the possible interaction between temperature and precipitation. We estimate a set of new models using interaction terms of the climatic variables. We offer a comparison of non-spatial, SAR and SEM panel fixed-effect models for the five main dependent variables in Tables 10, 11, 12, 13 and 14.[7] There are two main findings. First, the interaction of the climate change variables does not influence the pervasive impact of rising temperature on agricultural development. Additionally the interaction term is mostly insignificant once the main climatic variable is the temperature. Second, the significance of the precipitation (both level and index) increases with the use of interaction variables. However, the impact of the interaction term and the precipitation depends on the model specification. Overall, we conclude that considering the interaction between temperature and precipitation does not change our prior discussion on the negative influence of climate change on agricultural development across Turkish regions.

4.2.3 Spatial Heterogeneity

Our analyses confirm that those Turkish regions realizing worsening climatic conditions experience a harmful environment for agricultural development. These results are robust to the inclusion of different spatial batteries and the possible endogeneity of climate change. While spatial auto-correlation is embedded within spatial econometric models, the impact of spatial heterogeneity is neglected. In the case of spatial heterogeneity, parameter estimate of global models can be misleading at the local level. In other words, the observed overall relationship between climate change and agricultural development can be spatially variable across the territory of Turkey. Given the implications of climatic factors vary across Turkish regions (see e.g., Tayanç et al. (2009), Ergüner et al. (2019)), examining local models would provide more in-depth implications of climate change. To examine the spatial variability, we estimate a set of local spatial models.

An essential dimension of local spatial models is the bandwidth selection, which determines the extent of the local neighborhood effects. Our main analyses are from MGWR type local models that allow

[7] As the SDMs can be simplified to SAR and SEM in the benchmark models we skip their estimation. These results are available upon request.

for differet bandwidths at the variable level. A second important dimension of the bandwidth is the applied Kernel function. An adaptive approach allows for differing bandwidths at the local level and therefore guarantees that each regression unit will have the same number of the nearest neighbor. On the contrary, a fixed approach restricts the use of only several data points. In our preliminary analyses, we use both types of Kernel functions. Tables 15 and 16 provide the results for local coefficients' selected thresholds for adaptive bi-square and fixed Gaussian Kernel functions, respectively. Results are reported for four different sets of models where agricultural development is controlled via agricultural value-added, agricultural employment, inflation and food inflation, respectively. In the majority of the benchmark models, the average temperature has the highest significant impact. Hence, we use average temperature as the core climate change variable in the spatial heterogeneity analyses. Results for individual years provide evidence that there is a sizable variation for the parameter estimates. Moreover, there are non-monotonic relations which imply that at some certain locations relationship between climate change and agriculture development is unlike the prior expectations. This finding is consistent both for adaptive and fixed Kernel functions. However, a careful inspection reveals that MGWR results are sensitive to bandwidth formation (adaptive vs. fixed) in some instances.

To examine the possible sensitivity to the preferred Kernel, we examine the historical evolution of the related parameters estimates' range in Figures 7. In general, the spatial variability of the parameter estimates is more stable and visible for agricultural value-added and employment. However, the parameter estimates are more volatile for models with overall and food inflation during the sample period. It is also worth highlighting that spatial variability is higher for the models that adopt the fixed Kernel. Overall, our combined results (Tables 15 and 16; Figure 7) do not show significant volatility based on the Kernel choices.

A central value-added aspect of local models is the possibility to visualize the spatial distribution of parameter estimates. This could provide additional insight into the geographical variation of the proposed relationships. In this part of our analysis, we estimate GWR and MWGR models for two selected dependent variables: (i) agricultural value-added, (ii) agricultural productivity. Note that, for each local model specification we adopt the fixed Kernel for bandwidths.[8] Moreover, we also implement the IV estimation strategy for both GWR and MWGR models.

Our first set of results for the spatial distribution of the parameter estimates for average temperature on agricultural value-added are provided in Figure 8. In general, the most decisive negative impact of

[8]Note that, we also estimate GWR and MWGR models with an adaptive Kernel. While results are comparable, MGWR models with adaptive Kernel suffer from residual spatial auto-correlation. These results are available upon request.

the rising average temperature on agricultural value-added is observed among the far eastern territory of Turkey. While there are some differences in GWR and MWGR models, results from GWR-IV and MGWR-IV are comparable. The magnitude of the negative effect of temperature on agriculture value-added is the largest for provinces (specifically south eastern) geography. In a recent study examining the ecoregions under climate change, the results of Ergüner et al. (2019) demonstrate that the ecoregion in southeastern Turkey will shrink significantly, and the Euphrates-Tigris river basin is at moderate climate risk, which is an essential site for agricultural production. With the IV estimation results, the non-monotonic relations are quite visible as some central and western regions realize a surprising positive link between rising temperature and agricultural value-added. This pattern might be partially related to the shifting nature of production in some certain agricultural products. White et al. (2006); Bindi and Olesen (2011); Ovalle-Rivera et al. (2015) highlight that increasing temperature in specific regions might shift some certain agricultural products (wine and coffee) and have a positive influence on local agricultural production. Furthermore, in a recent study, Arslantaş and Yeşilırmak (2020) found that there has been an apparent increase in the length of the growing season in western Anatolia, which may have improved the overall agricultural value-added. Note that the local impact of climate change on agricultural development is non-significant in most non-eastern regions. Finally, the overall goodness of fit (measured by the R-squared) is spatially variable as well. Once again, models' explanatory power is higher among the eastern regions of Turkey (Figure 9). We also provide the spatial distribution of the residuals from the related models in Figure 10. Results suggest a lack of clustering, thus spatial auto-correlation of the models' residuals.[9]

Second, we implement the same set of analyses for the impact of the average temperature on agricultural productivity. The spatially varying impact of climate change on agricultural productivity is provided in Figure 11. Our results show that, even though we detect a positive significant coefficient for climate change in the global models, our local estimates indicate sizable spatial insignificance for most Turkish provinces. Besides, MGWR and MGWR IV models point out the possibility of spatial instability. For a set of eastern regions, we detect a negative relationship between climate change and agricultural productivity. This finding is in line with the findings when we use agriculture value-added as a dependent variable. On the contrary, the positive impact originates among the far western regions. These results are important from a number of different pillars. First, our local estimates show that the impact of climate change on agricultural productivity is harmful for the rural and agriculturally developed south eastern provinces.

[9] Moran's I for the GWR and MGWR models' residuals are statistically insignificant. These results can be provided upon request.

Second, the positive impact of climate change which we detect in the global models, originates mostly from the agriculturally less-developed western regions. Therefore, even though we find a positive link between rising temperature and agricultural productivity in the global models, our local estimates are consistent with our main arguments. The agriculture dominant and rural regions are going to be hit adversely from the side effects of the climate change in Turkey. Note that the explanatory power of the models exhibits local instability as well. The local R-squared is highest among the western regions (Figure 12). Finally, residuals of the local models show almost no sign of spatial clustering (Figure 13).

5 Conclusion

According to the United Nations' (UN) Intergovernmental Panel on Climate Change (IPCC), limiting global warming to 1.5^{o}C is a central target for meeting the sustainable development goals of the UN. Even though there are tremendous attempts to implement global and country-specific policies against climate change's adverse effects, developing countries still realize a policy bias considering the trade-off between economic growth and environmental well-being. However, as the adverse effects of climate change are more visible, countries are now on the edge of a new policy framework that will enable cohesion for environmental and economic priorities.

This paper scrutinizes the impact of climate change on the agricultural and less developed regions of a developing country, Turkey. Our preliminary results show a sizable variation in the temporal and spatial evolution of climate change in Turkey, which largely explains the variation in agricultural development. Our results point out that the continuous rise in the average temperature and the deviation from the historical temperature trends (SI) explain the agricultural outcomes at the province level. In general, those regions realizing an increase in temperature generate lower value-added and employment in the agriculture sector. Moreover, the same set of regions are more influenced by the local trends in the overall price levels and the prices of foods (agricultural products). These first sets of results are also valid when spatial externalities are also considered. It is worth highlighting that the existence of spatial mechanisms is vital from a policy perspective. Implementing policies to mitigate the adverse effects of climate change is expected to have spatial spillovers across regions. In other words, any positive influence of policy on agricultural development in a location will have a positive influence on the nearby surrounding. This positive externality argument will be a key element for countries like Turkey, where policy is centralized and inflexible.

Additionally, we consider a set of robustness analyses. First, our results are robust to the control of endogeneity via shift-share instruments for average temperature and precipitation trends in Turkey. Second, we include an interaction term for climate change. Our results for the pervasive impact of the rising temperature are virtually unchanged. In the meantime impact of decreasing precipitation becomes visible once interaction between temperature and precipitation is included. In our view, these results support our central arguments that various forms of climate change influence agricultural development. Additionally, we also checked for the impact of climate change on agricultural productivity and found that rising temperature seems to match with better agricultural productivity among the Turkish regions. This could be because climate change has increased the length of the growing season in most parts of Turkey. Finally, we estimate a set of local models to control for spatial heterogeneity. Our results reveal that climate change has a spatially varying impact on agricultural development at the province level. Our analyses show that this spatial variability is robust to different (M)GWR setups. We focus on two agriculture indicators, namely agricultural value-added and productivity. We find out that the negative impact of the average temperature on agricultural value-added is strongest among Turkey's underdeveloped rural eastern regions. These results confirm the global regression results (negative impact of climate change) but also underlines the exact locality of the pervasive impact (south eastern regions). Additionally, our results for agricultural productivity are striking. Once again, we detect a negative relationship between rising temperature and some of the rural and underdeveloped south eastern regions, and the coefficient of the positive effect is highest for the western areas. These results are vital as they contradict with the global regression results which suggest a positive link between climate change and agricultural productivity. Therefore, we highlight the importance of evaluating regional variants of the global regressions to better understand the true impact of climate change at the very local level.

Overall, our results show that the impact of climate change will not be equally distributed across the Turkish regions. The local estimation results demonstrate that climate change's impact on the agriculture value-added and agricultural productivity would amplify the development gap between the eastern-western divide in Turkey. From the policy perspective, these results validate that the social and economic isolation of the eastern geography is also reflected in the region's vulnerability to climate change. Considering agricultural production as the primary form of economic activity in eastern Turkey, our results point out the rising economic risk of climate change for this under-developed, isolated, and forgotten territory of the country. Therefore, geographically tailored climate change adaptation policies should prioritize eastern regions to mitigate the negative consequences of climate change, contributing to reducing spatial economic inequality.

An important dimension for investigating agricultural production is its peculiar production structure. For instance, the regional differences in agricultural value-added can be linked with regional differences in product patterns. Additionally, producers may switch from vegetables and wheat to fruit and cotton from year to year. This might be rooted in product choices, seasonality and price variations of different agricultural products. While climate change is a potential candidate to understand the transition among different agricultural choices, additional explanations are worth discussing. For instance, the cost of agricultural production, local and national policies that affect the choices of the agriculture sector is important. Input cost increase and attitude of the government towards subsidization of the sector will inevitably impact the agricultural production patterns change. These are also valuable lines of discussion for further research. We believe our findings on the effects of climate change on agriculture sector will open up new debates to apprehend the different dimensions of agricultural development.

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Tables

Table 1: Descriptive Statistics

	Mean	**Std.**	**Min**	**Max**	**Moran's I**
Average Temperature (2004)	13.150	3.377	3.600	19.908	0.539*** (0.071)
Average Precipitation (2004)	56.205	31.025	17.960	214.133	0.144*** (0.068)
SI (Average Temperature, 2004)	-0.187	0.239	-0.853	0.423	0.209*** (0.072)
SI (Average Precipitation, 2004)	-0.076	0.871	-2.093	1.610	0.371*** (0.072)
Population Density (ln, 2004)	4.160	0.796	2.385	7.715	0.379*** (0.07)
Agriculture (%GDP, 2004)	0.405	0.166	0.005	0.705	0.643*** (0.072)
Agriculture (%Employment, 2004)	0.168	0.075	0.003	0.363	0.203*** (0.072)
Inflation (2004)	0.082	0.012	0.054	0.104	0.668*** (0.072)
Food Inflation (2005)	5.114	1.216	2.700	7.740	0.361*** (0.072)
Average Temperature (2019)	14.423	3.236	5.242	20.967	0.501*** (0.072)
Average Precipitation (2019)	55.371	27.657	13.533	170.275	0.181*** (0.07)
SI (Average Temperature, 2019)	1.168	0.470	-0.458	2.518	0.159*** (0.07)
SI (Average Precipitation, 2019)	-0.124	1.055	-2.189	2.722	0.366*** (0.072)
Population Density (ln, 2019)	4.297	0.865	2.399	7.979	0.42*** (0.07)
Agriculture (%GDP, 2019)	0.277	0.124	0.012	0.547	0.591*** (0.072)
Agriculture (%Employment, 2019)	0.142	0.073	0.001	0.341	0.335*** (0.071)
Inflation (2019)	0.160	0.008	0.124	0.177	0.476*** (0.07)
Food Inflation (2019)	20.036	0.957	17.750	22.270	0.344*** (0.072)

Notes: *** represents significant spatial auto-correlation at 1% significance level

Table 2: Panel Fixed Effect Models (I)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: y= Agricultural VA (%)								
Average Temperature	-2.238***				-1.598***			
	(0.188)				(0.223)			
Average Precipitation		0.002				0.017		
		(0.012)				(0.011)		
SI (Average Temperature)			-2.077***				-1.436***	
			(0.185)				(0.222)	
SI (Average Precipitation)				0.011				0.235
				(0.158)				(0.145)
Observations	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296
R-squared	0.093	0.000	0.090	0.000	0.152	0.111	0.147	0.112
Number of id	81	81	81	81	81	81	81	81
Controls	No	No	No	No	Yes	Yes	Yes	Yes
Spatial Dimension	No	No	No	No	No	No	No	No
Panel B: y= Agricultural Employment (%)								
Average Temperature	-2.238***				-1.598***			
	(0.188)				(0.223)			
Average Precipitation		0.002				0.017		
		(0.012)				(0.011)		
SI (Average Temperature)			-2.077***				-1.436***	
			(0.185)				(0.222)	
SI (Average Precipitation)				0.011				0.235
				(0.158)				(0.145)
Observations	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296
R-squared	0.093	0.000	0.090	0.000	0.152	0.111	0.147	0.112
Number of id	81	81	81	81	81	81	81	81
Controls	No	No	No	No	Yes	Yes	Yes	Yes
Spatial Dimension	No	No	No	No	No	No	No	No

Notes: Standard errors are clustered at NUTS 3 level and given in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3: Panel Fixed Effect Models (II)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel C: y= Inflation (%)								
Average Temperature	0.017***				0.013***			
	(0.001)				(0.001)			
Average Precipitation		-0.000				-0.000		
		(0.000)				(0.000)		
SI (Average Temperature)			0.017***				0.013***	
			(0.001)				(0.001)	
SI (Average Precipitation)				-0.001				-0.002**
				(0.001)				(0.001)
Observations	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296
R-squared	0.188	0.000	0.192	0.000	0.266	0.170	0.265	0.173
Number of id	81	81	81	81	81	81	81	81
Controls	No	No	No	No	Yes	Yes	Yes	Yes
Spatial Dimension	No	No	No	No	No	No	No	No
Panel D: y= Food Inflation (%)								
Average Temperature	2.476***				1.969***			
	(0.138)				(0.135)			
Average Precipitation		-0.012				-0.028***		
		(0.012)				(0.010)		
SI (Average Temperature)			2.399***				1.907***	
			(0.101)				(0.117)	
SI (Average Precipitation)				-0.204				-0.426***
				(0.144)				(0.119)
Observations	1,215	1,215	1,215	1,215	1,215	1,215	1,215	1,215
R-squared	0.193	0.001	0.204	0.002	0.266	0.164	0.271	0.167
Number of id	81	81	81	81	81	81	81	81
Controls	No	No	No	No	Yes	Yes	Yes	Yes
Spatial Dimension	No	No	No	No	No	No	No	No

Notes: Standard errors are clustered at NUTS 3 level and given in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Spatial Fixed Effect Panel Models (A)

y: Agricultural VA (%)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Average Temperature	-0.002*	-0.003**	-0.001									
	(0.001)	(0.001)	(0.002)									
Average Precipitation				0.000	-0.000	-0.000						
				(0.000)	(0.000)	(0.000)						
SI (Average Temperature)							-0.002**	-0.003***	-0.001			
							(0.001)	(0.001)	(0.002)			
SI (Average Precipitation)										0.000	-0.000	-0.000
										(0.001)	(0.001)	(0.001)
ρ	0.419***		0.419***	0.425***		0.421***	0.417***		0.417***	0.426***		0.421***
	(0.046)		(0.046)	(0.048)		(0.048)	(0.046)		(0.046)	(0.047)		(0.044)
λ		0.409***			0.420***			0.406***			0.422***	
		(0.055)			(0.062)			(0.055)			(0.061)	
LR Test (Spatiality)	141.14 [0.00]	112.06 [0.00]	141.20 [0.00]	145.70 [0.00]	111.38 [0.00]	148.09 [0.00]	139.61 [0.00]	110.84 [0.00]	139.95 [0.00]	145.57 [0.00]	111.56 [0.00]	148.69 [0.00]
Wald Test (ρ=0)	82.09 [0.00]		83.61 [0.00]	80.11 [0.00]		76.91 [0.00]	81.75 [0.00]		83.04 [0.00]	82.50 [0.00]		78.28 [0.00]
Wald Test (λ=0)		55.67 [0.00]			46.17 [0.00]			54.58 [0.00]			48.50 [0.00]	
Wald Test (WxClimate=0)			0.03 [0.87]			3.26 [0.07]			0.18 [0.67]			2.87 [0.09]
Observations	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296
R-squared	0.346	0.372	0.345	0.346	0.371	0.346	0.347	0.371	0.347	0.346	0.370	0.346
Number of id	81	81	81	81	81	81	81	81	81	81	81	81
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial Dimension	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial Durbin Term	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes

Notes: Standard errors are clustered at NUTS 3 level and given in parentheses. P-values are in brackets. LR Test has the null hypotheses of validity of the non-spatial model. Wald test for spatial mechanisms has the null hypothese for the insignificance of spatial mechanisms. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Spatial Fixed Effect Panel Models (B)

y: Agricultural employment (%)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Average Temperature	-0.445***	-0.741**	-0.322									
	(0.123)	(0.311)	(0.347)									
Average Precipitation				0.001	-0.004	-0.004						
				(0.008)	(0.012)	(0.011)						
SI (Average Temperature)							-0.393***	-0.588*	-0.185			
							(0.121)	(0.304)	(0.338)			
SI (Average Precipitation)										0.011	-0.035	-0.032
										(0.102)	(0.151)	(0.145)
ρ	0.756***		0.756***	0.768***		0.767***	0.758***		0.757***	0.768***		0.767***
	(0.025)		(0.025)	(0.024)		(0.024)	(0.025)		(0.025)	(0.024)		(0.024)
λ		0.777***			0.787***			0.778***			0.787***	
		(0.027)			(0.025)			(0.027)			(0.025)	
LR Test (Spatiality)	784.87 [0.00]	766.58 [0.00]	785.05 [0.00]	834.99 [0.00]	832.96 [0.00]	835.54 [0.00]	790.51 [0.00]	777.94 [0.00]	791.12 [0.00]	834.57 [0.00]	826.61 [0.00]	834.77 [0.00]
Wald Test (ρ=0)	941.84 [0.00]		940.68 [0.00]	1048.97 [0.00]		1054.77 [0.00]	955.43 [0.00]		944.35 [0.00]	1058.17 [0.00]		1065.68 [0.00]
Wald Test (λ=0)		842.69 [0.00]			988.85 [0.00]			858.29 [0.00]			987.63 [0.00]	
Wald Test (WxClimate=0)			0.17 [0.68]			0.61 [0.43]			0.52 [0.47]			0.24 [0.62]
Observations	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296
R-squared	0.496	0.103	0.5	0.466	0.307	0.468	0.469	0.195	0.467	0.465	0.291	0.466
Number of id	81	81	81	81	81	81	81	81	81	81	81	81
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial Dimension	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial Durbin Term	No	No	No	No	No	No	No	No	No	No	No	No

Notes: Standard errors are clustered at NUTS 3 level and given in parentheses. P-values are in brackets. LR Test has the null hypotheses of validity of the non-spatial model. Wald test for spatial mechanisms has the null hypothese for the insignificance of spatial mechanisms. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Spatial Fixed Effect Panel Models (C)

y: Inflation (%)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Average Temperature	0.000**	-0.000	-0.000									
	(0.000)	(0.001)	(0.001)									
Average Precipitation				0.000	0.000*	0.000*						
				(0.000)	(0.000)	(0.000)						
SI (Average Temperature)							0.000**	-0.000	-0.000			
							(0.000)	(0.001)	(0.001)			
SI (Average Precipitation)										0.000	0.000	0.000
										(0.000)	(0.000)	(0.000)
ρ	0.968***		0.967***	1.029***		0.971***	0.968***		0.967***	0.971***		0.971***
	(0.005)		(0.005)	(0.001)		(0.005)	(0.005)		(0.005)	(0.004)		(0.005)
λ		0.973***			0.973***			0.973***			0.973***	
		(0.005)			(0.005)			(0.005)			(0.005)	
LR Test (Spatiality)	3962.74 [0.00]	3955.36 [0.00]	3967.71 [0.00]	3996.40 [0.00]	4115.75 [0.00]	4119.61 [0.00]	3960.61 [0.00]	3956.18 [0.00]	3967.99 [0.00]	4113.13 [0.00]	4110.85 [0.00]	4114.69 [0.00]
Wald Test (ρ=0)	39367.69 [0.00]		33825.86 [0.00]	1.8e+06 [0.00]		45650.08 [0.00]	38472.39 [0.00]		33285.74 [0.00]	47528.90 [0.00]		45889.60 [0.00]
Wald Test (λ=0)		46556.86 [0.00]			43170.24 [0.00]			45715.70 [0.00]			43366.49 [0.00]	
Wald Test (WxClimate=0)			2.37 [0.14]			1.20 [0.27]			1.17 [0.28]			1.54 [0.22]
Observations	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296
R-squared	0.048	0.004	0.067	0.001	0.001	0.014	0.098	0.002	0.133	0.013	0.001	0.015
Number of id	81	81	81	81	81	81	81	81	81	81	81	81
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial Dimension	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial Durbin Term	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes

Notes: Standard errors are clustered at NUTS 3 level and given in parentheses. P-values are in brackets. LR Test has the null hypotheses of validity of the non-spatial model. Wald test for spatial mechanisms has the null hypothese for the insignificance of spatial mechanisms. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Spatial Fixed Effect Panel Models (D)

y: Food Inflation	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Average Temperature	0.101***	0.125	0.117									
	(0.035)	(0.099)	(0.101)									
Average Precipitation				0.001	0.004	0.004						
				(0.002)	(0.003)	(0.003)						
SI (Average Temperature)							0.105***	0.159**	0.150*			
							(0.031)	(0.078)	(0.080)			
SI (Average Precipitation)										0.009	0.077**	0.072*
										(0.030)	(0.037)	(0.037)
ρ	0.952***		0.952***	0.957***		0.956***	0.951***		0.952***	0.957***		0.956***
	(0.005)		(0.005)	(0.004)		(0.004)	(0.005)		(0.005)	(0.004)		(0.004)
λ		0.961***			0.961***			0.961***			0.962***	
		(0.004)			(0.004)			(0.004)			(0.004)	
LR Test (Spatiality)	3173.79 [0.00]	3158.52 [0.00]	3173.84 [0.00]	3324.40 [0.00]	3318.11 [0.00]	3328.23 [0.00]	3168.38 [0.00]	3153.77 [0.00]	3168.85 [0.00]	3319.65 [0.00]	3315.86 [0.00]	3326.83 [0.00]
Wald Test (ρ=0)	37485.95 [0.00]		35169.06 [0.00]	50773.97 [0.00]		49123.54 [0.00]	37886.14 [0.00]		35285.56 [0.00]	51518.91 [0.00]		48712.28 [0.00]
Wald Test (λ=0)		58490.96 [0.00]			59378.62 [0.00]			58015.55 [0.00]			59511.88 [0.00]	
Wald Test (WxClimate=0)			0.03 [0.86]			3.67 [0.06]			0.41 [0.52]			6.91 [0.01]
Observations	1,215	1,215	1,215	1,215	1,215	1,215	1,215	1,215	1,215	1,215	1,215	1,215
R-squared	0.019	0.004	0.018	0.004	0.000	0.005	0.038	0.015	0.033	0.004	0.000	0.005
Number of id	81	81	81	81	81	81	81	81	81	81	81	81
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial Dimension	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial Durbin Term	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes

Notes: Standard errors are clustered at NUTS 3 level and given in parentheses. P-values are in brackets. LR Test has the null hypotheses of validity of the non-spatial model.
Wald test for spatial mechanisms has the null hypothese for the insignificance of spatial mechanisms. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 8: Panel Fixed Effect 2SLS Models (IV Setup with shift-share variables as instruments)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	y: Agricultural VA (%)		y: Agricultural Employment (%)		y: Inflation (%)		y: Food Inflation (%)	
Average Temperature	-0.003*		-1.338**		0.021***		3.382***	
	(0.001)		(0.568)		(0.002)		(0.254)	
Average Precipitation		0.001***		-0.072		0.000		-0.062**
		(0.000)		(0.050)		(0.000)		(0.025)
First Stage F Statistic	38.28 [0.00]	43.55 [0.00]	38.28[0.00]	43.55 [0.00]	38.28 [0.00]	43.55 [0.00]	40.60 [0.00]	54.51 [0.00]
Anderson-Rubin Wald Test	1.84 [0.16]	8.37 [0.00]	3.9 [0.02]	1.61 [0.20]	22.72 [0.00]	0.01 [0.99]	29.92 [0.00]	3.45 [0.04]
Underidentification Test	71.849 [0.00]	32.702 [0.00]	71.849 [0.00]	32.702 [0.00]	71.849 [0.00]	32.702 [0.00]	72.933 [0.00]	35.418 [0.00]
Hansen J Statistics	0.027 [0.87]	2.492 [0.11]	0.869 [0.35]	1.076 [0.30]	3.765 [0.05]	0.025 [0.88]	3.983 [0.05]	0.061 [0.80]
Endogeneity Test	0.007 [0.93]	9.641 [0.00]	0.054 [0.82]	2.702 [0.10]	16.967 [0.00]	0.270 [0.60]	22.114 [0.00]	1.900 [0.17]
Weak Indetification Test	245.893	42.166	245.893	42.166	245.893	42.166	234.257	48.635
Observations	1,296	1,291	1,296	1,291	1,296	1,291	1,215	1,210
R-squared	0.118	-0.020	0.151	0.069	0.229	0.165	0.210	0.151
Number of id	81	81	81	81	81	81	81	81
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial Dimension	No	No	No	No	No	No	No	No

Notes: Standard errors are clustered at NUTS 3 level and given in parentheses. P-values are given in brackets.
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Spatial Fixed Effect Panel Models with alternative dependent variable

y: Output per hectar	(1) SAR	(2) SEM	(3) SDM	(4) SAR	(5) SEM	(6) SDM	(7) SAR	(8) SEM	(9) SDM	(10) SAR	(11) SEM	(12) SDM
Average Temperature	0.3130**	0.6703***	0.7596**									
	(0.1231)	(0.2002)	(0.3281)									
Average Precipitation				0.0017	0.0060	0.0056						
				(0.0036)	(0.0054)	(0.0064)						
SI (Average Temperature)							0.2436**	0.5245***	0.4863*			
							(0.0999)	(0.1681)	(0.2600)			
SI (Average Precipitation)									0.4561***	-0.0073	0.0265	0.0023
									(0.0660)	(0.0593)	(0.0868)	(0.0965)
ρ	0.4434***		0.4544***	0.4718***		0.4723***	0.4498***			0.4720***		0.4722***
	(0.0663)		(0.0679)	(0.0621)		(0.0621)	(0.0652)			(0.0618)		(0.0618)
λ		0.4685***			0.4888***			0.4672***			0.4875***	
		(0.0733)			(0.0725)			(0.0713)			(0.0733)	
LR Test (Spatiality)	158.85 [0.00]	145.83 [0.00]	168.69 [0.00]	186.89 [0.00]	155.13 [0.00]	168.69 [0.00]	163.91 [0.00]	145.08 [0.00]	168.69 [0.00]	187.00 [0.00]	153.94 [0.00]	168.69 [0.00]
Wald Test (ρ=0)	44.78 [0.00]		44.82 [0.00]	57.79 [0.00]		57.88 [0.00]	47.58 [0.00]		47.69 [0.00]	58.36 [0.00]		58.41 [0.00]
Wald Test (λ=0)		40.85 [0.00]			45.47 [0.00]			42.99 [0.00]			44.23 [0.00]	
Wald Test (W*Climate=0)			2.67 [0.10]			0.93 [0.33]			1.40 [0.24]			0.03 [0.85]
Observations	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296
R-squared	0.0265	0.0245	0.0268	0.0268	0.0237	0.0263	0.0287	0.0267	0.0284	0.0268	0.0240	0.0268
Number of id	81	81	81	81	81	81	81	81	81	81	81	81
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial Dimension	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial Durbin Term	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes

Notes: Standard errors are clustered at NUTS 3 level and given in parentheses. P-values are in brackets. LR Test has the null hypotheses of validity of the non-spatial model. Wald test for spatial mechanisms has the null hypothesis for the insignificance of spatial mechanisms. *** p<0.01, ** p<0.05, * p<0.1

Table 10: Spatial Fixed Effect Panel Models with interaction variable (A)

y: Agricultural Output	(1) Non-Spat	(2) SAR	(3) SEM	(4) Non-Spat	(5) SAR	(6) SEM	(7) Non-Spat	(8) SAR	(9) SEM	(10) Non-Spat	(11) SAR	(12) SEM
Average Temperature	-0.0027**	-0.0016*	-0.0032**									
	(0.0010)	(0.0009)	(0.0014)									
Average Precipitation				0.0004***	0.0002**	0.0003**						
				(0.0001)	(0.0001)	(0.0001)						
SI (Average Temperature)							-0.0030***	-0.0020**	-0.0035***			
							(0.0009)	(0.0008)	(0.0012)			
SI (Average Precipitation)										-0.0003	-0.0008	-0.0015
										(0.0009)	(0.0008)	(0.0010)
Avrg. Temp. * Avrg. Precip.	0.0000	0.0000	-0.0000	-0.0000***	-0.0000**	-0.0000***						
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)						
SI (Avrg. Temp.) * SI (Avrg. Precip.)							0.0015***	0.0009**	0.0008	0.0013**	0.0012**	0.0015**
							-0.0005	(0.0004)	(0.0005)	(0.0006)	(0.0006)	(0.0007)
ρ		0.4184***			0.4223***			0.4113***			0.4257***	
		(0.0457)			(0.0470)			(0.0459)			(0.0470)	
λ			0.4121***			0.4151***			0.3998***			0.4231***
			(0.0539)			(0.0590)			(0.0556)			(0.0609)
LR Test (Spatiality)		139.66 [0.00]	110.93 [0.00]		143.02 [0.00]	110.61 [0.00]		128.86 [0.00]	100.13 [0.00]		144.50 [0.00]	112.10 [0.00]
Wald Test (ρ=0)		83.79 [0.00]			80.72 [0.00]			80.18 [0.00]			81.95 [0.00]	
Wald Test (λ=0)			58.41 [0.00]			49.55 [0.00]			51.61 [0.00]			48.28 [0.00]
Observations	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296
R-squared	0.1190	0.3460	0.3720	0.1149	0.3451	0.3721	0.1263	0.3478	0.3707	0.1139	0.3453	0.3691
Number of id	81	81	81	81	81	81	81	81	81	81	81	81
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial Dimension	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Spatial Durbin Term	No	No	No	No	No	No	No	No	No	No	No	No

Notes: Standard errors are clustered at NUTS 3 level and given in parentheses. P-values are in brackets. LR Test has the null hypotheses of validity of the non-spatial model. Wald test for spatial mechanisms has the null hypothesis for the insignificance of spatial mechanisms. *** p<0.01, ** p<0.05, * p<0.1

Table 11: Spatial Fixed Effect Panel Models with interaction variable (B)

y: Agricultural Employment	(1) Non-Spat	(2) SAR	(3) SEM	(4) Non-Spat	(5) SAR	(6) SEM	(7) Non-Spat	(8) SAR	(9) SEM	(10) Non-Spat	(11) SAR	(12) SEM
Average Temperature	-1.6666***	-0.4444***	-0.7178**									
	(0.2363)	(0.1412)	(0.3133)									
Average Precipitation				0.2614***	0.0834**	0.0866*						
				(0.0459)	(0.0384)	(0.0514)						
SI (Average Temperature)							-1.4888***	-0.3965***	-0.5921*			
							(0.2392)	(0.1325)	(0.3055)			
SI (Average Precipitation)										0.4484*	0.0779	0.0268
										(0.2518)	(0.1644)	(0.2077)
Avrg. Temp. * Avrg. Precip.	0.0011*	-0.0000	-0.0006	-0.0157***	-0.0053**	-0.0059*						
	(0.0006)	(0.0005)	(0.0006)	(0.0029)	(0.0022)	(0.0031)						
SI (Avrg. Temp.) * SI (Avrg. Precip.)							0.1864	0.0102	-0.0829	-0.2941	-0.0920	-0.0908
							(0.1202)	(0.0788)	(0.1051)	(0.2011)	(0.1247)	(0.1530)
ρ		0.7563***			0.7596***			0.7576***			0.7672***	
		(0.0248)			(0.0241)			(0.0246)			(0.0235)	
λ			0.7770***			0.7824***			0.7782***			0.7871***
			(0.0266)			(0.0255)			(0.0264)			(0.0250)
LR Test (Spatiality)		782.66 [0.00]	771.15 [0.00]		804.32 [0.00]	793.66 [0.00]		789.96 [0.00]	778.45 [0.00]		842.07 [0.00]	831.40 [0.00]
Wald Test (ρ=0)		927.10 [0.00]			990.50 [0.00]		944.74 [0.00]				1062.13 [0.00]	
Wald Test (λ=0)			855.30 [0.00]			943.62 [0.00]		869.96 [0.00]				993.76 [0.00]
Observations	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296
R-squared	0.1534	0.4954	0.1109	0.1389	0.4938	0.0224	0.1486	0.4694	0.1758	0.1135	0.4669	0.2811
Number of id	81	81	81	81	81	81	81	81	81	81	81	81
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial Dimension	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Spatial Durbin Term	No	No	No	No	No	No	No	No	No	No	No	No

Notes: Standard errors are clustered at NUTS 3 level and given in parentheses. P-values are in brackets. LR Test has the null hypotheses of validity of the non-spatial model. Wald test for spatial mechanisms has the null hypothesis for the insignificance of spatial mechanisms. *** p<0.01, ** p<0.05, * p<0.1

Table 12: Spatial Fixed Effect Panel Models with interaction variable (C)

y: Inflation	(1) Non-Spat	(2) SAR	(3) SEM	(4) Non-Spat	(5) SAR	(6) SEM	(7) Non-Spat	(8) SAR	(9) SEM	(10) Non-Spat	(11) SAR	(12) SEM
Average Temperature	0.0136***	0.0003*	-0.0005									
	(0.0009)	(0.0002)	(0.0006)									
Average Precipitation				-0.0026***	-0.0001***	-0.0000						
				(0.0003)	(0.0000)	(0.0000)						
SI (Average Temperature)							0.0125***	0.0004**	-0.0001			
							(0.0010)	(0.0002)	(0.0005)			
SI (Average Precipitation)										-0.0068***	0.0001	0.0005**
										(0.0009)	(0.0002)	(0.0002)
Avrg. Temp. * Avrg. Precip.	-0.0000	0.0000	0.0000*	0.0002***	0.0000***	0.0000						
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)						
SI (Avrg. Temp.) * SI (Avrg. Precip.)							0.0005	0.0001	-0.0000	0.0064***	0.0001	-0.0003
							(0.0010)	(0.0001)	(0.0002)	(0.0010)	(0.0002)	(0.0002)
ρ		0.9685***			0.9677***			0.9681***			0.9707***	
		(0.0048)			(0.0049)			(0.0050)			(0.0045)	
λ			0.9733***			0.9731***			0.9732***			0.9732***
			(0.0045)			(0.0047)			(0.0045)			(0.0047)
LR Test (Spatiality)		3963.59 [0.00]	3957.11 [0.00]		3973.52 [0.00]	3961.72 [0.00]		3966.27 [0.00]	3959.79 [0.00]		4076.65 [0.00]	4064.85 [0.00]
Wald Test (ρ=0)		39948.64 [0.00]			38279.58 [0.00]			38237.67 [0.00]			46348.64 [0.00]	
Wald Test (λ=0)			46087.33 [0.00]			43320.79 [0.00]			45772.19 [0.00]			43756.16 [0.00]
Observations	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296
R-squared	0.2668	0.0507	0.0049	0.2634	0.0598	0.0011	0.2652	0.0987	0.0028	0.2024	0.0161	0.0032
Number of id	81	81	81	81	81	81	81	81	81	81	81	81
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial Dimension	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Spatial Durbin Term	No	No	No	No	No	No	No	No	No	No	No	No

Notes: Standard errors are clustered at NUTS 3 level and given in parentheses. P-values are in brackets. LR Test has the null hypotheses of validity of the non-spatial model. Wald test for spatial mechanisms has the null hypothesis for the insignificance of spatial mechanisms. *** p<0.01, ** p<0.05, * p<0.1

Table 13: Spatial Fixed Effect Panel Models with interaction variable (D)

y: Food Inflation	(1) Non-Spat	(2) SAR	(3) SEM	(4) Non-Spat	(5) SAR	(6) SEM	(7) Non-Spat	(8) SAR	(9) SEM	(10) Non-Spat	(11) SAR	(12) SEM
Average Temperature	2.0645***	0.0976***	0.1185									
	(0.1455)	(0.0344)	(0.0966)									
Average Precipitation				-0.3843***	-0.0184***	0.0013						
				(0.0430)	(0.0062)	(0.0086)						
SI (Average Temperature)							1.9276***	0.0987***	0.1662**			
							(0.1407)	(0.0309)	(0.0790)			
SI (Average Precipitation)										-1.0914***	-0.0342	0.0592
										(0.1290)	(0.0328)	(0.0403)
Avrg. Temp. * Avrg. Precip.	-0.0015**	0.0001	0.0003	0.0228***	0.0012***	0.0002						
	(0.0006)	(0.0001)	(0.0002)	(0.0025)	(0.0004)	(0.0005)						
SI (Avrg. Temp.) * SI (Avrg. Precip.)							-0.0706	0.0221	0.0589*	0.8698***	0.0560*	0.0237
							(0.1264)	(0.0284)	(0.0331)	(0.1239)	(0.0306)	(0.0370)
ρ		0.9521***			0.9524***			0.9516***			0.9554***	
		(0.0048)			(0.0049)			(0.0048)			(0.0046)	
λ			0.9609***			1.0292***			0.9607***			0.9616***
			(0.0040)			(0.0009)			(0.0040)			(0.0039)
LR Test (Spatiality)		3166.00 [0.00]	3153.65 [0.00]		3178.09 [0.00]	3021.49 [0.00]		3166.35 [0.00]	3154.01 [0.00]		3287.38 [0.00]	3130.78 [0.00]
Wald Test (ρ=0)		39467.55 [0.00]			37428.94 [0.00]			39429.76 [0.00]			42784.55 [0.00]	
Wald Test (λ=0)			57609.99 [0.00]			1.2e+06 [0.00]			58068.36 [0.00]			59611.00 [0.00]
Observations	1,215	1,215	1,215	1,215	1,215	1,215	1,215	1,215	1,215	1,215	1,215	1,215
R-squared	0.2712	0.0190	0.0033	0.2637	0.0167	0.0006	0.2710	0.0376	0.0140	0.1944	0.0073	0.0004
Number of id	81	81	81	81	81	81	81	81	81	81	81	81
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial Dimension	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Spatial Durbin Term	No	No	No	No	No	No	No	No	No	No	No	No

Notes: Standard errors are clustered at NUTS 3 level and given in parentheses. P-values are in brackets. LR Test has the null hypotheses of validity of the non-spatial model.
Wald test for spatial mechanisms has the null hypothesis for the insignificance of spatial mechanisms. *** p<0.01, ** p<0.05, * p<0.1

Table 14: Spatial Fixed Effect Panel Models with interaction variable (E)

y: Output per hectar	(1) Non-Spat	(2) SAR	(3) SEM	(4) Non-Spat	(5) SAR	(6) SEM	(7) Non-Spat	(8) SAR	(9) SEM	(10) Non-Spat	(11) SAR	(12) SEM
Average Temperature	0.5068***	0.3120**	0.6549***									
	(0.1242)	(0.1270)	(0.1978)									
Average Precipitation				-0.0547**	-0.0268	-0.0325						
				(0.0268)	(0.0246)	(0.0298)						
SI (Average Temperature)							0.4348***	0.2534**	0.5234***			
							(0.1074)	(0.1055)	(0.1690)			
SI (Average Precipitation)										-0.0088	-0.0118	0.0063
										(0.0802)	(0.0746)	(0.0931)
Avrg. Temp. * Avrg. Precip.	0.0000	0.0000	0.0003	0.0037**	0.0018	0.0025						
	(0.0002)	(0.0002)	(0.0003)	(0.0017)	(0.0015)	(0.0019)						
SI (Avrg. Temp.) * SI (Avrg. Precip.)							-0.0444	-0.0342	0.0075	0.0190	0.0063	0.0288
							(0.0435)	(0.0414)	(0.0592)	(0.0496)	(0.0407)	(0.0460)
ρ		0.4434***			0.4615***			0.4495***			0.4720***	
		(0.0662)			(0.0629)			(0.0652)			(0.0619)	
λ			0.4699***			0.4741***			0.4675***			0.4874***
			(0.0732)			(0.0734)			(0.0722)			(0.0734)
LR Test (Spatiality)		158.84 [0.00]	146.72 [0.00]		174.74 [0.00]	144.04 [0.00]		170.23 [0.00]	158.11 [0.00]		192.26 [0.00]	161.55 [0.00]
Wald Test (ρ=0)		44.84 [0.00]			53.82 [0.00]			47.51 [0.00]			58.20 [0.00]	
Wald Test (λ=0)			41.26 [0.00]			41.67 [0.00]			41.97 [0.00]			44.11 [0.00]
Observations	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296	1,296
R-squared	0.2453	0.0265	0.0243	0.2263	0.0269	0.0240	0.2386	0.0286	0.0267	0.2157	0.0268	0.0240
Number of id	81	81	81	81	81	81	81	81	81	81	81	81
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial Dimension	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spatial Durbin Term	No	No	No	No	No	No	No	No	No	No	No	No

Notes: Standard errors are clustered at NUTS 3 level and given in parentheses. P-values are in brackets. LR Test has the null hypotheses of validity of the non-spatial model. Wald test for spatial mechanisms has the null hypothesis for the insignificance of spatial mechanisms. *** p<0.01, ** p<0.05, * p<0.1

Table 15: MGWR Results: Impact of Average temperature (Adaptive Kernel)

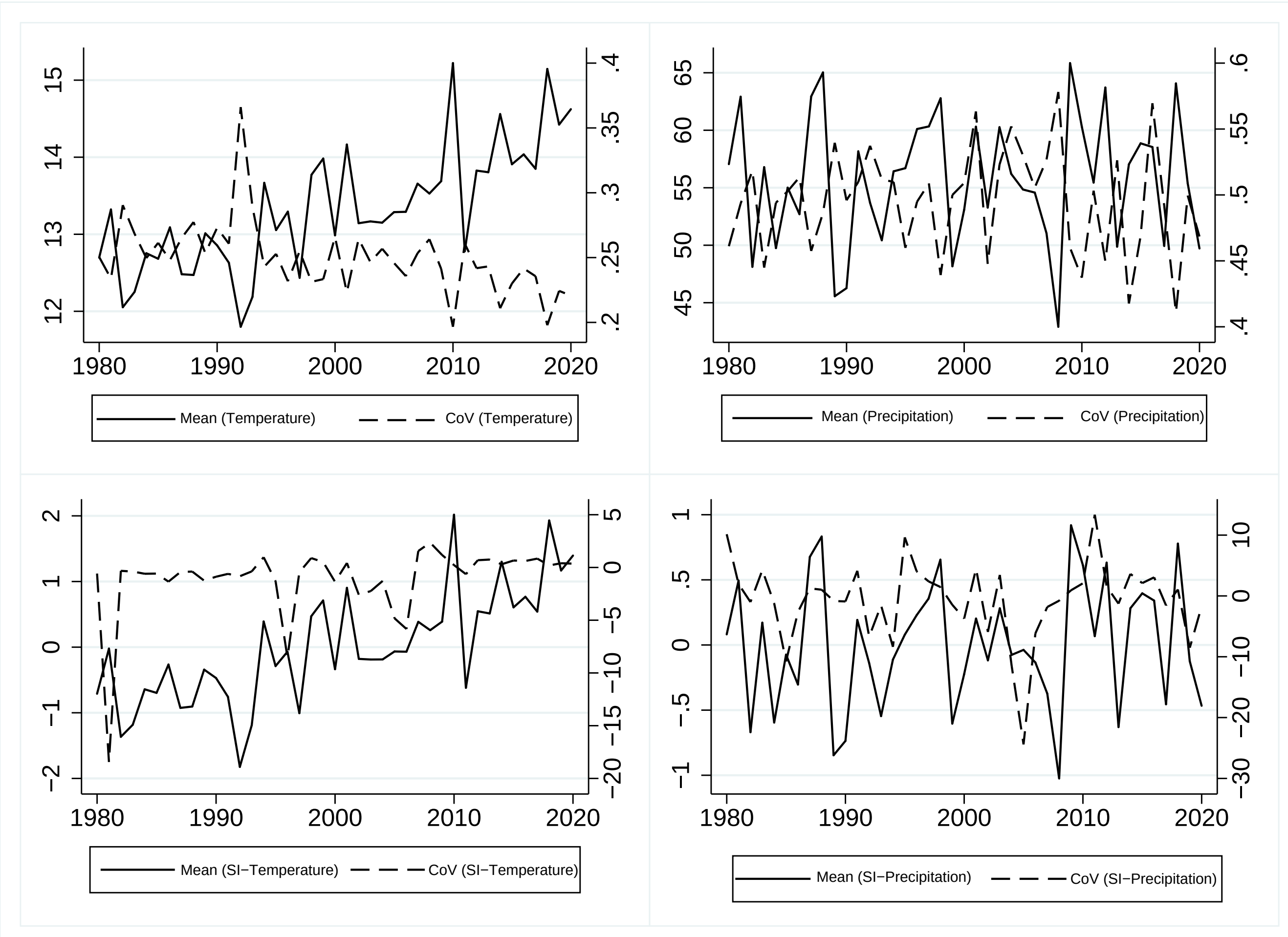
	y=Agricultural VA (%)				y= Agricultural Employment (%)			
	Mean	Min	Median	Max	Mean	Min	Median	Max
2004	-0.224	-0.394	-0.287	0.028	-0.019	-0.439	0.006	0.304
2005	-0.144	-0.448	-0.151	0.203	0.036	-0.409	0.095	0.329
2006	-0.06	-0.494	-0.009	0.282	0.076	-0.463	0.131	0.459
2007	-0.06	-0.457	0.019	0.199	0.047	-0.413	0.131	0.371
2008	-0.058	-0.408	0.057	0.151	0.067	-0.435	0.12	0.44
2009	-0.076	-0.33	0.024	0.094	0.085	-0.32	0.099	0.367
2010	-0.033	-0.247	0.017	0.144	0.105	-0.405	0.18	0.451
2011	-0.046	-0.418	-0.001	0.238	0.037	-0.452	0.057	0.416
2012	-0.114	-0.304	-0.075	0.035	0.061	-0.464	0.088	0.479
2013	-0.082	-0.397	-0.076	0.185	0.029	-0.414	0.067	0.371
2014	-0.176	-0.405	-0.115	-0.006	0.035	-0.365	0.071	0.373
2015	-0.183	-0.538	-0.13	0.067	0.006	-0.438	0.074	0.329
2016	-0.131	-0.548	-0.105	0.208	0.056	-0.46	0.109	0.421
2017	-0.066	-0.452	-0.03	0.21	0.05	-0.464	0.109	0.408
2018	0.016	-0.371	0.068	0.277	0.017	-0.356	0.061	0.342
2019	0.019	-0.401	0.088	0.272	-0.016	-0.43	-0.007	0.365
	y= Inflation (%)				y=Food Inflation (%)			
	Mean	Min	Median	Max	Mean	Min	Median	Max
2004	0.118	-0.492	0.239	0.567				
2005	-0.214	-0.546	-0.189	0.13	-0.127	-0.54	-0.079	0.161
2006	-0.462	-0.603	-0.5	-0.269	-0.362	-0.68	-0.273	-0.172
2007	-0.059	-0.156	-0.068	0.101	0.248	-0.11	0.186	0.734
2008	-0.417	-0.467	-0.425	-0.321	-0.222	-0.345	-0.183	-0.135
2009	0.161	0.029	0.08	0.33	0.21	0.184	0.213	0.25
2010	-0.094	-0.4	-0.125	0.312	-0.096	-0.128	-0.097	-0.057
2011	0.125	-0.232	0.197	0.376	0.104	-0.392	0.233	0.351
2012	-0.267	-0.298	-0.273	-0.209	-0.22	-0.246	-0.22	-0.194
2013	-0.037	-0.167	-0.05	0.095	0.246	0.17	0.252	0.307
2014	-0.294	-0.379	-0.325	-0.16	-0.341	-0.807	-0.27	-0.004
2015	0.036	-0.327	-0.005	0.391	-0.141	-0.441	-0.086	0.106
2016	0.516	0.413	0.547	0.59	0.403	0.063	0.304	0.918
2017	0.205	-0.085	0.175	0.56	0.319	0.299	0.32	0.339
2018	0.515	0.387	0.569	0.612	0.583	0.271	0.591	0.794
2019	0.231	-0.33	0.28	0.703	0.166	-0.226	0.28	0.349

Table 16: MGWR Results: Impact of Average temperature (Fixed Kernel-Gaussian)

	y=Agricultural VA (%)				y= Agricultural Employment (%)			
	Mean	Min	Median	Max	Mean	Min	Median	Max
2004	-0.183	-0.184	-0.183	-0.183	0.007	-0.666	0.076	0.492
2005	-0.181	-0.303	-0.174	-0.065	-0.001	-0.553	0.072	0.367
2006	-0.005	-0.98	-0.058	1.061	0.024	-0.567	0.093	0.427
2007	0.014	-0.472	-0.004	0.553	0.033	-0.48	0.121	0.376
2008	0.101	-0.221	-0.1	0.019	0.009	-0.47	0.1	0.343
2009	-0.049	-0.267	-0.003	0.106	0.035	-0.403	0.066	0.348
2010	0.07	-0.335	0.029	0.921	0.11	-0.595	0.187	0.539
2011	-0.031	-0.528	-0.027	0.661	-0.012	-0.648	-0.014	0.413
2012	-0.035	-0.64	-0.038	0.586	0.023	-0.576	0.047	0.502
2013	-0.165	-0.321	-0.152	-0.056	-0.016	-0.485	0.028	0.344
2014	-0.169	-0.36	-0.134	-0.044	0.042	-0.416	0.114	0.394
2015	-0.208	-0.434	-0.165	-0.076	-0.059	-0.443	-0.009	0.26
2016	-0.182	-0.452	-0.145	-0.004	-0.051	-0.43	0.008	0.244
2017	-0.021	-0.745	0.001	0.738	-0.038	-0.459	0.033	0.241
2018	0.05	-0.627	0.048	0.696	-0.069	-0.28	-0.044	0.119
2019	0.064	-0.759	0.094	0.742	-0.138	-0.139	-0.138	-0.137
	y= Inflation (%)				y=Food Inflation (%)			
	Mean	Min	Median	Max	Mean	Min	Median	Max
2004	0.136	-0.707	0.242	0.809				
2005	-0.219	-0.48	-0.214	0.124	-0.211	-1.078	-0.304	0.706
2006	-0.159	-0.762	-0.162	0.611	-0.051	-0.568	-0.017	0.52
2007	-0.168	-0.171	-0.168	-0.166	0.188	-0.412	0.204	0.718
2008	-0.156	-0.739	-0.234	0.509	-0.011	-0.411	-0.032	0.34
2009	0.16	0.023	0.141	0.32	0.156	0.156	0.156	0.156
2010	0.073	-0.688	0.129	1.215	-0.261	-0.261	-0.261	-0.26
2011	0.053	-0.545	0.115	0.551	-0.049	-0.433	0.063	0.153
2012	-0.262	-0.263	-0.262	-0.262	-0.188	-0.189	-0.188	-0.188
2013	0.033	-0.19	0.053	0.187	0.339	0.339	0.339	0.34
2014	-0.416	-0.863	-0.449	0.35	-0.286	-1.04	-0.228	0.437
2015	-0.048	-1.023	-0.025	0.861	-0.084	-0.085	-0.084	-0.083
2016	0.528	0.493	0.53	0.561	0.468	-0.859	0.377	1.473
2017	0.02	-0.02	0.018	0.074	0.201	0.201	0.201	0.201
2018	0.398	0.397	0.398	0.399	0.288	-1.044	0.311	1.15
2019	0.077	-0.144	0.089	0.263	0.064	-0.759	0.094	0.742

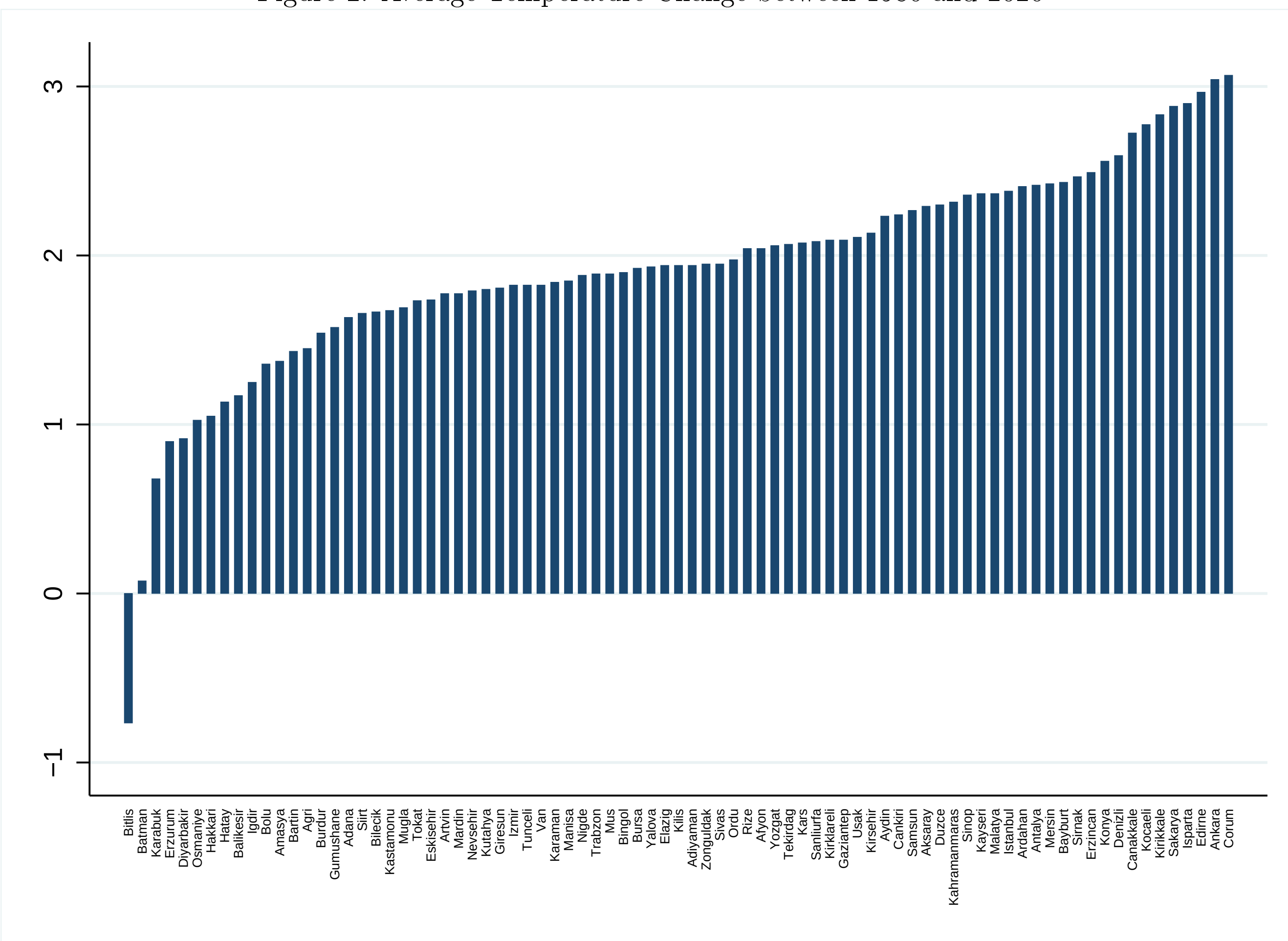
Figures

Figure 1: Historical Evolution of Climatic Conditions in Turkey



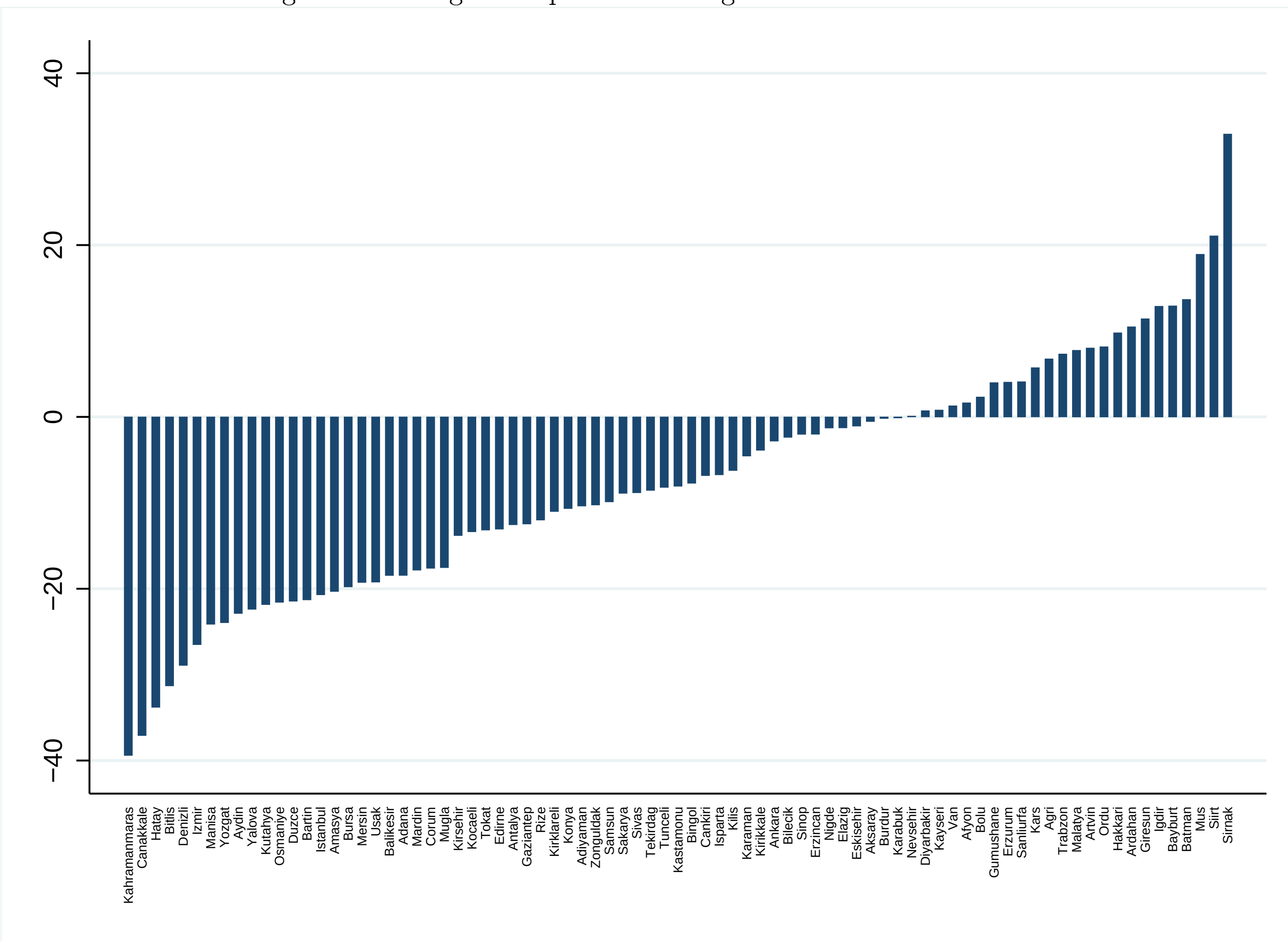
Source: MD (2020), Authors' own calculations
Notes: Right and left axis is mean and CoV respectively.

Figure 2: Average Temperature Change between 1980 and 2020



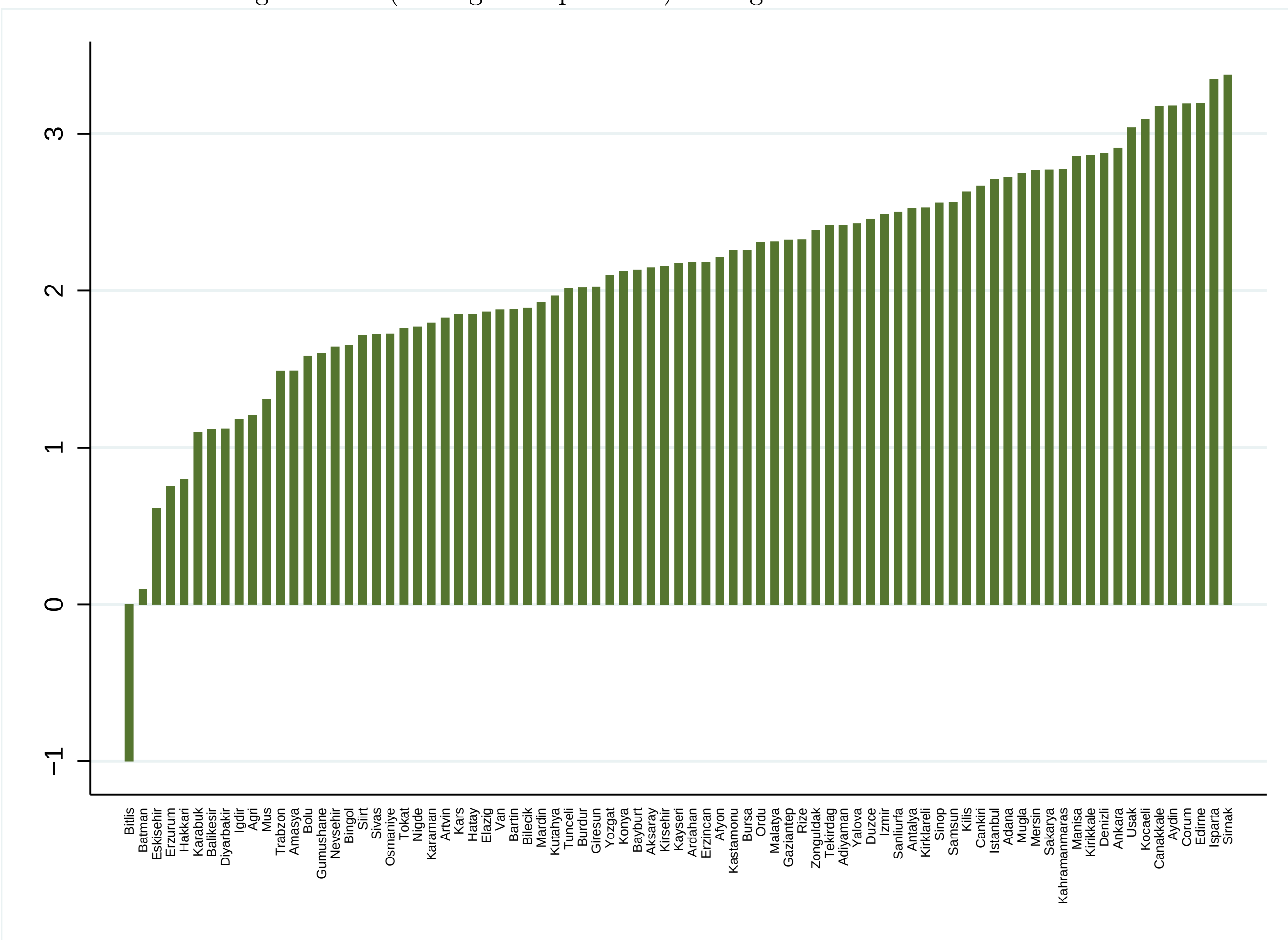
Source: MD (2020), Authors' own calculations

Figure 3: Average Precipitation Change between 1980 and 2020



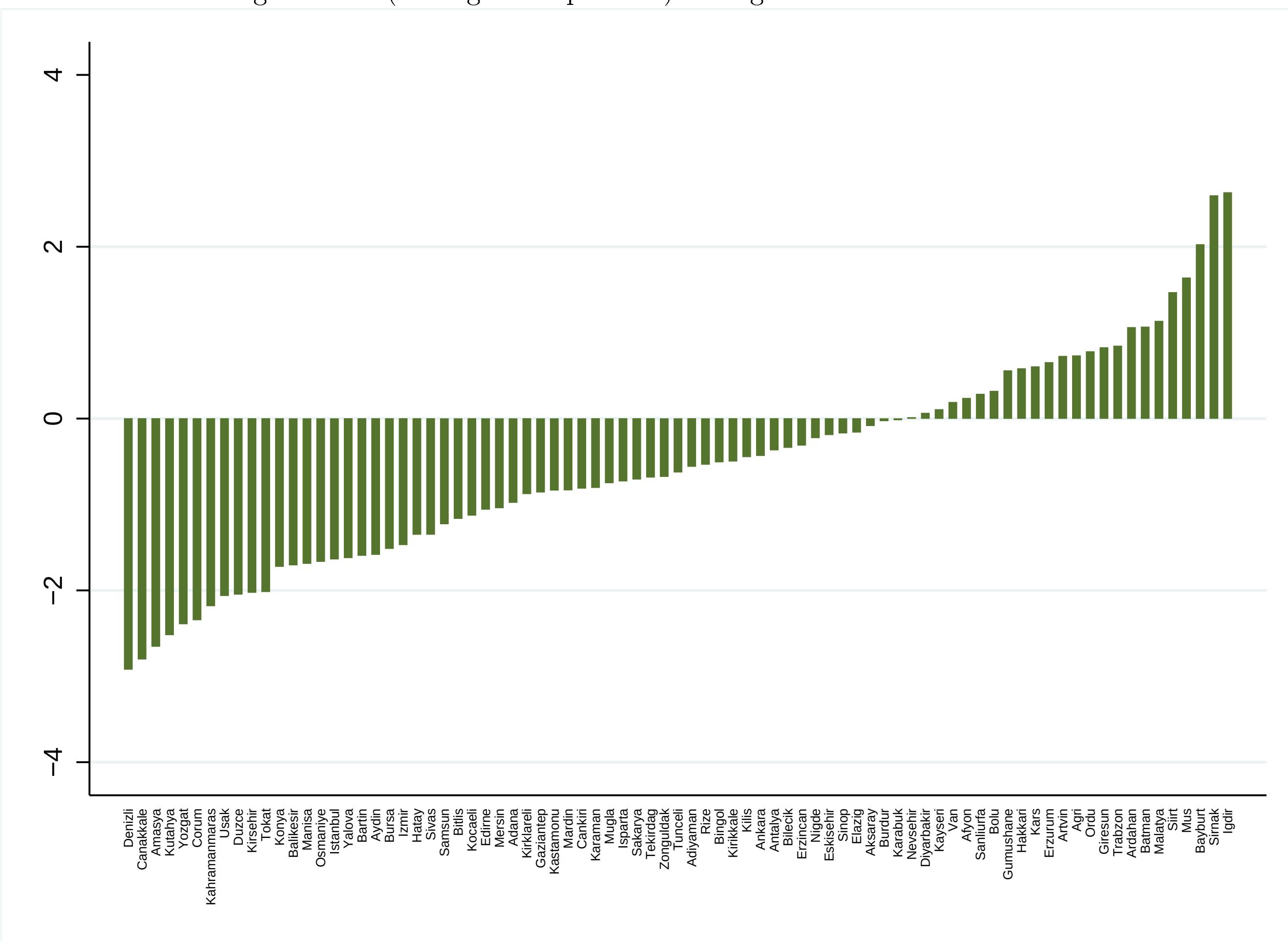
Source: MD (2020), Authors' own calculations

Figure 4: SI (Average Temperature) Change between 1980 and 2020



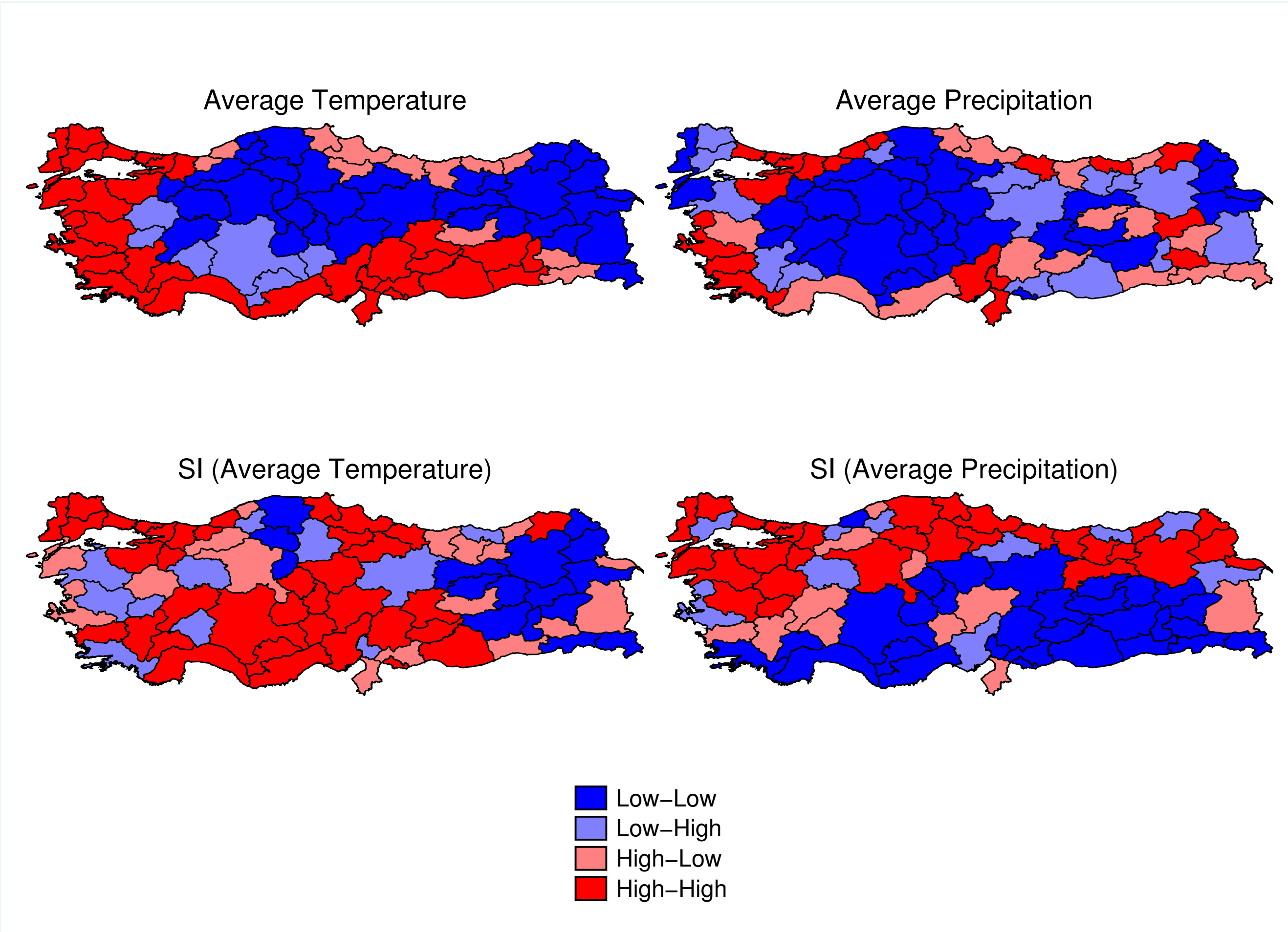
Source: MD (2020), Authors' own calculations

Figure 5: SI (Average Precipitation) Change between 1980 and 2020



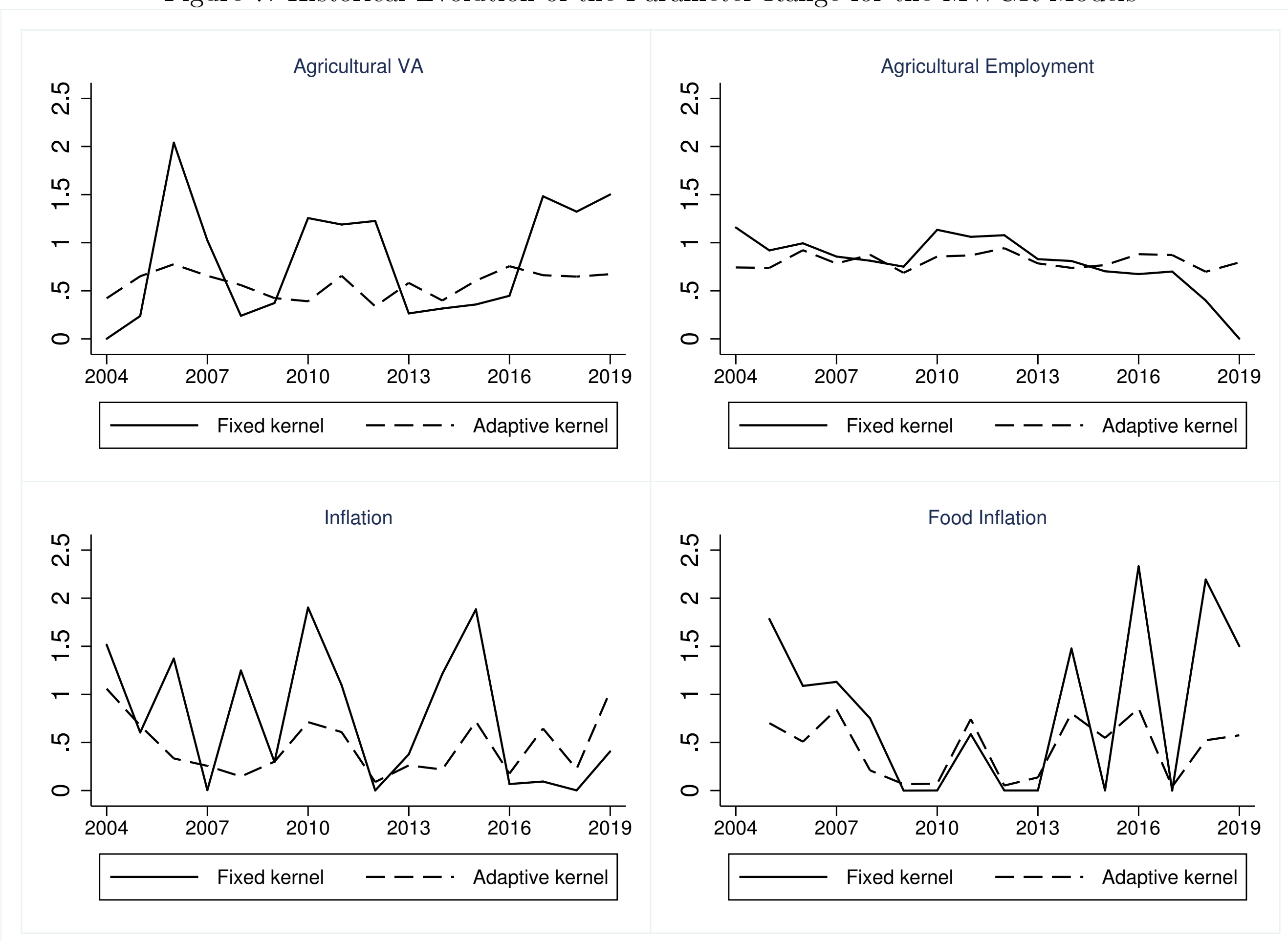
Source: MD (2020), Authors' own calculations

Figure 6: LISA Analyses for Climate Change (2004-2019 Averages)



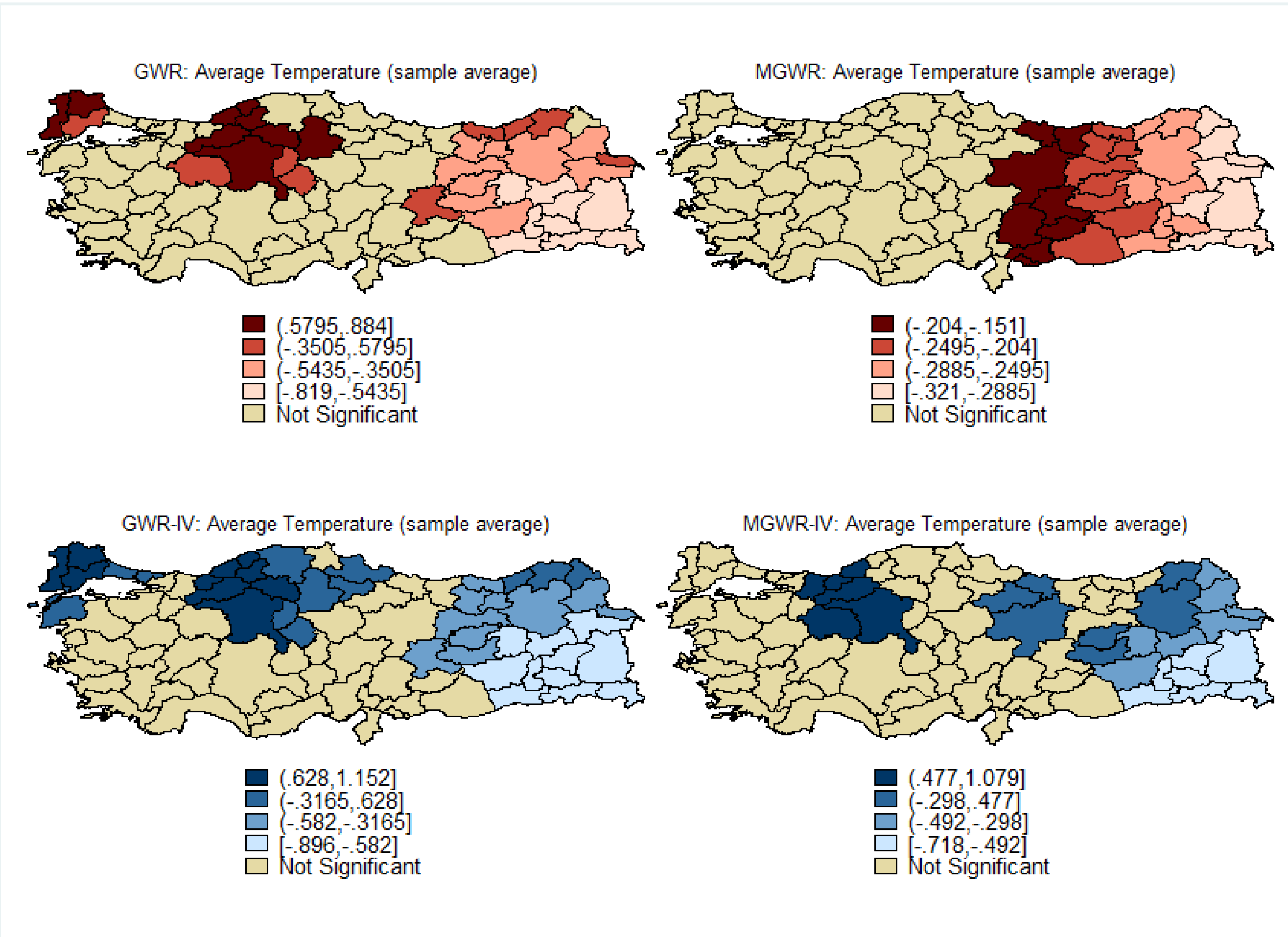
Source: MD (2020), Authors' own calculations

Figure 7: Historical Evolution of the Parameter Range for the MWGR Models



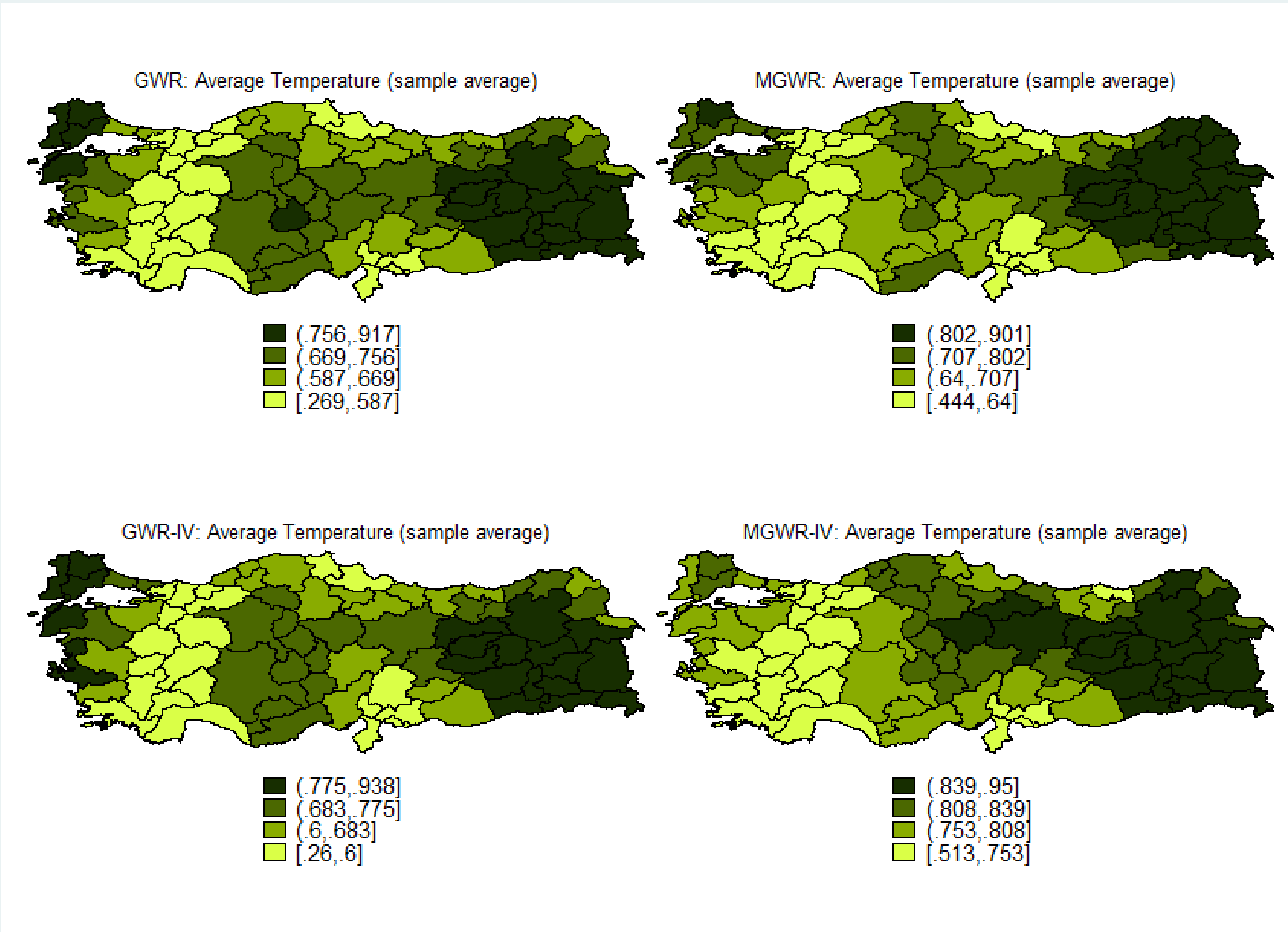
Source: MD (2020), Authors' own calculations

Figure 8: Spatial variability of parameter estimates for the impact of climate change on agricultural value added (2004-2019 Averages)



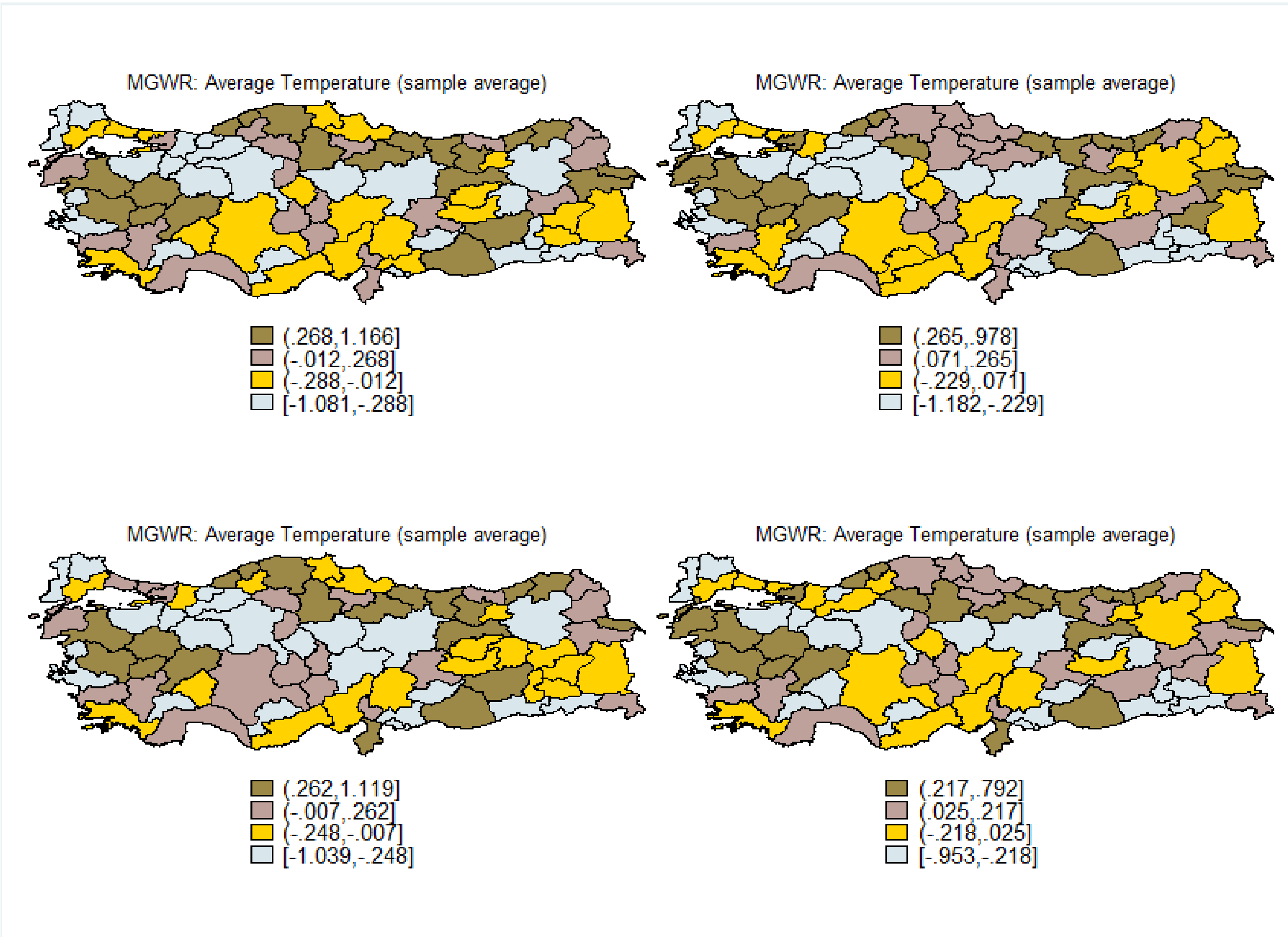
Source: MD (2020), Authors' own calculations

Figure 9: Spatial variability of R-squared for the impact of climate change on agricultural value added (2004-2019 Averages)



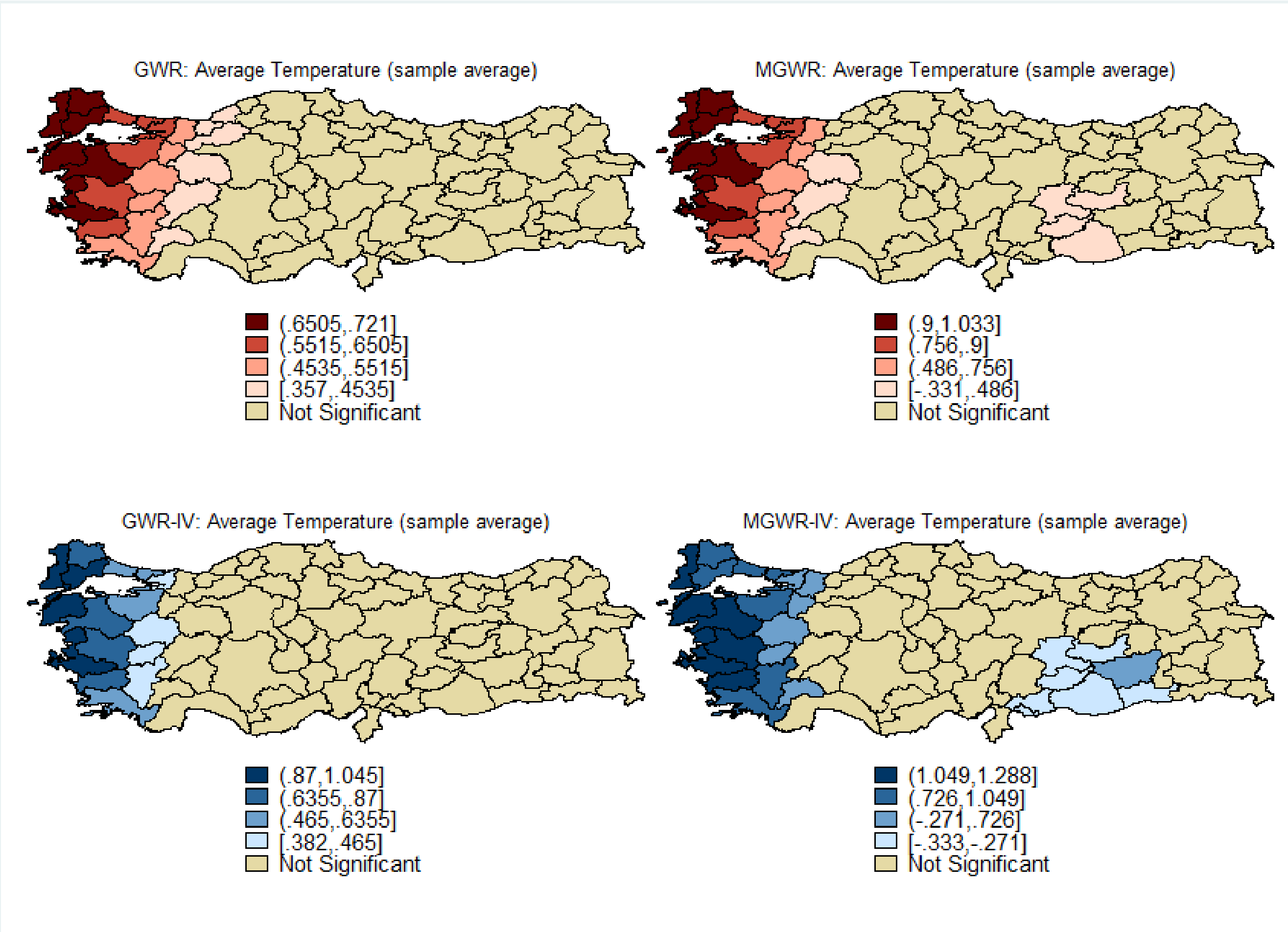
Source: MD (2020), Authors' own calculations

Figure 10: Spatial variability of Residuals for the impact of climate change on agricultural value added (2004-2019 Averages)



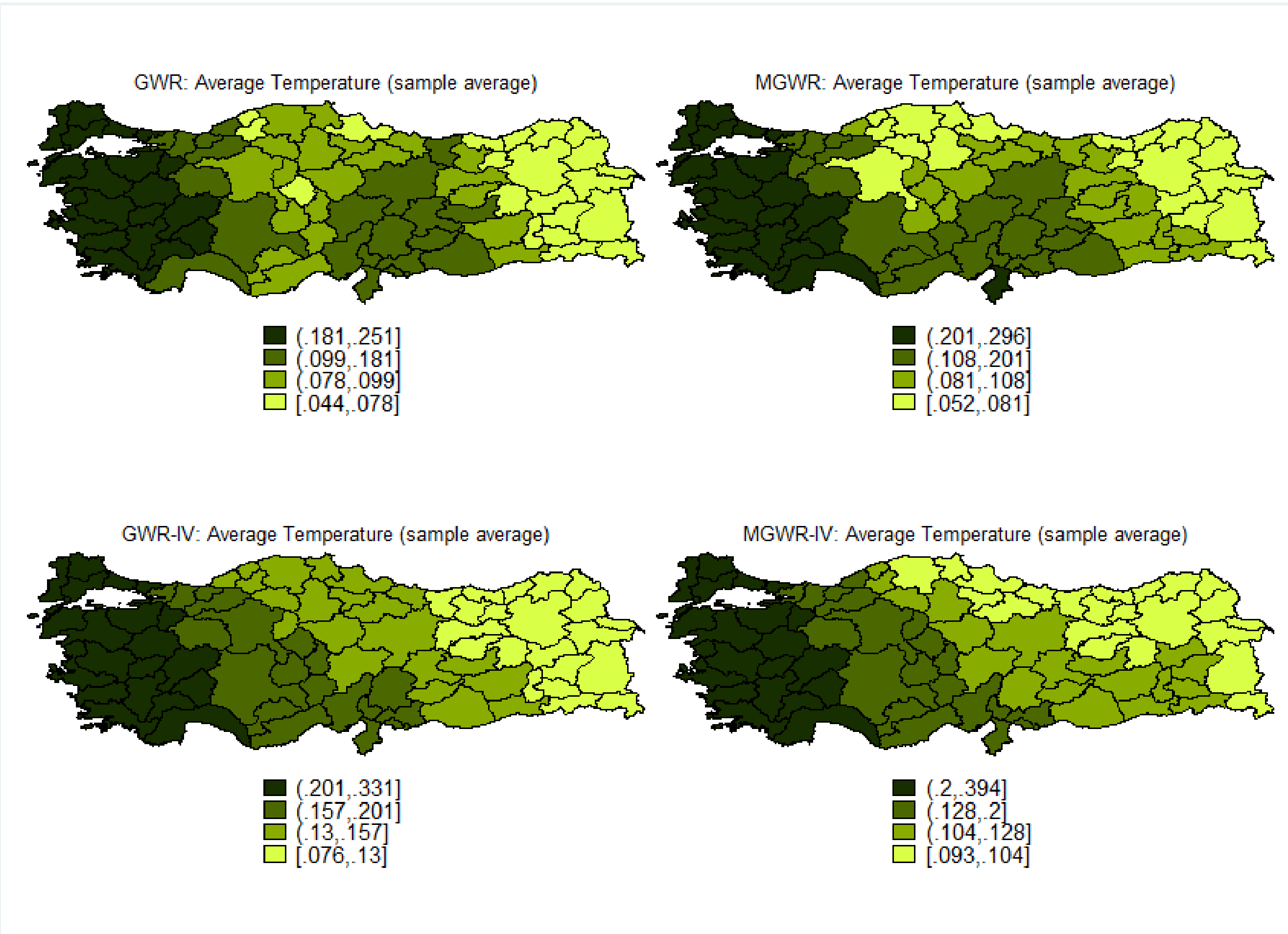
Source: MD (2020), Authors' own calculations

Figure 11: Spatial variability of parameter estimates for the impact of climate change on agricultural productivity (2004-2019 Averages)



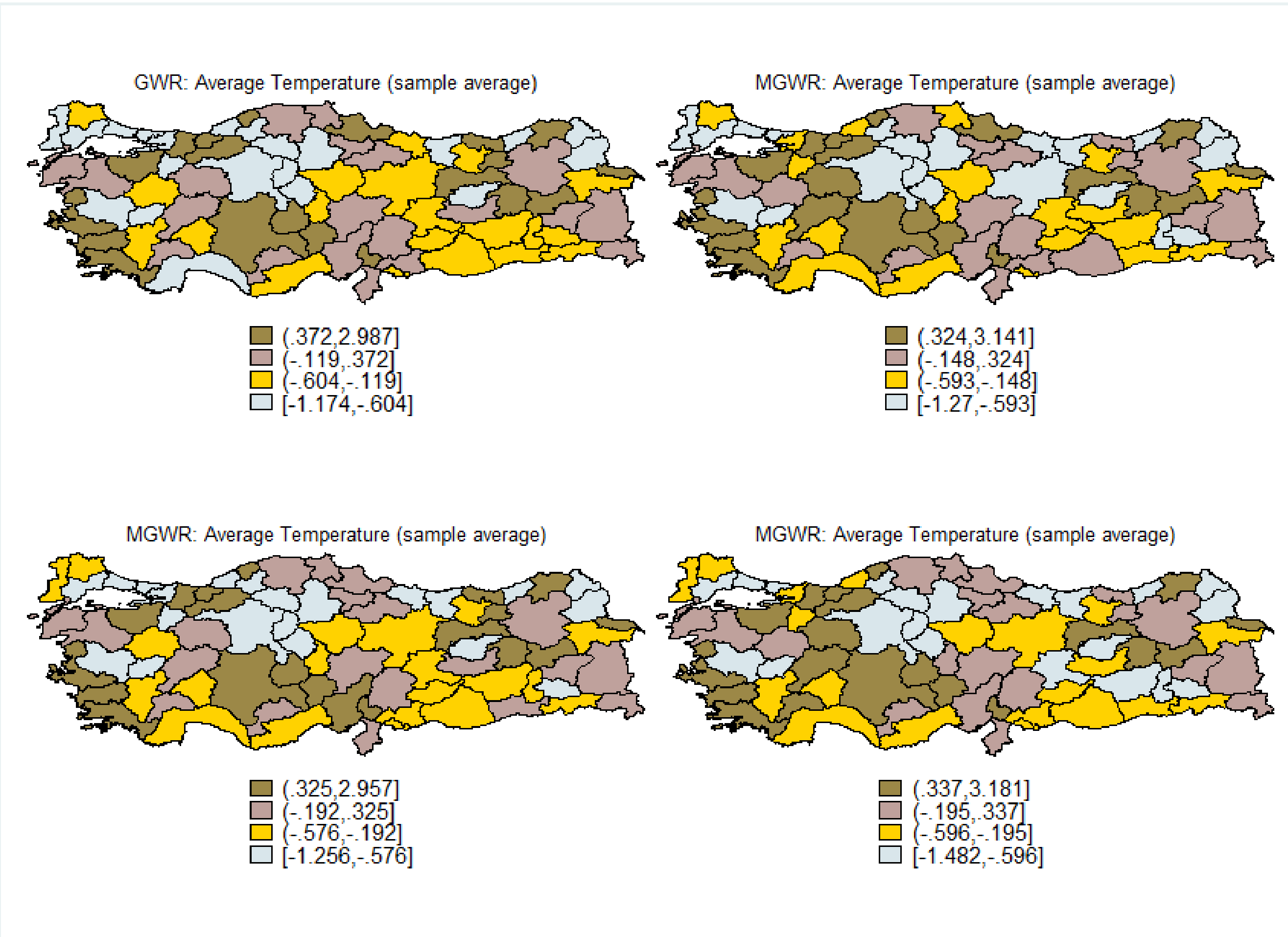
Source: MD (2020), Authors' own calculations

Figure 12: Spatial variability of R-squared for the impact of climate change on agricultural productivity (2004-2019 Averages)



Source: MD (2020), Authors' own calculations

Figure 13: Spatial variability of Residuals for the impact of climate change on agricultural productivity (2004-2019 Averages)



Source: MD (2020), Authors' own calculations