A spatial analysis of the relationship between agricultural output and input factors in Turkey

T. Edward YU*, Dayton M. LAMBERT*, Seong-Hoon CHO*,
Ahmet Ali KOÇ**, Gülden BÖLÜK**, Seung Gyu KIM***

Jel code: C21, Q11, R11

Abstract

Serving as a primary role in Turkey's society and economy, the agricultural sector presents a wide range of farming activities driven by distinctive climatic and geographical conditions. This study estimated a spatial agricultural production function using spatially-varying coefficient models to enhance our understanding about the diverse relationship between agricultural output and input factors across Turkey. Findings suggest spatial variation in the impact of labor, tractor, and fertilizer uses on agricultural output at the regional and provincial levels. The goodness of fit of both spatial models outperformed an aspatial model estimated with OLS (Ordinary Least Squares). The comparative advantage of input factors in different regions/provinces found in our study implies the importance of considering spatial factors in policy mechanisms tailored to different regions given their topography features, socioeconomic milieus, and resource endowments.

Key words: *Turkey, agricultural output, spatial variation, geographically weighted regression.*

Résumé

En Turquie, le secteur agricole joue un rôle primordial au niveau de la société et de l'économie. Il se caractérise par une gamme très variée d'activités liées aux conditions géographiques et climatiques spécifiques du pays. Dans cette étude, nous avons estimé une fonction spatiale de la production agricole à travers les modèles de coefficients variables dans l'espace pour mieux comprendre la corrélation entre les intrants et les extrants agricoles. Les résultats ont montré une variation dans l'espace de l'impact de la main d'œuvre, des tracteurs et des engrais sur la production agricole à l'échelle régionale et des provinces. L'ajustement des deux modèles spatiaux a permis d'obtenir des résultats meilleurs par rapport au modèle non-spatial estimé à l'aide des Moindres Carrés Ordinaires (MCO). L'avantage comparatif des intrants dans les différentes régions/provinces retenues souligne l'importance d'intégrer les facteurs spatiaux dans les dispositifs de politique élaborés en considérant les conditions topographiques, les facteurs socio-économiques et les ressources des différentes régions.

Mots-clés: Turquie, production agricole, variation spatiale, régression pondérée géographiquement

1. Introduction

Located on the land bridge between Europe and Asia, Turkey's distinctive climatic and geographical conditions have created a diversified environment for agricultural activities across the country. Agricultural production ranges from capital-intensive cultivation of high value crops in the western and southern regions to heavily subsidized and protected cereal and livestock production in the northern and north-eastern regions (Aerni, 2007). Given the diversity of agricultural activities, researchers have examined the relationships between agricultural production and input factors from regional and local perspectives. Some studies evaluated the factors affecting the production of specific crops in a region, for example, wheat in the Southeastern Anatolian Project region (Ozsbuncuoglu, 1998), cotton in the Izmir province (Uzmay *et al*., 2009) or canola in the Trakya region (Unakitan *et al*., 2010). In addition, research determining technical efficiencies in regional agricultural output has gradually increased (e.g. Demir and Mahmud, 2002; Abay *et al*., 2004; Tipi and Rehber, 2006). Research on energy use efficiency in fruit and vegetable production in various regions has also received recent attention (e.g. Erdal *et al*., 2009; Topak *et al*., 2009).

The aforementioned studies typically used micro-level data to evaluate the impact of farm inputs on output productivity for commodity producers in a given province or region of Turkey. Also, spatial relationships characterising agricultural output and input use were not considered in estimating agricultural production although ignoring spatial interactions between neighbouring provinces or regions may result in biased estimation. Agricultural production in a given province or county can affect its neighbouring provinces or counties because of their similar resources and human capital (Cho *et al*., 2007). Also, spill-overs from public agricultural research and development of public infrastructure may contribute agricultural productivity in a proximate region (Alston *et al.,* 2010, Tong *et al.,* 2013). Recently, Yu *et al*. (2014) have examined the implication of policy reform in 2001-2008 to agricultural production in Turkey using a spatial Durbin model that incorporates spatial autocorrelation among provinces. Their findings suggest that changes in the output elasticities of evaluated input factors in Turkey varied after the policy reform.

Although spatial patterns or interaction in agricultural production have been identified in Turkey, there is a lack of

* Department of Agricultural & Resource Economics, University of Tennessee, Knoxville, TN USA.
Corresponding author : tyu1@utk.edu
** Department of Economics, Akdeniz University,Antalya, Turkey.
***Department of Agricultural Economics Kyungpook National University, Daegu, Korea.

systematic assessment allowing spatial variation in the relationship between agricultural output and input uses across the country. The aspatial models or spatial autocorrelation models (e.g. spatial Durbin model) typically assume that the marginal responses to explanatory variables are fixed over space, and estimate the regression coefficients for each explanatory variable for the whole study area instead of each spatial zone/region. This approach neglects spatial heterogeneity in the marginal responses to explanatory variables and estimates the mean of the spatial phenomena in the study area (Ali *et al*., 2007). Consequently, the approach has limitations for capturing the local/regional characteristics of agricultural activities given the wide diversity of habitats in Turkey.

Acknowledging this, the present study complements to the literature by taking spatial variation into account when assessing output elasticities of input factors in the agricultural sector of Turkey. The estimated output elasticities are varied by region through a discrete spatial regime model. In addition, a geographically weighted regression (GWR) model was applied to further illustrate how much the relationship between agricultural output and evaluated input factors may vary among provinces. In contrast to the national average agricultural output elasticities estimated in Yu *et al.* (2014), the spatially-explicit coefficients can provide valuable insights into the relative importance of inputs in different regions/provinces. The information of regional disparities in the marginal responses to farm inputs across the country can aid in the development of policy mechanisms tailored to different regions given the comparative advantage to certain physical landscape features, socioeconomic milieus, and resource endowments.

2. Empirical Models

In this study, we applied a Cobb-Douglas production function to represent Turkey's gross revenue of agricultural products (GRAP):

$$y_i = \gamma \prod_{k=1}^{K} x_{ik}^{\beta_k} \quad (1)$$

where, for province i, y_i represents output (GRAP); x_{ik} are input factors of production ($k = 1,\ldots,3$) including agricultural labor, tractors, and fertilizer; γ is total factor productivity; and β_k is the contribution of each input k to output. Selection of these input factors was based on previous literature analyzing agricultural production in Turkey and other countries (e.g. Tipi and Rehber, 2006; Cho *et al*., 2007; Lambert and Cho, 2008; Tipi *et al*., 2009; Yu *et al.,* 2014)[1].

Under the assumption that production is stochastic, equation (1) can be rewritten as:

[1] The Durbin-Wu-Hausman endogeneity test of each input factor was conducted and we failed to reject the hypothesis of exogenous variables using the chi-square test at the 5% statistical level. Anderson's (1951) LM statistics rejected the hypothesis that the instrumental variables are not identified. The weak instrument robust tests (Dufour, 2003) also rejected the hypothesis that the instrumental variables were weakly identified. Test results can be obtained from the authors.

$$y_i = \gamma \prod_{k=1}^{K} x_{ik}^{\beta_k} \varepsilon_i \quad (2)$$

where ε_i is a random shock. By adopting a discrete spatial regime model that allows the structural covariates to vary across regions (Lambert *et al*., 2008; Lambert and McNamara, 2009; McGranahan *et al*., 2010), equation (2) is modified as:

$$y_i = \prod_{r=1}^{R} e^{\gamma_r z_r} \prod_{r=1}^{R} \prod_{k=1}^{K} x_{ik}^{z_r \beta_{rk}} \varepsilon_i \quad (3)$$

where, for province i, z_r, is a regional dummy, γ_r is a vector of parameters for the regional dummy, and β_{rk} is a vector of parameters for the interactions between input factors and the regional dummy.

By taking the natural log on both sides of the equation (3), the relationship between agricultural output and input uses can be estimated as a linearized model. The log-log form of discrete spatial regime model for a given year is:

$$\ln(y_i) = \sum_r^R \gamma_r z_r + \sum_r^R \sum_k^K z_r \beta_{rk} \ln(x_{ik}) + \ln(\varepsilon_i) \quad (4)$$

Spatial heterogeneity, with respect to the output impact of farm inputs across region, can be evaluated by testing the joint hypothesis that all of the coefficients of the dummy variable and interaction terms jointly equal zero; that is, $\gamma_r = 0$ and $\beta_{rk} = 0$ for all r and k.

In addition to representing regional heterogeneity as a discrete process, the method of GWR (Fotheringham *et al*., 2003) was used to explore the spatial variability characterizing Turkey's input use and agricultural productivity. Spatial heterogeneity at the provincial level under GWR, which is smaller than the regional level, was evaluated by testing the spatial variability of individual parameters generated by the agricultural production function. The Cobb-Douglas production function estimated using GWR modifies equation (2):

$$y_i = \gamma_i \prod_{k=1}^{K} x_{ik}^{\beta_{k(a_i,b_i)}} \varepsilon_i \quad (5)$$

where (a_i, b_i) denotes the location coordinates for the centroid of province i, while β_k (a_i, b_i) are localized parameters for province i corresponding with input k. Linearizing equation (5) using logarithms:

$$\ln(y_i) = \gamma_i + \sum_k^K \beta_{k(a_i,b_i)} \ln(x_{ik}) + \ln(\varepsilon_i) \quad (6)$$

Equation (6) was estimated using the GWR model following the approach suggested by Fotheringham and Brunsdon (1999).

3. Methods and Data

3.1. Exploratory Spatial Data Analysis

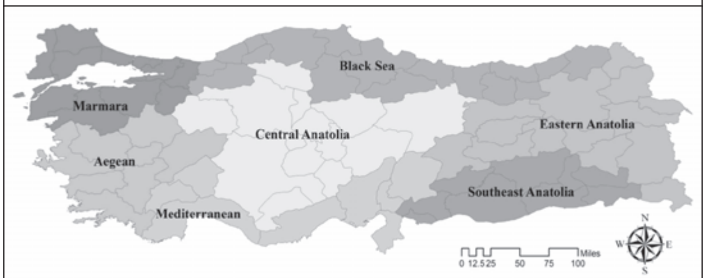
To explore the spatial relationship of variables, the Moran's indices (referred to as "Moran's I", Anselin, 1988) associated with output and input variables based on weight matrices using different numbers of the nearest neighbour provinces (h) were generated to explore the spatial association of inputs and production. The indices were used to identify the role of distance decay on the variables.

3.2. Model Estimation and Specification

Following the classic "specific to general" strategy for specifying spatial process models (Anselin, 1988), this study started with a basic aspatial model that does not explicitly account for spatial autocorrelation and spatial heterogeneity to evaluate the relationship between agricultural production and input use. The aspatial model was estimated with ordinary least squares (OLS), referred to as the "aspatial model," using robust standard errors. The residuals of the aspatial model were tested using a robust Lagrange Multiplier (LM) (Florax and De Graaff, 2004) for spatial lag and spatial error, respectively. A modified model taking into account spatial error and/or spatial lag was estimated (Anselin and Florax, 1995) if those issues were detected in the OLS residuals.

In addition to identifying spatial autocorrelation in the residuals from the aspatial model, the variation in the impact of farm inputs on output across regions were also examined. A discrete spatial regime model in the Cobb-Douglas function that allows the structural covariates and the residual covariate to vary across the regions was estimated (referred to as the "regional spatial regime model" in equation (4)). Based on the climate, human habitat, and topography, Turkey is divided into seven census-defined geographical regions including a total of 81 provinces (see Figure 1).

Figure 1- *Regions of Turkey.*



This study used seven regions (Marmara, Aegean, Mediterranean, Black Sea, Central Anatolia, Eastern Anatolia, and Southeast Anatolia) to account for region-specific spatial heterogeneity by capturing the variation in the climate and agricultural output. The residuals of the regional spatial regime model were tested using a robust LM (Florax and De Graaff, 2004) for spatial lag and spatial error, respectively. A spatial heterogeneity test on the agricultural output elasticities at the *regional* level was conducted using the joint F-test. An orthogonal restriction was imposed on the coefficients associated with the dummy variables. The constraint on the regional dummy variable tested whether the effects of input uses on agricultural output in the particular region are different from the national average in Turkey (Lambert *et al*., 2004).

The spatial heterogeneity at the *provincial* level was examined by testing the spatial variability of the individual parameters generated by a production function estimate via GWR (referred to as the "provincial spatial regime model" in equation (6)). GWR adds values to the discrete spatial regime model mainly because the result of GWR is a set of local regression parameters for each province, thus the output enables us to examine local parameter estimates, thereby enabling assessment of the input factor-output elasticities across the country.

The significance of the spatial variability of individual parameter estimates in GWR was examined following the F-test in Leung *et al.* (2000). The null hypotheses is the set of parameters $\{\beta_{1k}, i = 1,2, ..., n\}$ of x_k do not vary significantly across the space, i.e. $\beta_{1k} = \beta_{2k} = \dots \beta_{nk,}$ for a given k. Statistical significance of the F-test indicates a rejection of the null hypothesis assuming that the individual parameter estimates are invariant over space. In addition, an F-test with the null hypothesis of no significant difference between the residual sum of squares of the aspatial and provincial spatial regime models for the given data was conducted to test whether the provincial spatial regime model outperformed the aspatial model in terms of goodness of fit (Leung *et al.,* 2000). The GWR adopted in this study was used primarily as a supplemental tool to explore the spatial variability of the data due to several criticisms associated with the application of the GWR as a tool to draw inferences regarding spatiality-varying relationships across the space (Jetz *et al*., 2005; Wheeler and Tiefelsdorf, 2005; Páez *et al*., 2008; Páez *et al*., 2009).

3.3. Data

Province-level data of the gross revenue of agricultural production (GRAP), rural population, agricultural land, number of tractors, and amount/quantity of chemical fertilizer use in 2007 was obtained from a nationwide survey by the TurkStat (2008a, 2008b). The TurkStat has discontinued the data series at the provincial level after 2007 so the data used in this study is the latest available provincial data of agricultural output and input uses. The GRAP includes the

Table 1 - *Statistics of mean and coefficients of variation of the output and input variables*

Regions [# of province]	GRAP (10^6 TRL/ha)	Labor (Person/ha)	Tractor (Car/ha)	Fertilizer (Tons/ha)
Nation [81]	649.64 (0.70)	1.38 (1.62)	0.05 (0.60)	0.38 (0.74)
Regional				
R1: Marmara [11]	1,074.56 (0.54)	3.35 (1.63)	0.09 (0.33)	0.64 (0.39)
R2: Aegean [8]	742.60 (0.57)	1.09 (0.47)	0.07 (0.29)	0.40 (0.30)
R3: Mediterranean [8]	884.78 (0.47)	1.24 (0.56)	0.06 (0.33)	0.67 (0.49)
R4: Black Sea [18]	758.01 (0.62)	1.55 (0.80)	0.05 (0.80)	0.36 (0.92)
R5: Central Anatolia [13]	265.70 (0.41)	0.32 (0.44)	0.03 (0.33)	0.26 (0.42)
R6: Eastern Anatolia [14]	553.07 (0.49)	1.13 (0.57)	0.02 (0.50)	0.12 (0.67)
R7: Southeast Anatolia [9]	326.69 (0.18)	0.88 (0.40)	0.02 (0.50)	0.39 (0.41)

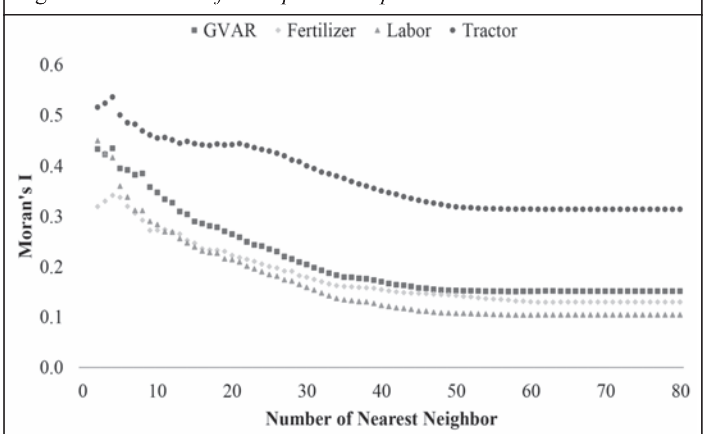
Note: The gross revenue of agricultural output (GRAP) is deflated to the value of 1998 Turkish Lira (TRL). 1 US$ = 262,204 Turkish Lira (TRL) based on an annual average exchange rate in 1998. Numbers in the parenthesis represent the coefficients of variation.

revenue of animal products, livestock, field crops, fruits, and vegetables in million constant 1998 Turkish Liras (TL). Agricultural employment data is not available at the provincial level in 2007, thus the rural population data was used as a proxy for agricultural labour since the current farm structure in Turkey is primarily comprised of small-sized, family-owned and highly-fragmented producers in most of the nation, except for the western and Mediterranean regions (OECD, 2011), the agricultural producers are generally well represented by the rural population. The number of tractors was used to represent the level of machinery use. Table 1 summarizes the regional and national mean and coefficients of variation (CV) of the output and input variables.

4. Results and Discussion

The Moran's I of the output and input variables based on weight matrices using different numbers of the nearest neighbour provinces ranging from 1 through 81 (*h*) is illustrated in Figure 2. The indices suggest positive spatial autocorrelation for each variable. Also, the spatial autocorrelation of tractor use per ha of land was relatively higher than the other inputs. As expected, the spatial dependence of each variable decreased as more provinces are included in the neighbourhood definition; that is, the neighbourhood impact of a variable diminished when province connectivity increased. The panels show that the indices of GRAP and input variables reached stationarity when 60 neighbours, i.e. *h*=60, were used to define the spatial relation matrix.

Figure 2 - *Moran's I for output and input variables.*



The results of the aspatial model, estimated in equation (1) using robust standard errors, are summarized in Table 2. Statistical significance at the 5% level is denoted with asterisks in the table and in the following tables; those variables and test statistics are referred to as "significant" in the discussion onward. The hybrid weight matrix used in the test was generated from the product of the contiguity weight matrix with the number of the nearest neighbor provinces identified in Moran's I (*h*=60) and travel-time distance matrix. Based on both LM spatial error and LM spatial lag tests, the statistics reject the null hypothesis that the residuals of the aspatial models were spatially autocorrelated at the 5% level for the model. The aspatial model explains about 61% of the variance in the data of 2007. Agricultural labor significantly affected GRAP, with an associated output elasticity of 0.59.

Table 2 - *Coefficients and statistics of aspatial and regional spatial regime models.*

Variable	Aspatial model	egional spatial regime model
Intercept	6.76 (0.000)*	7.63 (0.000)*
Labor	0.59 (0.000)*	0.41 (0.000)*
Tractor	0.11 (0.178)	0.39 (0.000)*
Fertilizer	0.06 (0.349)	0.14 (0.067)
R1 (Marmara)		1.38(0.002)*
R1 × Labor		-0.17(0.032)*
R1 × Tractor		0.57(0.001)*
R1 × Fertilizer		-0.27(0.002)*
R2 (Aegean)		-0.30(0.434)
R2 × Labor		0.28(0.016)*
R2 × Tractor		-0.43(0.012)*
R2 × Fertilizer		0.86(0.000)*
R3 (Mediterranean)		0.95(0.235)
R3 × Labor		0.16(0.413)
R3 × Tractor		0.26(0.302)
R3 × Fertilizer		-0.11(0.603)
R4 (Black Sea)		-1.10(0.015)*
R4 × Labor		0.08(0.550)
R4 × Tractor		-0.40(0.000)*
R4 × Fertilizer		0.01(0.959)
R5 (Central Anatolia)		-0.02(0.986)
R5 × Labor		-0.13(0.693)
R5 × Tractor		0.13(0.735)
R5 × Fertilizer		-0.17(0.579)
R6 (Eastern Anatolia)		0.74(0.117)
R6 × Labor		0.24(0.159)
R6 × Tractor		0.22(0.099)
R6 × Fertilizer		-0.23(0.007)*
LM error statistics	2.06 (0.152)	0.00 (0.979)
LM lag statistics	1.28 (0.257)	1.17 (0.280)
Adj-R^2	0.61	.75
F-test		2.77 (0.001)

Note: Numbers in parenthesis represent the p-value. Asterisk (*) indicates statistical significance at the 5% level.

The estimates of the regional spatial regime model in equation (3) with robust standard errors, including the output elasticities of three farm inputs, six regional dummy variables, and the interactions of those regional dummy variables with each input factor, are also presented in Table 2. The *p*-value of robust LM spatial error (0.98) and LM spatial lag (0.28) tests suggest that the residuals of the model with a regional spatial regime were not spatially autocorrelated. The joint F-test with *p*-value of 0.001 on the coefficients associated with the regional dummy variables and interaction terms indicates that not all of those variables equal zero, suggesting that the impact of input factors on agricultural output was variant across the regions in Turkey. Finally, the adjusted *R*-square of the regional spatial regime model improved to 0.75 from the 0.61 associated with the aspatial model, suggesting the former model incorporating spatial heterogeneity has a better goodness-of-fit comparing to the aspatial model.

After incorporating spatial heterogeneity in the regional spatial regime model, the output elasticities of labor and

Table 3 - Test statistics of provincial spatial regime model estimated using GWR.

Variable	Statistics
Stability F-test	
Labor	4.40 (0.017)*
Tractor	5.74 (0.004)*
Fertilizer	0.81 (0.374)
Goodness-of-fit F-test	3.30 (0.032)*

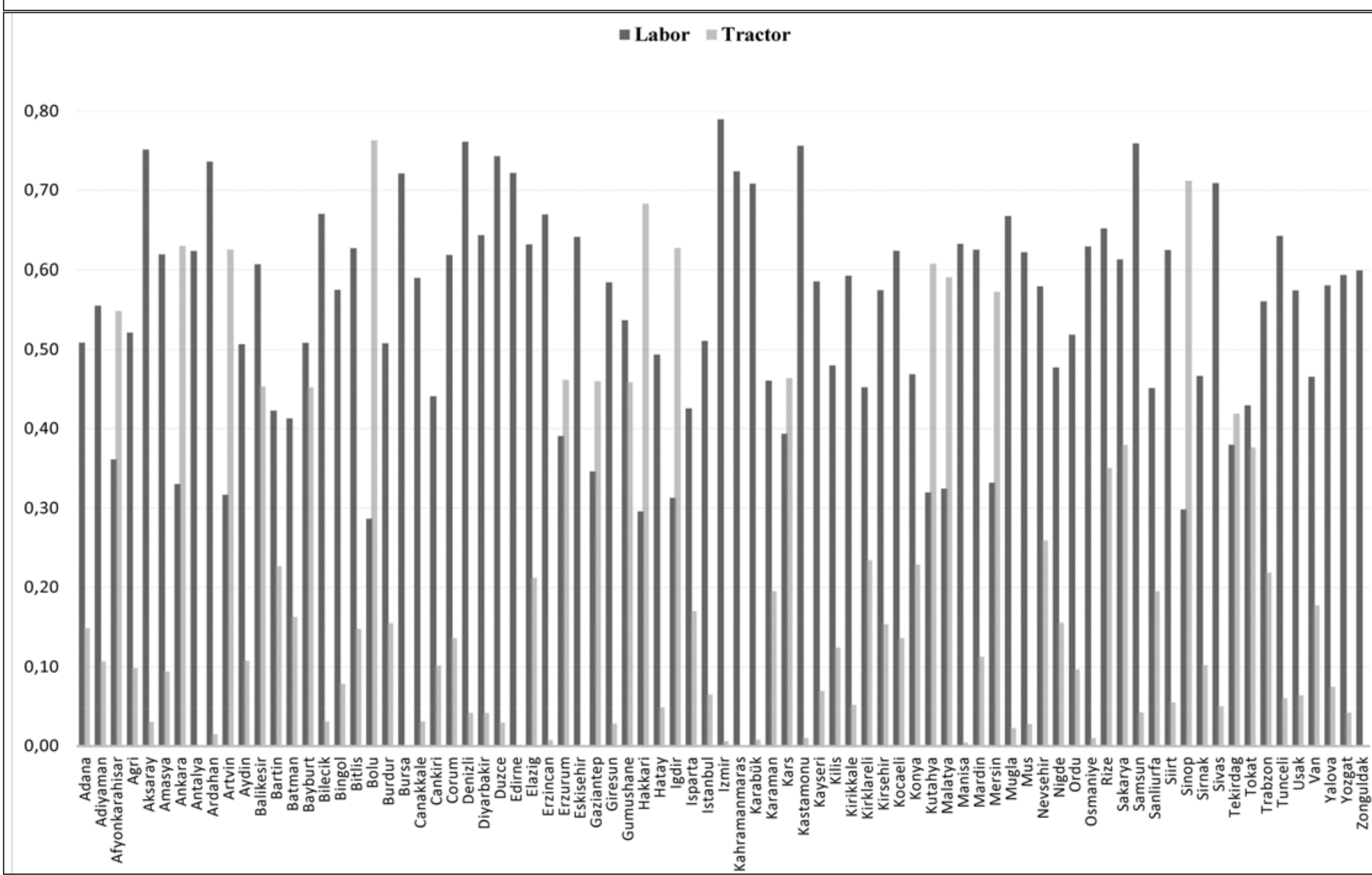
Note: Numbers in parenthesis represent the p-value. Asterisk (*) indicates statistical significance at the 5% level.

tractor use were significant. A one percent increase in agricultural labor and tractor use per ha increased agricultural production by 0.41% and 0.39%, respectively, on average across the nation. In Marmara, the GRAP and the output elasticity of tractor use was higher than the national average since both the dummy variable associated with Marmara and the interaction terms of Marmara dummy variable and tractor use were significantly positive. This is likely due to the relatively large farm size in the region which is suitable for capital-intensive inputs, i.e. large machinery, for local agricultural production. In addition, field crops are the major agricultural products in Marmara, which relies on tractor utilization to enhance the operation efficiency and demands less labor use in Marmara.

The spatial heterogeneity in the output elasticities of input uses is also found in other regions. For example, the agricultural output in the Black Sea and its tractor use was less productive when compared to the average across the regions due to the small farm size and steep slope land in the region. In addition, the productivity of tractor in the Aegean region was lower than the national average, whereas the output impact of fertilizer and labor use was higher than the average of other regions. This is likely driven by regional cotton, nuts, tobacco and fresh fruit and vegetable production that rely on fertilizer and labor primarily. The output impact of fertilizer use in Eastern Anatolia was lower than the national average as crop land is limited and livestock is primary agricultural activity. Chemical fertilizer is substituted with animal manure in major part of the region.

The spatial variability test of the parameters generated by GWR in equation (5) is summarized in Table 3. The F-test suggests that the null hypothesis of spatial stationarity is rejected for the provincial output elasticities of labor and tractor estimated in GWR. In addition, the significance of a goodness-of-fit F-test implies that the provincial spatial regime model taking into account continuous spatial heterogeneity performs better than the aspatial model. Figure 3 further illustrates the diverse impact of labor and tractor on agricultural output across 81 provinces. The output elasticity of labor extended from 0.29 to 0.71, with the highest in

Figure 3 - *The estimated elasticities of labor and tractor on provincial agricultural output using GWR.*



Izmir Province and the lowest in Bolu Province. The range for the output elasticity of tractor fell between 0.001 in Kahramanmaras Province and 0.76 in Bolu Province. The wide variations in the marginal contribution of labor and tractor to aggregate agricultural output by province, comparable to the findings from the discrete spatial regime model, are again related to diverse agricultural activities from distinctive climatic and geographical conditions in Turkey.

The findings present an important policy implication in the agricultural sector in Turkey. Improvement of the productivity and efficiency in the agricultural sector has been one of the key policy priorities in Turkey over the years. Although the growth in the productivity and efficiency in the agricultural sector has been observed after various policy reforms since 1980s, the growth rate of agricultural productivity is still considerably behind other sectors (OECD, 2011). The comparative advantage of input factors in different regions/provinces found in our study provide useful information to enhance the agricultural productivity. For instance, optimizing the use of tractors in Bolu or Sinop Provinces will further strengthern its agricultural sector. Similarly, increase labor force in the Provinces of Izmir, Denizli or Samsun can stimulate more agricultural output. For the less productive input uses in various regions/provinces, such as tractor use in Antala Province or labor use in Hakkari Province, agricultural output can be improved through alternative management strategies or personnel tranining to better fit the local condition. To further improve the productivity and efficiency of agricultural production, administrators need to recognize relative strengths and weaknesss in regional/provincial agricultural sector and develop a flexible system which effectively enhances agricultural production by region than in a sole-aggregated policy approach.

5. Conclusion

Serving as a fundamental role in Turkish society and economy, the agricultural sector includes a wide range of farming activities due to distinctive climatic and geographical conditions. In contrast to previous studies, this study examined the relationships of agricultural output and input factors taking into account the regional disparities across the nation that constitute the observed relationships. An agricultural production function was estimated with the data of the year 2007 using two spatial regime models to capture the regional and provincial regional disparities, respectively, in the contribution of input factors to agricultural output.

Our findings suggest that the spatial variation in the responsiveness of output to changes in evaluated inputs, including labor, tractor, and fertilizer uses, was identified at both the regional and provincial levels in Turkey. The goodness of fit of both spatial models improved when comparing to the aspatial model. This implies that the effect of policy supports on local agricultural output does not only depend on the amount of resources given in a certain region/province, but also on the capability of the local agricultural sector (Sassi, 2010). Therefore, policy inferences derived from the aspatial model would not be sufficient to suit local settings; while the GWR approach is likely more efficient in forming policy at a refined local or regional level. Confirmation of the spatial variation helps decision makers develop policy mechanisms tailored to individual provinces, which can enhance the relative strengths of provincial or regional agricultural activities.

References

Abay, C., Miran B. and Günden C., 2004. An analysis of input use efficiency in tobacco production with respect to sustainability: the case study of Turkey. *Journal of Sustainable Agriculture*, 24(3): 123-143.

Aerni P., 2007. Agriculture in Turkey - structural change, sustainability and EU-compatibility. *International Journal of Agricultural Resources, Governance and Ecology*, 6(4-5): 429-439.

Ali K., Partridge M.D. and Olfert M.R., 2007. Can geographically weighted regressions improve regional analysis and policy making? *International Regional Science Review*, 30(3): 300-329.

Alston J.M., Anderson M.A., James J.S., and Pardey P.G., 2010. The economic returns to U.S. Public agricultural research. *American Journal of Agricultural Economics*, 93(5): 1257-1277.

Anderson T.W., 1951. Estimating linear restrictions on regression coefficients for multivariate normal distributions. *Annals of Mathematical Statistics,* 22: 327-51.

Anselin L., 1988. *Spatial econometrics: methods and models*. Boston: Kluwer Academic Publishers.

Anselin L. and Florax R., 1995. *New directions in spatial econometrics*. Berlin: Springer-Verlag.

Anselin L., Varga A. and Acs Z., 1997. Local geographic spillovers between university research and high technology innovations. *Journal of Urban Economics*, 42(3): 422-448.

Cho S., Chen Z., Yen S.T. and English B.C., 2007. Spatial variation of output-input elasticities: evidence from Chinese county-level agricultural production data. *Papers in Regional Science*, 86(1): 139-157.

Demir N. and Mahmud S.F., 2002. Agro-climatic conditions and regional technical inefficiencies in agriculture. *Canadian Journal of Agricultural Economics,* 50(3): 269-280.

Dufour J-M., 2003. Identification, weak instruments, and statistical inference in econometrics. *Canadian Journal of Economics,* 36(4): 767-808.

Erdal H., Esengun K., Erdal G., 2009. The functional relationship between energy inputs and fruit yield: a case study of stake tomato in Turkey. *Journal of Sustainable Agriculture*, 33: 835-847.

Florax R.J. and De Graaff T., 2004. The performance of diagnostic tests for spatial dependence in linear regression models: a meta-analysis of simulation studies. In: Anselin L., Florax R. and Rey S.J. (eds). *Advances in spatial econometrics: methodology, tools and applications*. New York: Springer-Verlag, pp. 29-65.

Fotheringham A.S. and Brunsdon C., 1999. Local forms of spatial analysis. *Geographical Analysis*, 31(4): 340-358.

Fotheringham A., Brunsdon C. and Charlton M., 2003. *Geographically weighted regression: the analysis of spatially varying relationships*. Chichester: John Wiley & Sons.

Jetz W., Rahbek C. and Lichstein J.W., 2005. Local and global approaches to spatial data analysis in ecology. *Global Ecology and Biogeography*, 14(1): 97-98.

Lambert D.M. and Cho S., 2008. Forecasting input demand shocks on China's gross value of agricultural output. *The Review of Regional Studies*, 38(3): 343- 359.

Lambert D.M., Lowenberg-Deboer J. and Bongiovanni R., 2004. A comparison of four spatial regression models for yield monitor data: a case study from Argentina. *Precision Agriculture*, 5(6): 579-600.

Lambert D.M. and McNamara K.T., 2009. Location determinants of food manufacturers in the U.S., 2000 - 2004: Are nonmetropolitan counties competitive? *Agricultural Economics*, 40(6): 617-630.

Lambert D.M., Wilcox M., English A. and Stewart L., 2008. Ethanol plant location determinants and county comparative advantage. *Journal of Agricultural and Applied Economics*, 40(1): 117-135.

Leung Y., Mei C.L. and Zhang W.X., 2000. Statistical tests for spatial nonstationarity based on the geographically weighted regression model. *Environment and Planning A*, 32(1): 9-32.

McGranahan D.A., Wojan T.R. and Lambert D.M., 2010. The rural growth trifecta: outdoor amenities, creative class and entrepreneurial context. *Journal of Economic Geography*, 11(3):529-557.

Organization for Economic Co-operation and Development (OECD). 2011. *Evaluation of agricultural policy reforms in Turkey*. http://www.oecd-ilibrary.org/agriculture-and-food/evaluation-of-agricultural-policy-reforms-in-turkey_9789264113220-en.

Ozsbuncuoglu I.H., 1998. Production function estimation for wheat: a case of study of southeastern Anatolian project region. *Agricultural Economics*, 18(1): 75-87.

Páez A., Farber S. and Wheeler D., 2009. Multicollinearity in geographically weighted regression coefficients: results from a new simulation experiment. In: *Proceedings of the III World Conference of the Spatial Econometrics Association, Barcelona, 8-10 July 2009*.

Páez A., Long F. and Farber S., 2008. Moving window approaches for hedonic price estimation: an empirical comparison of modeling techniques. *Urban Studies*, 45(8): 1565-1581.

Sassi M., 2010. OLS and GWR approaches to agricultural convergence in the EU-15. *International Advanced Economic Research*, 16(1): 96-108.

Tipi T., Çetin B. and Vardar A., 2009. An analysis of energy use and input costs for wheat production in Turkey. *Journal of Food, Agriculture & Environment*, 7(2): 352-356.

Tipi T. and Rehber E., 2006. Measuring technical efficiency and total factor productivity in agriculture: the case of the South Marmara region of Turkey. *New Zealand Journal of Agricultural Research*, 49(2): 137-145.

Tong T., Yu T.E., Cho S., Jensen K., De La Torre Ugarte D. 2013. Evaluating the spatial spillover effects of transportation infrastructure on agricultural output across the United States. *Journal of Transport Geography*, 30: 47-55.

Topak R., Acar B. and Ugurlu N., 2009. Analysis of energy use and input costs for irrigation in field crop production: a case study for the Konya plain of Turkey. *Journal of Sustainable Agriculture*, 33(7): 757-771.

Turkish Statistical Institute (TurkStat), 2008a. *Agricultural Structure 2007 (production, price, value*). Ankara: State Institute of Statistics Publications.

Turkish Statistical Institute (TurkStat), 2008b. *General Agricultural Census 2007*. Ankara: State Institute of Statistics Publications.

Unakitan G., Hurma H. and Yilmaz F., 2010. An analysis of energy use efficiency of canola production in Turkey. *Energy*, 35(9): 3623-3627.

Uzmay A., Isin F. and Koyubenbe N., 2009. Farmers' behaviors regarding the decrease in the area of cotton plantations of Turkey: Izmir case. *Spanish Journal of Agricultural Research,* 7(2): 248-256.

Wheeler D. and Tiefelsdorf M., 2005. Multicollinearity and correlation among local regression coefficients in geographically weighted regression. *Journal of Geographical Systems*, 7(2): 161-187.

Yu T., Cho S., Koç A.A., Bölük G., Kim S.G. and Lambert D.M., 2014. Evaluating spatial and temporal variation in agricultural output elasticities in Turkey. *Agricultural Economics*, 45(3): 279-290.