The shadow price of fossil groundwater

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Abstract

On the basis of a translog production function, a fixed effects panel data model has been estimated to calculate the shadow prices of non-renewable groundwater for citrus, maize and sugarcane using data of the twelve largest non-renewable groundwater using countries. Shadow prices of non-renewable groundwater were positive for citrus and maize during the period 1991-2013, while shadow prices for sugarcane were negative during the same period. The positive shadow prices indicate that farmers could increase their yield by adding extra non-renewable groundwater. The negative shadow prices imply that non-renewable groundwater is used inefficiently since yield is decreased by adding extra non-renewable groundwater.

Contents

1 Introduction

Demand for surface water and groundwater increases worldwide. Drivers are the increasing world population and increasing standard of living resulting in a higher demand for food (Aeschbach-Hertig & Gleeson, 2012; Kiani & Abbasi, 2012; Wada et al., 2010; Wada et al., 2014). In most arid and semiarid areas, agriculture is the largest user of water for crop irrigation during the growing season (Nikouei & Ward, 2013). In those areas, where surface water availability is limited, additional water originates mainly from groundwater resources. Use of groundwater is effective for food production in the short term, but in the long run it is not sustainable (Kiani & Abbasi, 2012). When groundwater extraction exceeds groundwater recharge, this may result in overexploitation and depletion of aquifers (Wada et al., 2010; Wada et al., 2014). Figure 1 shows a map of the ratio between the groundwater footprint and the aquifer area for several countries across the world. Gleeson et al. (2012) define the groundwater footprint as "the area required to sustain groundwater use and groundwater use dependent ecosystem services of a region of interest". According to Gleeson et al. (2012), almost 80% of the global aquifers can sustain themselves.

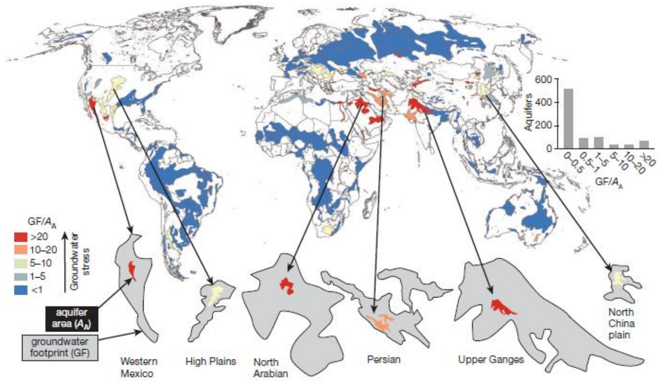

Figure 1: Groundwater footprints for six major aquifers (Gleeson et al., 2012)

Arid areas are dependent on groundwater for food production. For example, the North China Plain is essential for China's food provision by providing half of the wheat and one-third of the maize produced in China (Aeschbach-Hertig & Gleeson, 2012). In those areas groundwater depletion threatens agricultural production and eventually may lead to a decline in production as water for irrigation becomes less accessible. Decreasing supply of food crops may lead to a rise in food prices as groundwater becomes scarcer and water withdrawal costs increase. Figure 1 shows that in particular poorer parts of the world are vulnerable to groundwater depletion. Trade in agricultural crops may lead to relatively more indirect water supplies for countries that import groundwater depleting crops (Dalin et al., 2017). Consequently, depletion of aquifers may affect world food supplies and eventually increase inequality between consumers in richer and poorer parts of the world.

According to Konikow & Kendy (2005) depletion can be considered both as a reduction in volume of groundwater and a reduction in quality of fresh groundwater. Quality of residual water in aquifers deteriorates by leakage from the land surface; saline or contaminated water from neighbouring aquifers and sea water intrusion in coastal areas (Aeschbach-Hertig & Gleeson, 2012; Konikow & Kendy, 2005). Depletion is expected to exaggerate effects from climate change. As more extreme weather circumstances like droughts and floods will occur, the buffering capacity of groundwater becomes more important for food production (Taylor et al., 2013). Periods of extreme droughts will increase demand for irrigation water, while periods of heavy rainfall will change the recharge and discharge process. Groundwater depletion also contributes to global sea level rise as it reduces terrestrial water storage capacities and transfers fossil groundwater to the active hydrological cycle (Wada et al., 2012; Wada et al., 2016).

In many countries, a well-functioning market for water does not exist and the price of groundwater is not determined by supply and demand. The supply of groundwater is unknown and farmers may not consider the needs of future generations in their production decisions. Therefore, the price of groundwater paid by users does not reflect the scarcity. Often, policy with respect to groundwater use is insufficient or lacking as well. In those countries, groundwater is freely available for land owners who buy a water pump installation (Famiglietti, 2014). The price paid for groundwater consists of the water extraction costs and transport costs and does not reflect to the real value of the resource (Ziolkowska, 2015). Therefore, the price of water used for irrigation is below the actual value (Ziolkowska, 2015). This may result in inefficient water allocation and depletion of aquifers (OECD, 2015; Ziolkowska, 2015). The farmer is assumed to be a price taker and a profit maximiser. The higher the profit, the higher the chance that the firm will survive. Therefore, production decisions are based on maximising profit, i.e. the farmer will continue production until the marginal costs are equal to the marginal revenue. Given the marginal cost of the water input, which is the price the farmer pays for water, the farmer will add water until he reaches maximum profit. When the price of water is lower than the actual value, the farmer faces lower marginal costs and he will use more water until he reaches maximum profit, which may result in depletion.

“Knowledge about the actual value of water as a resource is very limited” (Ziolkowska, 2015). The actual value of water as a resource, which is unknown, can be approached by the shadow price of water. Ziolkowska (2015) defines the actual value of water for irrigation as the shadow price of water: “the ratio between the production net returns and the total amount of water used for irrigating the respective crops”. Several economic definitions of the shadow price of water are available in literature, see He et al. (2007). In this paper, we define the shadow price of water as the marginal value of water, which is the crop value produced by the last m3 of non-renewable groundwater. A relatively low shadow price indicates that the application of non-renewable groundwater can generate higher crop value for crops with a higher shadow price. Changing production to crops with a higher shadow price may provide opportunities to reduce non-renewable groundwater use or generate higher crop yields per m3 of non-renewable groundwater.

This paper aims at determining the shadow price of non-renewable groundwater used to produce major agricultural crops in the twelve largest non-renewable groundwater consuming countries. The main research question is: What is the shadow price of non-renewable groundwater for major agricultural crops in countries that use large quantities of non-renewable groundwater? In order to answer this question, three sub questions are formulated:

1. How to build a theoretical model for determination of shadow prices?
2. How to solve the empirical model including the available data?
3. What are the inefficiencies in non-renewable groundwater use of countries that use large quantities of non-renewable groundwater?

Chapter 2 provides the theoretical background. Chapter 3 describes the available data. Chapter 4 contains the empirical model used for estimation in Stata, followed by the results in Chapter 5. The paper ends with conclusions and a general discussion.

2 Theoretical framework

This chapter describes how the shadow price of non-renewable groundwater is derived from a production function. Frank (2010) defines a production function as "the relationship that describes how inputs are transformed into output". The shadow price is calculated by multiplying the marginal product of non-renewable groundwater by the crop output price. The marginal product of non-renewable groundwater is determined by estimating a production function and taking the partial derivative with respect to non-renewable groundwater. In this chapter, we describe two types of production functions that can be used for determining the marginal product. Firstly, we describe the Cobb-Douglas production function and secondly the trans-log production function, which is a generalisation of the Cobb-Douglas production function. Appendix A shows the intermediate steps for deriving the marginal products of all three production functions.

We start with the Cobb-Douglas production function which is most widely used. We consider the inputs land, labour and capital; three types of water inputs (green, blue and non-renewable groundwater[1]) and variable inputs. The Cobb-Douglas production function is represented by the following equation:

$$Y = \beta_0 \cdot A^{\beta 1} \cdot L^{\beta 2} \cdot K^{\beta 3} \cdot GW^{\beta 4} \cdot BW^{\beta 5} \cdot NRGW^{\beta 6} \cdot X^{\beta 7} \tag{1}$$

where Y= crop production, A= area, L= labour, K= capital, GW= green water, BW= blue water, NRGW= non-renewable groundwater, X= variable inputs and β's are model coefficients. This equation can be rewritten into log form for estimation purposes:

$$lnY = ln\beta_0 + \sum_{i=1}^{n} \beta_i \, lnI_i \tag{2}$$

where I_i= inputs (area, labour, capital, green water, blue water, non-renewable water and variable inputs). The marginal product of non-renewable groundwater (MP_{NRGW}) is derived by taking the partial derivative of crop production with respect to non-renewable groundwater:

$$MP_{NRGW} = \frac{\partial Y}{\partial NRGW} = \beta_6 \cdot \frac{Y}{NRGW} \tag{3}$$

Multiplying the marginal product by the crop output price gives the shadow price:

$$P_{shadow} = p_{output} \cdot MP_{NRGW} \tag{4}$$

[1] The types of water inputs are green water (evapotranspiration flows), blue water (withdrawal from rivers, surface water and renewable groundwater) and non-renewable groundwater (Oki & Kanae, 2006).

where P_{shadow}= shadow price and p_{output}= crop output price.

The Cobb-Douglas production function assumes that all inputs are substitutes and that the elasticity of substitution between inputs is equal to one. This implies that our model assumes that green, blue and groundwater are substitutes. However, the hydrological model (which provides the data for the water inputs) states that green, blue and non-renewable groundwater are applied in sequence (Wada et al., 2014). If we include this statement in our model, all types of water should be aggregated into one water input. In that case, the marginal product of water is the marginal product of the last applied water source. This reflects a situation where on the margin only one out of three water sources will adjust due to a change in one of the other variables. Still, the farmer may have a choice in application of blue water or non-renewable groundwater and the amounts of both. We prefer to analyse the different effects of green water (the amount of green water applied is not influenced by the farmer) and water applied by the farmer on the crop yield. Therefore, we decide to include green water (GW) as a separate input and blue water together with non-renewable groundwater as a separate input (WI) in the production functions. The marginal product of the water input is equal to the marginal product of non-renewable groundwater, if non-renewable groundwater is applied.

Estimating a trans-log production function may be more appropriate since this functional form allows for more flexibility and does not impose that all inputs are substitutes and that the substitution elasticity equals 1, in contrast to the Cobb-Douglas production function. An F-test can be performed to decide if the trans-log production function is more appropriate than the Cobb-Douglas production function. A trans-log production function is represented by the following equation:

$$lnY = ln\beta_0 + \sum_{i=1}^{n} \beta_i \, lnI_i + \frac{1}{2}\sum_{i=1}^{n} \beta_{ii} \, lnI_i^{\,2} + \sum_{i\ <}^{n} \sum_{j}^{n} \beta_{ij} \, lnI_i lnI_j \tag{5}$$

where Y= crop production; I_i and I_j are inputs (area, labour, capital, GW, WI and variable inputs) and β_i, β_{ii} and β_{ij} are model coefficients. The marginal product of the water input is derived by taking the partial derivative of crop production with respect to the water input:

$$MP_{WI} = \frac{\partial lnY}{\partial lnWI} \cdot \frac{Y}{WI} = (\gamma_0 + \gamma_1 lnWI + \gamma_2 lnA + \gamma_3 lnL + \gamma_4 lnK + \gamma_5 lnWI) \cdot \frac{Y}{WI} \tag{6}$$

where $\gamma_0 = \beta_5$, $\gamma_1 = \beta_{65}$, $\gamma_2 = \beta_{15}$, $\gamma_3 = \beta_{25}$, $\gamma_4 = \beta_{35}$ and $\gamma_5 = \beta_{45}$.

3 Data

This chapter describes the data used for our empirical research. We provide a general description of our data, the correlation coefficients and the outcomes of panel unit root tests. For our research, we selected the twelve largest non-renewable groundwater using countries, which are: China, Egypt, India, Iran, Italy, Mexico, Pakistan, Saudi Arabia, South Africa, Spain, Turkey and USA (Bierkens et al., 2016). The focus is on maize, sugarcane and citrus, since we want to estimate production functions for high and low water consumption crops. Sugarcane and maize have relatively high crop water needs, while citrus has relatively low crop water needs compared to the standard grass (FAO, 1986). Moreover, these crops are produced by a large part of the twelve countries, see Appendix B for an overview of the most important crops produced by each country.

For each crop, we have production (tonnes), total area (ha) and producer prices (USD/tonne) retrieved from the FAO database. Data for production and area are available from 1961-2014 and data for producer prices are available from 1991-2014 (FAO, 2016a, 2016b). Water consumption rates (km^3) are retrieved from the global hydrological model (PCRGLOB-WB) developed by Wada et al. (2014). This model provides data for three water sources: actual evapotranspiration (green water); surface water and renewable groundwater (blue water) and non-renewable groundwater used by plants, for the period 1971-2010. Data on the amount of capital, labour and variable inputs per crop are not available. Therefore, we use agricultural value added per worker (USD) as proxy for capital, employment in agriculture (1000 persons) as proxy for labour and fertiliser (kg/ ha) as proxy for variable inputs. Data for fertiliser are retrieved from the Worldbank database and available for all twelve countries from 2003-2014. Data for agricultural value added per worker and employment in agriculture are also retrieved from the Worldbank database for the same period, but there are many missing observations. For the period 2003-2010, all observations for agricultural value added per worker and employment in agriculture are available for Italy, South Africa, Spain and the USA.

Table 1 contains the means, standard deviations and minimum and maximum values of the available data for citrus, maize and sugarcane, produced by the countries in our sample. India does not produce any significant amount of citrus, therefore data for India are not included in the estimation of citrus. Italy, Saudi Arabia, Spain and Turkey do not produce (any significant amount of) sugarcane (see Appendix B). Therefore, data of these countries cannot be included for this crop. Large differences exist between the minimum and maximum values of production, hectares grown and water application for all three commodities (Table 1). Considering the means of water application, sugarcane uses most non-renewable groundwater compared to citrus and maize, while maize uses most green water compared to the other crops. Considering each crop separately, citrus and sugarcane use most blue water and maize uses most green water.

Table 1: Summary statistics for the variables in the production functions of citrus, maize and sugarcane: production (tonnes), area (ha), GW (km^3), BW (km^3) and NRGW (km^3)

	Variable	Mean	Std. Dev.	Min. Value	Max. Value
Citrus	Production	3633975	4164741	7800	2.65E+07
	Area	243068	322227	1350	2196000
	GW	494.89	890.11	0.17	4004.66
	BW	746.74	1079.33	6.30	5018.64
	NRGW	166.71	187.76	6.81	734.73
Maize	Production	3.01E+07	6.39E+07	606	3.33E+08
	Area	5974784	9123658	392	3.50E+07
	GW	11514.90	22572.77	0.02	99322.94
	BW	8469.98	13698.01	1.10	97237.98
	NRGW	528.81	757.48	1.87	4856.50
Sugarcane	Production	5.31E+07	7.11E+07	578000	3.56E+08
	Area	852016	1108850	4536	5150000
	GW	2632.36	3556.06	15.55	15215.94
	BW	4636.64	6126.94	52.95	25762.30
	NRGW	1290.72	2152.67	10.25	10390.09

Table 2 gives an overview of the correlation coefficients of the variables for citrus, maize and sugarcane. A more extensive overview of all correlation coefficients, including the quadratic terms and cross terms of the variables, is provided in Appendix D. Overall, the correlation coefficients between the water inputs are rather high (Table 4). Blue water and green water are highly correlated for all three crops. For sugarcane, blue water and green water are also highly correlated with non-renewable groundwater. This may lead to multicollinearity and biased estimators when the production functions are estimated. A possible explanation for the high correlations coefficients is a common trend, due to e.g. technological progress, in our data. Therefore, we add a time variable into our empirical model. Using two water inputs instead of three water inputs may also reduce the risk of multicollinearity.

Table 2: Correlation coefficients for variables in the production functions of citrus, maize and sugarcane

		Production	Area	GW	BW	NRGW
Citrus	Production	1.0000				
	Area	0.7705	1.0000			
	GW	0.5346	0.8271	1.0000		
	BW	0.5289	0.8264	0.9907	1.0000	
	NRGW	0.2208	0.2712	0.2092	0.2668	1.0000
Maize	Production	1.0000				
	Area	0.9294	1.0000			
	GW	0.9591	0.9190	1.0000		
	BW	0.8207	0.8530	0.8784	1.0000	
	NRGW	0.2832	0.5172	0.2740	0.4350	1.0000
Sugarcane	Production	1.0000				
	Area	0.9861	1.0000			
	GW	0.9607	0.9607	1.0000		
	BW	0.9756	0.9863	0.9857	1.0000	
	NRGW	0.8387	0.8774	0.7515	0.8424	1.0000

For stationarity testing we used the Levin–Lin–Chu test, which tests for unit roots in panel datasets. The null hypothesis states that each time series contains a unit root and the alternative hypothesis states that each time series is stationary (Baltagi, 2008). In a stationary process, the mean, variance and covariance of the error term are constant over time. A non-stationary variable cannot be used for predicting the future based on observations in the past. Details about the Levin–Lin–Chu test are available in the Stata manual (Stata, 2015). Table 3 provides an overview of the panel variables of citrus, maize and sugarcane. In this table, *yes* means that the data are stationary and *no* means that the data are nonstationary. Using the natural logarithm of the data solves the non-stationarity problem to a large extent. Still, the production data of maize and the blue water and non-renewable groundwater data of sugarcane are nonstationary (Table 3). This problem is largely solved by panel data estimation since this estimation method uses the first differences of the data. Appendix C contains all panel graphs and panel unit root tests for the variables of citrus, maize and sugarcane.

Table 3: Results of the panel stationarity tests for the variables in the production functions of citrus, maize and sugarcane, where yes means stationary and no means nonstationary

	Citrus		**Maize**		**Sugarcane**	
	Original	*Ln*	*Original*	*Ln*	*Original*	*Ln*
Production	No	Yes	No	No	Yes/No*	Yes
Yield	No	Yes	No	Yes	Yes	Yes
GW	No	Yes	Yes	Yes	Yes/No*	Yes
BW	No	Yes	No	Yes	No	No
NRGW	No	Yes	Yes/No*	Yes	Yes/No*	No

** Yes/No: Depends on the addition of a trend in the Levin-Lin-Chu test, see Appendix C for the details.*

4 Empirical model

Several alternative model specifications and estimation methods exist for estimating the production functions. We decide to perform our estimations with a trans-log specification, since this functional form allows for more flexibility than the Cobb-Douglas production function (see Chapter 2). We start with estimating the production function per country, including the proxies for the input variables, using OLS. Data are available for the following four countries: Italy, South Africa, Spain and the USA for the period 2003-2010. However, due to the limited number of observations per country, the available degrees of freedom are insufficient and it is not possible to calculate unbiased and efficient estimators. Therefore, we estimate the following production function for the four countries together (i.e. cross-section):

$$\begin{aligned}\ln Y_i = {} & \beta_0 + \beta_1 lnA_i + \beta_2 lnEmp_i + \beta_3 lnAVA_i + \beta_4 lnGW_i + \beta_5 lnWI_i + \beta_6 lnFer_i + 0.5\beta_7 lnA_i{}^2 \\ & + 0.5\beta_8 lnEmp_i{}^2 + 0.5\beta_9 lnAVA_i{}^2 + 0.5\beta_{10} lnGW_i{}^2 + 0.5\beta_{11} lnWI_i{}^2 \\ & + 0.5\beta_{12} lnFer_i{}^2 + \beta_{13} lnA_i \cdot lnEmp_i + \beta_{14} lnA_i \cdot lnAVA_i + \beta_{15} lnA_i \cdot lnGW_i \\ & + \beta_{16} lnA_i \cdot lnWI_i + \beta_{17} lnA_i \cdot lnFer_i + \beta_{18} lnEmp_i \cdot lnAVA_i + \beta_{19} lnEmp_i \cdot lnGW_i \\ & + \beta_{20} lnEmp_i \cdot lnWI_i + \beta_{21} lnEmp_i \cdot lnFer_i + \beta_{22} lnAVA_i \cdot lnGW_i + \beta_{23} lnAVA_i \\ & \cdot lnWI_i + \beta_{24} lnAVA_i \cdot lnFer_i + \beta_{25} lnGW_i \cdot lnWI_i + \beta_{26} lnGW_i \cdot lnFer_i + \beta_{27} lnWI_i \\ & \cdot lnFer_i + \beta_{28} ln\mathrm{t} + \mu_i\end{aligned} \tag{7}$$

where Y= production, A= area, Emp= employment in agriculture, AVA= agricultural value added per worker, GW= green water, WI= aggregate water input (blue water and non-renewable groundwater), Fer= fertiliser, i= number of observations= 1, …, 32 and μ_i= random error term. The estimation results are available in Appendix E. However, Italy and Spain do not produce sugarcane. Consequently, the production function for sugarcane cannot be estimated and estimation results for sugarcane are not available in Appendix E.

The estimation results may be improved by using the data of all countries (i.e. cross-section), which ensures enough degrees of freedom. Unfortunately, data of proxy variables for some inputs are not available for all countries, so these data cannot be included. Therefore, the following equation is estimated:

$$
\begin{aligned}
lnY_{it} = \ & \beta_0 + \beta_1 lnA_{it} + \beta_2 lnGW_{it} + \beta_3 lnWI_{it} + 0.5\beta_4 (lnA_{it})^2 + 0.5\beta_5 (lnGW_{it})^2 \\
& + 0.5\beta_6 (lnWI_{it})^2 + \beta_7 lnA_{it} \cdot lnGW_{it} + \beta_8 lnA_{it} \cdot lnWI_{it} + \beta_9 lnGW_{it} \cdot lnWI_{it} \\
& + \beta_{10} lnt_{it} + \sum_{i=1}^{12} \beta_{10+i}\, Dum_i + \varepsilon_{it}
\end{aligned}
\tag{8}
$$

where i= country= 1,…,12[2], t= year= 1,...,40 and Dum= country dummy variable. In this regression, all observations are taken together and we assume that the observations are not related over time. We include a dummy for each country to distinguish country specific effects. The production function of maize includes twelve country dummies. The productions functions of citrus and sugarcane include eleven and eight country dummies respectively. The USA is used as reference country. Appendix F contains the regression results for OLS estimation including the country dummy variables.

An alternative for a cross-section model with country dummies is panel data estimation. Panel data analysis allows for repeated observations over the same units during a number of periods (Verbeek, 2012). Both a fixed effects model and random effects model can be estimated. A fixed effects model contains a unit specific intercept and is represented by the following equation:

$$
lnY_{it} = \alpha_i + \sum_{i=1}^{n} \beta_i\, lnI_{it} + \frac{1}{2}\sum_{i=1}^{n} \beta_{ii}\, lnI_{it}{}^2 + \sum_{i\ <}^{n}\sum_{j}^{n} \beta_{ij}\, lnI_{it} lnI_{jt} + \varepsilon_{it}
\tag{9}
$$

where I= inputs (A, GW and WI), α_i= unit specific intercept, ε_{it}= residual term, i and j= country= 1,…,12 and t= year= 1,...,40. Estimation of fixed effects is based on within variation (variation over time for a given unit). The random effects model combines within and between variation (variation between units) and is represented by the following equation:

$$
lnY_{it} = \mu + \sum_{i=1}^{n} \beta_i\, lnI_{it} + \frac{1}{2}\sum_{i=1}^{n} \beta_{ii}\, lnI_{it}{}^2 + \sum_{i}^{n}\sum_{j}^{n} \beta_{ij}\, lnI_{it} lnI_{jt} + \alpha_i + \varepsilon_{it}
\tag{10}
$$

where μ= intercept, α_i= individual specific residual (not varying over time) and ε_{it} = common residual term. See Appendix A for derivation of the panel data production funtions for yield.

A fixed effects model can be considered as rather similar to the model with country dummies since the country specific effects are estimated by the unit specific intercepts. However, a fixed effects model has less parameters to be estimated and less degrees of freedom compared to the model with country

[2] In equation (7) i means number of observations; in equation (8) - (11) i means number of countries.

dummy variables (Appendix F and Appendix G). Advantages of panel data estimation are the modelling of time and unit-specific effects; the potential omitted variable bias is smaller; separation of within and between variation; smaller effect of multicollinearity and more efficient estimates (Baltagi, 2008; Verbeek, 2012). Our estimations are likely to suffer from omitted variable bias, since no data are available for the labour, capital and variable inputs for the entire period. The water inputs are highly correlated which may enlarge the risk of multicollinearity. Therefore, panel data estimation is most appropriate for estimation of the production functions with our data. First-difference transformations in fixed effects estimation have the cost of losing one year of data for each variable and losing all time-invariant variables. Consequently, there is a trade-off between the loss of data and more efficient estimates.

Usually, total production is used as dependent variable in production functions. However, large differences in total production exist between the countries, see Appendix C for the graphs of total citrus, maize and sugarcane production per country. Therefore, it may be appropriate to use yield (production per ha) instead of total production as dependent variable, which enables comparison between countries. Using yield as dependent variable implies that the interpretation of the parameters of the production function is slightly different:

$$\begin{aligned} ln\left(\frac{Y_{it}}{A_{it}}\right) = {} & \gamma_0 + \gamma_1 lnA_{it} + \gamma_2\left(\frac{lnGW_{it}}{lnA_{it}}\right) + \gamma_3\left(\frac{lnWI_{it}}{lnA_{it}}\right) + \gamma_4 ln^2 A_{it} + \gamma_5\left(\frac{lnGW_{it}}{lnA_{it}}\right) lnA_{it} \\ & + \gamma_6\left(\frac{lnWI_{it}}{lnA_{it}}\right) lnA_{it} + \gamma_7\left(\frac{lnGW_{it}}{lnA_{it}}\right)^2 + \gamma_8\left(\frac{lnWI_{it}}{lnA_{it}}\right)^2 + \gamma_9\left(\frac{lnGW_{it}}{lnA_{it}}\right)\left(\frac{lnWI_{it}}{lnA_{it}}\right) \\ & + \gamma_{10} lnt_{it} + \varepsilon_{it} \end{aligned} \tag{11}$$

where $\gamma_0 = \beta_0$, $\gamma_1 = (\beta_1 + \beta_2 + \beta_3 - 1)$, $\gamma_2 = \beta_2$, $\gamma_3 = \beta_3$, $\gamma_4 = (0.5\beta_4 + \beta_7 + \beta_8 + 0.5\beta_5 + \beta_9 + 0.5\beta_6)$, $\gamma_5 = (\beta_7 + \beta_5 + \beta_9)$, $\gamma_6 = (\beta_8 + \beta_6 + \beta_9)$, $\gamma_7 = 0.5\beta_5$, $\gamma_8 = 0.5\beta_6$ and $\gamma_9 = \beta_9$. Appendix A shows the derivation of the trans-log production function for yield and a description of the marginal products. The regression results for both production and yield estimation are available in Appendix G.

5 Results

Three estimation methods, described in the previous chapter, could be used for calculation of the shadow prices: OLS estimation including proxy variables (model 1); OLS estimation including country dummy variables (model 2) and panel data estimation (model 3). First, the input elasticities are calculated to see if the estimated production function behaves like a translog production function (output is monotonically increasing in all inputs and diminishing marginal productivity) (Boisvert, 1982). The following formula is used for calculating the input elasticities (Boisvert, 1982):

$$e_i = \frac{\partial \ln y}{\partial \ln x_i} = \alpha_i + \sum_{j=1}^{n} \beta_{ij} \ln x_j \qquad (i = 1, \dots, n) \tag{12}$$

where y= production, x_j= input j and α_i and β_{ij} are unknown parameters. Table 4 shows the input elasticities for the green water variable and the water input variable in the production functions of citrus, maize and sugarcane. The calculations are performed for the OLS estimation methods including proxy variables and dummy variables.

Table 4: Input elasticities of the green water variable and the water input variable in the production functions of citrus, maize and sugarcane using OLS estimation

	Variable	OLS with proxies	OLS with dummies
Citrus	GW	0.69	-1.03
	WI	0.87	0.37
Maize	GW	0.23	-1.18
	WI	-0.22	0.36
Sugarcane	GW	n.a.	0.60
	WI	n.a.	-0.33

For model 1, the input elasticities are calculated for citrus and maize since no estimation results are available for sugarcane. For both crops, the green water and water inputs are relatively inelastic (absolute value of the input elasticity is smaller than 1), which implies that the production is not very sensitive to a change in water input. Both input elasticities of citrus are positive, in accordance to the assumption of the translog production function. However, the water input elasticity of maize is negative, which is not in accordance with the assumption of the translog production function. Moreover, none of the estimated parameters is significant (see Appendix E) and just four countries could be included to estimate the production functions of citrus and maize. Therefore, we conclude that the estimation results of model 1 are insufficient to be used for the calculation of the shadow prices.

For model 2, the water input elasticities are relatively inelastic. This is reasonable for citrus and maize since these crops are relatively low water consuming crops. However, for sugarcane we would expect a higher water input elasticity since this crop is a high water consuming crop (and in particular blue water). The water input elasticities of citrus and maize are positive, in contrast to the water input elasticity of sugarcane. The negative water input elasticity for sugarcane is not what we expected according to the assumptions of the translog production function but reasonable since sugarcane is produced in wet areas with water abundance. The green water inputs for citrus and maize are rather elastic (absolute value of the input elasticity is greater than 1), implying that citrus and maize production are relatively sensitive to a change in green water input. However, the negative elasticities are not in accordance with the assumptions of the translog production function. Considering the advantages of model 3 compared to model 2 (described in Chapter 4) and the negative input elasticities in model 2, we decide not to use the estimation results of model 2 for the calculation of the shadow prices. Table 5 shows the input elasticities for model 3. When production is estimated, the input elasticity of area is larger than 1 for all three crops. Indicating that there are increasing returns to scale (an increase in area results in a higher increase in output). For citrus and maize, all input elasticities are positive which corresponds with the assumption of the translog production function. The water input elasticities for sugarcane are negative[3] (as in model 2). Possible reasons are an excess of water supply to sugarcane or insufficient data.

Table 4: Elasticities of the input variables in the production functions of citrus, maize and sugarcane using fixed effects panel estimation

	Citrus		**Maize**		**Sugarcane**	
	Production	Yield	Production	Yield	Production	Yield
Area	1.15	0.04	1.22	0.09	1.21	0.01
GW	0.06	0.02	0.49	0.50	0.49	0.44
WI	0.37	0.27	0.33	0.32	-0.29	-0.33

Hausman's specification test is performed to test if the fixed effects model or random effects model is appropriate. In the Hausman test two estimators are compared: the fixed effects estimator is consistent under the null and alternative hypothesis and the random effects estimator is consistent (and efficient) under the null hypothesis only (Verbeek, 2012). Details about the Hausman test are available in the Stata manual (Stata, 2015). Hausman's test indicated that the fixed effects model was most appropriate for all three crops. The estimation results for the fixed effects regression are offered in Table 6. Both production and yield are estimated for each crop. Table 6 shows that for most variables there is considerable variation. Moreover, many estimates are non-significant. The three reported R^2 measures are defined as the squared correlation coefficients between the actual and fitted values (Verbeek, 2012). They explain the within variation, between variation and overall variation (which is

[3] When a Cobb-Douglas production function for sugarcane yield is estimated, the elasticities of area, green water and water input are positive: 0.06, 0.32 and 0.39 respectively, see Appendix I for the estimates.

the sum of the within and between variation). For citrus yield, the model explains 36% of the within variation and 51% of the between variation, which is striking since fixed effects estimation is based on within variation.

Table 5: Fixed effects panel data estimates for the variables in the production functions of citrus, maize and sugarcane

Variable	**Fixed effects- Production**			**Fixed effects- Yield**		
	Citrus	Maize	Sugarcane	Citrus	Maize	Sugarcane
Area	-1.78***	1.18**	1.74	-0.02	0.67***	-0.24
	(0.68)	(0.50)	(1.48)	(0.23)	(0.08)	(0.20)
GW	0.60	-0.96	8.46***	1.07	-1.50*	16.13***
	(0.61)	(0.64)	(1.02)	(1.06)	(0.82)	(2.18)
WI	-0.62	2.76***	-11.39***	2.22	4.74***	-14.63***
	(1.29)	(1.05)	(2.43)	(1.76)	(1.06)	(2.84)
Area2	0.01	0.08***	0.31***	0.01*	-0.02***	0.01***
	(0.05)	(0.02)	(0.11)	(0.00)	(0.00)	(0.00)
GW2	0.16***	0.12**	0.50***	0.85***	1.00***	3.11***
	(0.05)	(0.05)	(0.08)	(0.20)	(0.25)	(0.48)
WI2	0.02	-0.08	1.55***	0.04	-0.30	6.79***
	(0.12)	(0.12)	(0.28)	(0.35)	(0.36)	(0.94)
Area*GW	-0.10***	-0.04	0.11	-0.10**	0.04	-0.64***
	(0.04)	(0.03)	(0.07)	(0.05)	(0.04)	(0.08)
Area*WI	0.24***	-0.02	-0.31**	0.02	-0.15***	0.60***
	(0.07)	(0.05)	(0.15)	(0.07)	(0.05)	(0.10)
GW*WI	-0.12**	-0.02	-0.90***	-1.48***	-0.98*	-10.27***
	(0.05)	(0.07)	(0.12)	(0.46)	(0.58)	(1.33)
t	0.02	0.15***	-0.01	0.01***	0.01***	0.00
	(0.02)	(0.02)	(0.02)	(0.00)	(0.00)	(0.00)
_cons	13.95*	-30.54***	33.11***	-1.89	-7.47***	2.25
	(6.61)	(4.91)	(11.71)	(2.82)	(0.93)	(2.89)
R^2 *within*	0.94	0.93	0.88	0.36	0.73	0.76
R^2 *between*	0.73	0.92	0.94	0.51	0.01	0.40
R^2 *overall*	0.75	0.90	0.93	0.28	0.00	0.18

Notes: *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Figure 2 shows the shadow prices of non-renewable groundwater for all three crops. The shadow prices are comparable between the countries since the estimation results of the yield production function are used to calculate the shadow prices. For citrus, Iran and China have the highest shadow price, while Egypt and Mexico have the lowest shadow price in 2013 (Figure 2(a)). Iran has relatively high output prices compared to the other countries. Shadow prices for Saudi Arabia are not included in the graph since not more than five output prices are available. Also for maize, Iran and China have the highest shadow prices in 2013. South Africa and the USA have the lowest shadow prices, indicating that a m3 of non-renewable groundwater generates the lowest crop value in those countries in 2013. Overall, the graph shows an upward trend in shadow prices between 1991-2013 (Figure 2(b)). The shadow prices for sugarcane are negative (Figure 2(c)). This is not what we expected and could be caused by adding to much groundwater to sugarcane or an inappropriate model for sugarcane yield estimation. Therefore, the results for sugarcane should be handled with care.

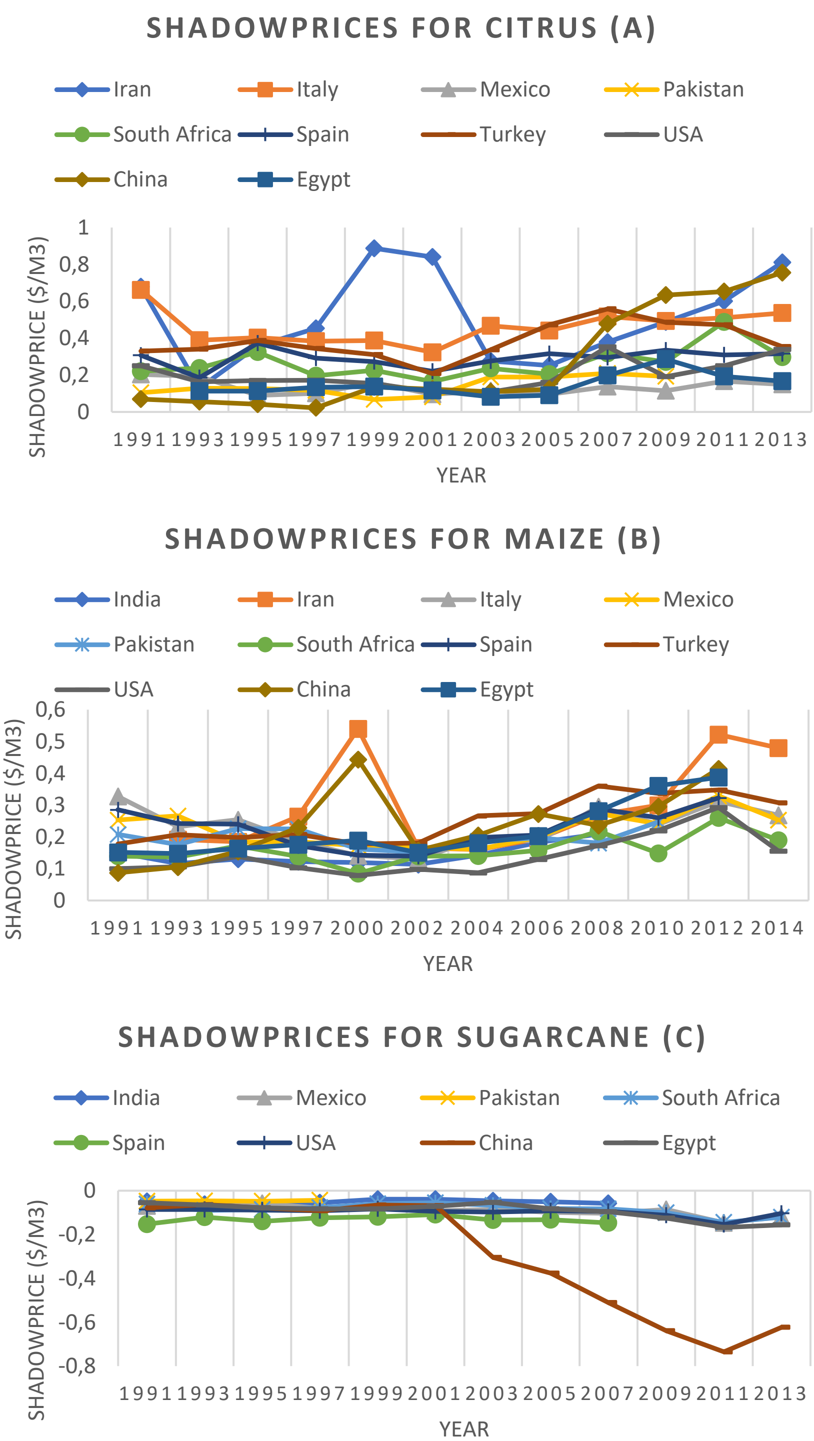

Figure 2: Shadow prices of non-renewable groundwater for citrus (a), maize (b) and sugarcane (c) between 1991 and 2014.

6 Conclusions and discussion

This chapter provides the answers on the research questions which are presented in Chapter 1. In addition, we deliver a general reflection on the model we used and show how the results are related to previous studies. On the basis of a translog production function, a fixed effects panel data model has been estimated to calculate the shadow prices of non-renewable groundwater for citrus, maize and sugarcane by including data of the twelve largest non-renewable groundwater using countries. Crop yield is used as dependent variable which enables comparison between the countries. Area, green water and water input (blue water and non-renewable groundwater) are the independent variables in our model. All independent variables are converted to inputs per hectare. Taking the partial derivative of crop yield with respect to the water input gives the marginal product of non-renewable groundwater. Multiplying the marginal product by the crop output price gives the shadow price. A fixed effects panel data model was most appropriate since this model results in more efficient estimates compared to other estimation methods. We tested if a fixed effects model would be more appropriate than a random effects model, which was not the case.

We found positive shadow prices for non-renewable groundwater applied to citrus and maize during the period 1991-2013, indicating that farmers could increase their yield by adding extra non-renewable groundwater. In 2013, shadow prices for citrus ranged between 0.81 USD/m3 and 0.15 USD/m3 and for maize between 0.53 USD/m3 and 0.19 USD/m3. For sugarcane, we found negative shadow prices, ranging between -0.10 USD/m3 and -0.62 USD/m3 in 2013. A negative shadow price implies that for each m3 non-renewable groundwater added yield is decreased, i.e. farmers could increase their profits when they decrease the non-renewable water input for sugarcane. Probably, risk plays an important role in the farmer's water application decision. Sugarcane is a high water consumption crop. Farmers may apply an excess of water since the price for water is low and they are avoiding the risk of lower yield due to a deficiency in water application. We recommend to calculate shadow prices for more crops. Results can be used to determine the optimal crop mix to be produced in a certain region, dependent on the aim of reducing non-renewable groundwater use or maximising crop yield per m3 of non-renewable groundwater. In the first case, farmers should produce a crop (mix) which generates the same profit but uses less non-renewable groundwater (i.e. crops that generate a higher value per added m3 of non-renewable groundwater). In the latter case, farmers produce the crop with the highest shadow price for non-renewable groundwater.

Our model might suffer from omitted variable(s) since no data were available for labour, capital and variable inputs for each country. These variables are usually included into a production function. In panel data estimation, the potential omitted variable bias is smaller compared to ordinary least squares estimation (Baltagi, 2008). We decided to estimate a translog production function however a Cobb-Douglas and quadratic production can be estimated as well. Our research obtained one marginal product for farmers in all countries together. The research may be further improved by estimating the production function for each country separately which results in a specific marginal product for each country. The production level for maximum profit is reached when the value of the marginal product is equal to zero. Comparison of marginal products between countries provides an inside in the production efficiency of crops per country. Some countries can produce a certain crop more efficiently and use groundwater more efficiently.

Groundwater depletion can be considered as an external cost. Other people (probably in the future) may face higher costs because of a shortage of non-renewable groundwater, while they are not involved in the decisions about groundwater use. These external costs are not included in the farmer's decision making. Therefore, government regulation should prevent groundwater depletion and encourage farmers to produce a crop mix that reduces non-renewable groundwater use. In order to reduce inefficient groundwater use, production of crops with a negative shadow price, like sugarcane, should be banned in regions with a risk of groundwater depletion. Regulations should be developed for the amount of non-renewable groundwater used for irrigation since a well-functioning market for water does not exist. In environmental policy two main types of economic instruments exist: price-based measures (e.g. taxes or charges) and rights-based measures (e.g. tradeable permits) (Carter, 2001). De Fraiture & Perry (2002) show that irrigation water demand is inelastic at low prices. The response of water demand to increased water charges is therefore low until a certain threshold (water price is equal to productive value), beyond that threshold water demand becomes elastic. Only a considerable increase in water prices can encourage farmers to use less water for irrigation (De Fraiture & Perry, 2002). Governments can maintain a ban on certain crops rather easy at relatively low costs, since it is visible which crop is produced. However, if the government sets charges or permits for groundwater use, this system should be monitored which involves additional costs. In some of the largest non-renewable groundwater using countries this system may also be vulnerable to corruption.

According to Kumar (2006), water use can be broadly divided into three categories: agricultural, industrial and domestic. In our research, we calculated shadow prices for agricultural water use. Liu and Chen (2008) calculated shadow prices for industrial water (all water used in the industrial sector) and productive water (all water used in agriculture, industry, construction and service sectors) in nine river basins in China in 1999. They found that shadow prices were higher for industrial water than for productive water for each river basin. Shadow prices for industrial water range between 0.18 RMB/ton

(≈0.03 USD/m3) and 5.13 RMB/ton (≈0.77 USD/m3), while shadow prices for productive water range between 0.02 RMB/ton (≈0.003 USD/m3) and 2.34 RMB/ton (≈0.35 USD/m3). Their explanation for the lower shadow price for productive water is that productive water mainly consists of agricultural water, which is free or very low priced in China. The shadow prices we found for China in 1999 (citrus 0.13 USD/m3 and maize 0.16 USD/m3) fit well within the range of shadow prices for productive water found by Liu and Chen (2008).

Kumar (2006) investigated the water demand of 92 manufacturing firms in India between 1996/97 and 1998/99. He found an average shadow price of 7.21 INR/m3 (≈0.11 USD/m3). This shadow price is comparable to the shadow price we found for maize in India (0.12 USD/m3 for 1996, 1997 and 1998), implying that the average value produced by the last m3 of water was not higher for the industrial sector than for maize production. Kumar (2006)found that the price elasticity for water in the industrial sector in India is high (-1.11 on average), so in this sector water charges may be more effective than in the agricultural sector. Ziolkowska (2015) analysed the shadow prices of irrigation water in three High Plain states in the USA: Texas, Kansas and Nebraska. The estimated values of shadow prices for maize were 0.07 USD/m3 (Texas Northern High Plain), 0.004 USD/m3 (Texas Southern High Plain), 0.06 USD/m3 (Kansas) and 0.02 USD/m3 (Nebraska) in 2010. These values are substantially lower than the shadow price of 0.22 USD/m3 which we found for maize in the USA in 2010. Shadow prices may differ per region, and therefore our model results may be further improved by estimating a production function per region rather than per country.

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Appendix A

This appendix shows a description of the three production functions and their partial derivatives with respect to non-renewable groundwater. It provides an overview of the parameters and marginal products, when either total production or yield (production/ha) is used as dependent variable. Firstly, we describe the Cobb-Douglas production function, secondly the trans-log production function and lastly the quadratic production function.

Cobb-Douglas production function

The Cobb-Douglas production function is represented by the following equation:

$$Y = \beta_0 \cdot A^{\beta 1} \cdot L^{\beta 2} \cdot K^{\beta 3} \cdot GW^{\beta 4} \cdot BW^{\beta 5} \cdot NRGW^{\beta 6}$$

This equation can be rewritten into log form for estimation purposes:

$$lnY = ln\beta_0 + \beta_1 lnA + \beta_2 lnL + \beta_3 lnK + \beta_4 lnGW + \beta_5 lnBW + \beta_6 lnNRGW$$

Taking the partial derivative of crop production with respect to non-renewable groundwater leads to the following marginal product:

$$MP_{NRGW} = \frac{\partial Y}{\partial NRGW} = \beta_6 \cdot \beta_0 \cdot A^{\beta 1} \cdot L^{\beta 2} \cdot K^{\beta 3} \cdot GW^{\beta 4} \cdot BW^{\beta 5} \cdot NRGW^{\beta 6-1} = \beta_6 \cdot \frac{Y}{NRGW}$$

$$MP_{NRGW} = \frac{\partial lnY}{\partial lnNRGW} \cdot \frac{Y}{NRGW} = \beta_6 \cdot \frac{Y}{NRGW}$$

The parameters of the Cobb-Douglas production function can be interpreted as input elasticities:

$$e_{NRGW} = \frac{\partial Y}{\partial NRGW} \cdot \frac{NRGW}{Y} = \beta_6 \frac{Y}{NRGW} \cdot \frac{NRGW}{Y} = \beta_6$$

When yield $\left(\frac{Y}{A}\right)$ is estimated, both sides of the production function are divided by area (A):

$$\left(\frac{Y}{A}\right) = \left(\frac{\beta_0 A^{\beta 1} \cdot L^{\beta 2} \cdot K^{\beta 3} \cdot GW^{\beta 4} \cdot BW^{\beta 5} \cdot NRGW^{\beta 6}}{A}\right)$$

$$\left(\frac{Y}{A}\right) = \left(\beta_0 \cdot A^{\beta 1} \cdot L^{\beta 2} \cdot K^{\beta 3} \cdot GW^{\beta 4} \cdot BW^{\beta 5} \cdot NRGW^{\beta 6}\right) \cdot A^{-1}$$

$$\left(\frac{Y}{A}\right) = \left(\frac{\beta_0}{A}\right) \cdot A^{\beta 1-1} \cdot \left(\frac{L}{A}\right)^{\beta 2} \cdot \left(\frac{K}{A}\right)^{\beta 3} \cdot \left(\frac{GW}{A}\right)^{\beta 4} \cdot \left(\frac{BW}{A}\right)^{\beta 5} \cdot \left(\frac{NRGW}{A}\right)^{\beta 6} =$$

$$\beta_0 \cdot A^{\beta 1-2} \cdot \left(\frac{L}{A}\right)^{\beta 2} \cdot \left(\frac{K}{A}\right)^{\beta 3} \cdot \left(\frac{GW}{A}\right)^{\beta 4} \cdot \left(\frac{BW}{A}\right)^{\beta 5} \cdot \left(\frac{NRGW}{A}\right)^{\beta 6}$$

Trans-log production function

The trans-log production function is represented by the following equation:

$$lnY = \beta_0 + \beta_1 lnA + \beta_2 lnL + \beta_3 lnK + \beta_4 lnGW + \beta_5 lnWI + 0.5\beta_{11} lnA^2 + 0.5\beta_{22} lnL^2 + 0.5\beta_{33} lnK^2 + 0.5\beta_{44} lnGW^2 + 0.5\beta_{55} lnWI^2 + \beta_{12} lnA \cdot lnL + \beta_{13} lnA \cdot lnK + \beta_{14} lnA \cdot lnGW + \beta_{15} lnA \cdot lnWI + \beta_{23} lnL \cdot lnK + \beta_{24} lnL \cdot lnGW + \beta_{25} lnL \cdot lnWI + \beta_{34} lnK \cdot lnGW + \beta_{35} lnK \cdot lnWI + \beta_{45} lnGW \cdot lnWI$$

Taking the partial derivative of crop production with respect to the water input leads to the following marginal product:

$$MP_{WI} = \frac{\partial lnY}{\partial lnWI} \cdot \frac{Y}{WI} = (\gamma_0 + \gamma_1 lnWI + \gamma_2 lnA + \gamma_3 lnL + \gamma_4 lnK + \gamma_5 lnGW) \cdot \frac{Y}{WI}$$

Where $\gamma_0 = \beta_5$, $\gamma_1 = \beta_{65}$, $\gamma_2 = \beta_{15}$, $\gamma_3 = \beta_{25}$, $\gamma_4 = \beta_{35}$ and $\gamma_5 = \beta_{45}$.

When yield $\left(\frac{Y}{A}\right)$ is used, all variables on both sides of the production function should be divided by area (A). First, we add and subtract lnA_{it} ($ln\left(\frac{Y}{A}\right) = lnY - lnA$):

$$\begin{aligned} ln\left(\frac{Y_{it}}{A_{it}}\right) = {} & \beta_0 + (\beta_1 + \beta_2 + \beta_3 - 1) lnA_{it} \\ & + \beta_2 ln\left(\frac{GW_{it}}{A_{it}}\right) \\ & + \beta_3 ln\left(\frac{WI_{it}}{A_{it}}\right) \\ & + 0.5\beta_4 ln^2 A_{it} \\ & + 0.5\beta_5 ln^2 GW_{it} - 0.5\beta_5 lnGW_{it} lnA_{it} + 0.5\beta_5 lnGW_{it} lnA_{it} \\ & + 0.5\beta_6 ln^2 WI_{it} - 0.5\beta_6 lnWI_{it} lnA_{it} + 0.5\beta_6 lnWI_{it} lnA_{it} \\ & + \beta_7 lnA_{it} \cdot lnGW_{it} - \beta_7 lnA_{it} \cdot lnA_{it} + \beta_7 lnA_{it} \cdot lnA_{it} \\ & + \beta_8 lnA_{it} \cdot lnWI_{it} - \beta_8 lnA_{it} \cdot lnA_{it} + \beta_8 lnA_{it} \cdot lnA_{it} \\ & + \beta_9 lnGW_{it} \cdot lnWI_{it} - \beta_9 lnGW_{it} \cdot lnA_{it} + \beta_9 lnGW_{it} \cdot lnA_{it} \\ & + \varepsilon_{it} = \end{aligned}$$

$$\begin{aligned} ln\left(\frac{Y_{it}}{A_{it}}\right) = {} & \beta_0 + (\beta_1 + \beta_2 + \beta_3 - 1) lnA_{it} + \beta_2 ln\left(\frac{GW_{it}}{A_{it}}\right) + \beta_3 ln\left(\frac{WI_{it}}{A_{it}}\right) \\ & + (0.5\beta_4 + \beta_7 + \beta_8) ln^2 A_{it} \\ & + \beta_7 lnA_{it} \cdot (lnGW_{it} - lnA_{it}) \\ & + \beta_8 lnA_{it} \cdot (lnWI_{it} - lnA_{it}) \\ & + (0.5\beta_5 + \beta_9) lnGW_{it} lnA_{it} \\ & + 0.5\beta_6 lnWI_{it} lnA_{it} \\ & + 0.5\beta_5 lnGW_{it}(lnGW_{it} - lnA_{it}) \\ & + 0.5\beta_6 lnWI_{it}(lnWI_{it} - lnA_{it}) \end{aligned}$$

$$+\beta_9 lnGW_{it} \cdot (lnWI_{it} - lnA_{it})$$
$$+\varepsilon_{it}$$

Next, we divide the remaining terms by area:

$$ln\left(\frac{Y_{it}}{A_{it}}\right) = \beta_0 + (\beta_1 + \beta_2 + \beta_3 - 1)lnA_{it} + \beta_2 ln\left(\frac{GW_{it}}{A_{it}}\right) + \beta_3 ln\left(\frac{WI_{it}}{A_{it}}\right)$$
$$+(0.5\beta_4 + \beta_7 + \beta_8)ln^2 A_{it}$$
$$+\beta_7 lnA_{it} \cdot (lnGW_{it} - lnA_{it})$$
$$+\beta_8 lnA_{it} \cdot (lnWI_{it} - lnA_{it})$$
$$+(0.5\beta_5 + \beta_9)lnGW_{it}lnA_{it} - (0.5\beta_5 + \beta_9)lnA_{it}lnA_{it} + (0.5\beta_5 + \beta_9)lnA_{it}lnA_{it}$$
$$+0.5\beta_6 lnWI_{it}lnA_{it} - (0.5\beta_6)lnA_{it}lnA_{it} + (0.5\beta_6)lnA_{it}lnA_{it}$$
$$+0.5\beta_5 lnGW_{it}(lnGW_{it} - lnA_{it}) - 0.5\beta_5 lnA_{it}(lnGW_{it} - lnA_{it})$$
$$+ 0.5\beta_5 lnA_{it}(lnGW_{it} - lnA_{it})$$
$$+0.5\beta_6 lnWI_{it}(lnWI_{it} - lnA_{it}) - 0.5\beta_6 lnA_{it}(lnWI_{it} - lnA_{it}) + 0.5\beta_6 lnA_{it}(lnWI_{it} - lnA_{it})$$
$$+\beta_9 lnGW_{it} \cdot (lnWI_{it} - lnA_{it}) - \beta_9 lnA_{it} \cdot (lnWI_{it} - lnA_{it}) + \beta_9 lnA_{it} \cdot (lnWI_{it} - lnA_{it})$$
$$+\varepsilon_{it} =$$

$$ln\left(\frac{Y_{it}}{A_{it}}\right) = \beta_0 + (\beta_1 + \beta_2 + \beta_3 - 1)lnA_{it} + \beta_2 ln\left(\frac{GW_{it}}{A_{it}}\right) + \beta_3 ln\left(\frac{WI_{it}}{A_{it}}\right)$$
$$+(0.5\beta_4 + \beta_7 + \beta_8)ln^2 A_{it}$$
$$+\beta_7 lnA_{it} \cdot (lnGW_{it} - lnA_{it})$$
$$+\beta_8 lnA_{it} \cdot (lnWI_{it} - lnA_{it})$$
$$+(0.5\beta_5 + \beta_9)(lnGW_{it} - lnA_{it})lnA_{it} + (0.5\beta_5 + \beta_9)lnA_{it}lnA_{it}$$
$$+(0.5\beta_6)(lnWI_{it} - lnA_{it})lnA_{it} + (0.5\beta_6)lnA_{it}lnA_{it}$$
$$+0.5\beta_5(lnGW_{it} - lnA_{it})(lnGW_{it} - lnA_{it}) + 0.5\beta_5 lnA_{it}(lnGW_{it} - lnA_{it})$$
$$+0.5\beta_6(lnWI_{it} - lnA_{it})(lnWI_{it} - lnA_{it}) + 0.5\beta_6 lnA_{it}(lnWI_{it} - lnA_{it})$$
$$+\beta_9(lnGW_{it} - lnA_{it})\ (lnWI_{it} - lnA_{it}) + \beta_9 lnA_{it} \cdot (lnWI_{it} - lnA_{it})$$
$$+\varepsilon_{it} =$$

$$ln\left(\frac{Y_{it}}{A_{it}}\right) = \beta_0 + (\beta_1 + \beta_2 + \beta_3 - 1)lnA_{it} + \beta_2 ln\left(\frac{GW_{it}}{A_{it}}\right) + \beta_3 ln\left(\frac{WI_{it}}{A_{it}}\right)$$
$$+(0.5\beta_4 + \beta_7 + \beta_8 + 0.5\beta_5 + \beta_9 + 0.5\beta_6)ln^2 A_{it}$$

$$+(\beta_7 + \beta_5 + \beta_9)(lnGW_{it} - lnA_{it})lnA_{it}$$

$$+(\beta_8 + \beta_6 + \beta_9)(lnWI_{it} - lnA_{it})lnA_{it}$$
$$+0.5\beta_5(lnGW_{it} - lnA_{it})(lnGW_{it} - lnA_{it})$$
$$+0.5\beta_6(lnWI_{it} - lnA_{it})(lnWI_{it} - lnA_{it})$$
$$+\beta_9(lnGW_{it} - lnA_{it})\ (lnWI_{it} - lnA_{it})$$
$$+\varepsilon_{it} =$$

$$ln\left(\frac{Y_{it}}{A_{it}}\right) = \beta_0 + (\beta_1 + \beta_2 + \beta_3 - 1)lnA_{it} + \beta_2 ln\left(\frac{GW_{it}}{A_{it}}\right) + \beta_3 ln\left(\frac{WI_{it}}{A_{it}}\right)$$
$$+(0.5\beta_4 + \beta_7 + \beta_8 + 0.5\beta_5 + \beta_9 + 0.5\beta_6)ln^2A_{it}$$
$$+(\beta_7 + \beta_5 + \beta_9)\left(\frac{lnGW_{it}}{lnA_{it}}\right)lnA_{it}$$
$$+(\beta_8 + \beta_6 + \beta_9)\left(\frac{lnWI_{it}}{lnA_{it}}\right)lnA_{it}$$
$$+0.5\beta_5\left(\frac{lnGW_{it}}{lnA_{it}}\right)^2$$
$$+0.5\beta_6\left(\frac{lnWI_{it}}{lnA_{it}}\right)^2$$
$$+\beta_9\left(\frac{lnGW_{it}}{lnA_{it}}\right)\left(\frac{lnWI_{it}}{lnA_{it}}\right)$$
$$+\varepsilon_{it} =$$

$$ln\left(\frac{Y_{it}}{A_{it}}\right) = \gamma_0 + \gamma_1 lnA_{it} + \gamma_2\left(\frac{lnGW_{it}}{lnA_{it}}\right) + \gamma_3\left(\frac{lnWI_{it}}{lnA_{it}}\right) + \gamma_4 ln^2A_{it} + \gamma_5\left(\frac{lnGW_{it}}{lnA_{it}}\right)lnA_{it}$$
$$+\gamma_6\left(\frac{lnWI_{it}}{lnA_{it}}\right)lnA_{it} + \gamma_7\left(\frac{lnGW_{it}}{lnA_{it}}\right)^2 + \gamma_8\left(\frac{lnWI_{it}}{lnA_{it}}\right)^2 + \gamma_9\left(\frac{lnGW_{it}}{lnA_{it}}\right)\left(\frac{lnWI_{it}}{lnA_{it}}\right)$$
$$+\varepsilon_{it}$$

Where $\gamma_0 = \beta_0$, $\gamma_1 = (\beta_1 + \beta_2 + \beta_3 - 1)$, $\gamma_2 = \beta_2$, $\gamma_3 = \beta_3$, $\gamma_4 = (0.5\beta_4 + \beta_7 + \beta_8 + 0.5\beta_5 + \beta_9 + 0.5\beta_6)$, $\gamma_5 = (\beta_7 + \beta_5 + \beta_9)$, $\gamma_6 = (\beta_8 + \beta_6 + \beta_9)$, $\gamma_7 = 0.5\beta_5$, $\gamma_8 = 0.5\beta_6$ and $\gamma_9 = \beta_9$.

Taking the partial derivative of yield with respect to the water input per hectare gives the following marginal product:

$$MP_{WI} = \frac{\partial ln\left(\frac{Y}{A}\right)}{\partial ln\left(\frac{WI}{A}\right)} \cdot \frac{\left(\frac{Y}{A}\right)}{\left(\frac{WI}{A}\right)} = \gamma_3 + \gamma_6 lnA + 2\gamma_8 ln\left(\frac{WI}{A}\right) + \gamma_9 ln\left(\frac{GW}{A}\right) \cdot \frac{\left(\frac{Y}{A}\right)}{\left(\frac{WI}{A}\right)}$$

Quadratic production function

The quadratic production function is represented by the following equation:

$$Y = \beta_0 + \beta_1 A + \beta_2 A^2 + \beta_3 L + \beta_4 L^2 + \beta_5 K + \beta_6 K^2 + \beta_7 GW + \beta_8 GW^2 + \beta_9 WI + \beta_{10} WI^2 + \beta_{11} A \cdot L + \beta_{12} A \cdot K + \beta_{13} A \cdot GW + \beta_{14} A \cdot WI + \beta_{15} L \cdot K + \beta_{16} L \cdot GW + \beta_{17} L \cdot WI + \beta_{18} K \cdot GW + \beta_{19} K \cdot WI + \beta_{20} GW \cdot WI$$

Taking the partial derivative of crop production with respect to the water input leads to the following marginal product:

$MP_{NRWI} = \frac{\partial Y}{\partial WI} = \gamma_0 + \gamma_1 WI + \gamma_2 A + \gamma_3 L + \gamma_4 K + \gamma_5 GW$

Where $\gamma_0 = \beta_9$, $\gamma_1 = 2\beta_{10}$, $\gamma_2 = \beta_{14}$, $\gamma_3 = \beta_{17}$, $\gamma_4 = \beta_{19}$ and $\gamma_5 = \beta_{20}$.

When yield $\left(\frac{Y}{A}\right)$ is used, both sides of the production function are divided by area (A):

$$\left(\frac{Y}{A}\right) = \left(\frac{\beta_0}{A}\right) + \beta_1\left(\frac{A}{A}\right) + \beta_2\left(\frac{A}{A}\right)^2 + \beta_3\left(\frac{L}{A}\right) + \beta_4\left(\frac{L}{A}\right)^2 + \beta_5\left(\frac{K}{A}\right) + \beta_6\left(\frac{K}{A}\right)^2 + \beta_7\left(\frac{GW}{A}\right) + \beta_8\left(\frac{GW}{A}\right)^2 + \beta_9\left(\frac{WI}{A}\right) + \beta_{10}\left(\frac{WI}{A}\right)^2 + \beta_{11}\left(\frac{A}{A}\right)\cdot\left(\frac{L}{A}\right) + \beta_{12}\left(\frac{A}{A}\right)\cdot\left(\frac{K}{A}\right) + \beta_{13}\left(\frac{A}{A}\right)\cdot\left(\frac{GW}{A}\right) + \beta_{14}\left(\frac{A}{A}\right)\cdot\left(\frac{WI}{A}\right) + \beta_{15}\left(\frac{L}{A}\right)\cdot\left(\frac{K}{A}\right) + \beta_{16}\left(\frac{L}{A}\right)\cdot\left(\frac{GW}{A}\right) + \beta_{17}\left(\frac{L}{A}\right)\cdot\left(\frac{WI}{A}\right) + \beta_{18}\left(\frac{K}{A}\right)\cdot\left(\frac{GW}{A}\right) + \beta_{19}\left(\frac{K}{A}\right)\cdot\left(\frac{WI}{A}\right) + \beta_{20}\left(\frac{GW}{A}\right)\cdot\left(\frac{WI}{A}\right) =$$

$$\left(\frac{Y}{A}\right) = \left(\frac{\beta_0}{A}\right) + (\beta_1 + \beta_2) + \beta_3\left(\frac{L}{A}\right) + \beta_4\left(\frac{L}{A}\right)^2 + \beta_5\left(\frac{K}{A}\right) + \beta_6\left(\frac{K}{A}\right)^2 + \beta_7\left(\frac{GW}{A}\right) + \beta_8\left(\frac{GW}{A}\right)^2 + \beta_9\left(\frac{WI}{A}\right) + \beta_{10}\left(\frac{WI}{A}\right)^2 + \beta_{11}\left(\frac{A}{A}\right)\cdot\left(\frac{L}{A}\right) + \beta_{12}\left(\frac{A}{A}\right)\cdot\left(\frac{K}{A}\right) + \beta_{13}\left(\frac{A}{A}\right)\cdot\left(\frac{GW}{A}\right) + \beta_{14}\left(\frac{A}{A}\right)\cdot\left(\frac{WI}{A}\right) + \beta_{15}\left(\frac{L}{A}\right)\cdot\left(\frac{K}{A}\right) + \beta_{16}\left(\frac{L}{A}\right)\cdot\left(\frac{GW}{A}\right) + \beta_{17}\left(\frac{L}{A}\right)\cdot\left(\frac{WI}{A}\right) + \beta_{18}\left(\frac{K}{A}\right)\cdot\left(\frac{GW}{A}\right) + \beta_{19}\left(\frac{K}{A}\right)\cdot\left(\frac{WI}{A}\right) + \beta_{20}\left(\frac{GW}{A}\right)\cdot\left(\frac{WI}{A}\right)$$

Taking the partial derivative of yield with respect to the water input per hectare leads to the following marginal product:

$$MP_{NRGW} = \frac{\partial\left(\frac{Y}{A}\right)}{\partial\left(\frac{NRGW}{A}\right)} = \gamma_0 + \gamma_1\left(\frac{WI}{A}\right) + \gamma_2\left(\frac{A}{A}\right) + \gamma_3\left(\frac{L}{A}\right) + \gamma_4\left(\frac{K}{A}\right) + \gamma_5\left(\frac{GW}{A}\right)$$

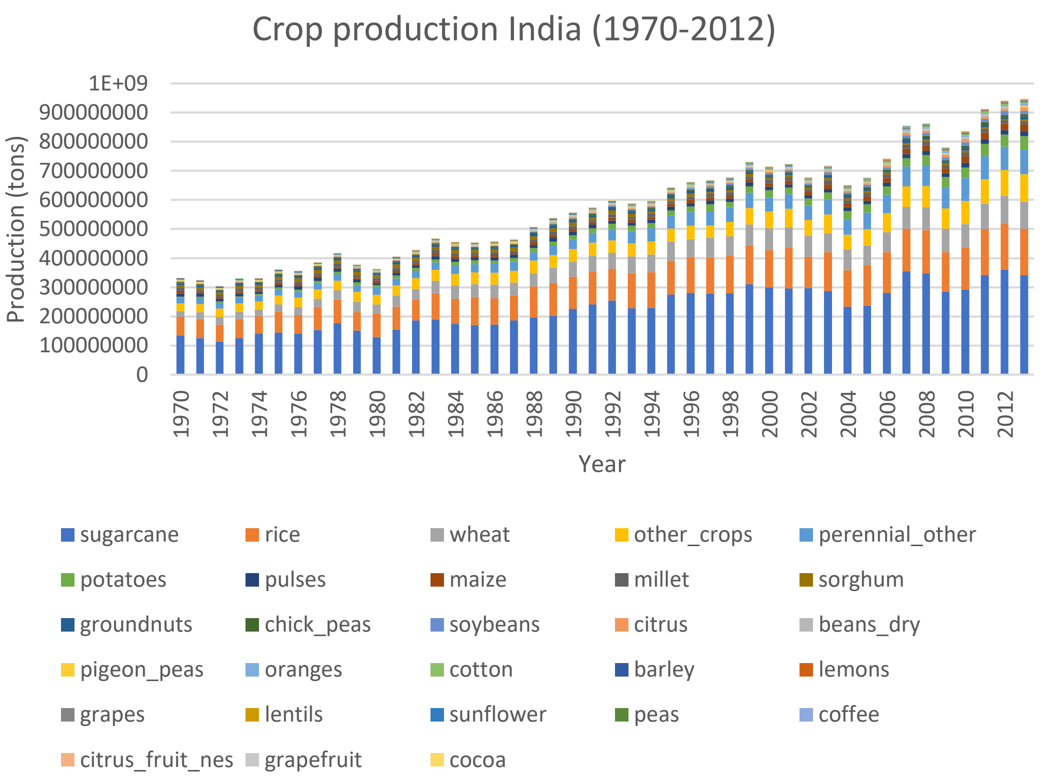
Where $\gamma_0 = \beta_9$, $\gamma_1 = 2\beta_{10}$, $\gamma_2 = \beta_{14}$, $\gamma_3 = \beta_{17}$, $\gamma_4 = \beta_{19}$ and $\gamma_5 = \beta_{20}$.

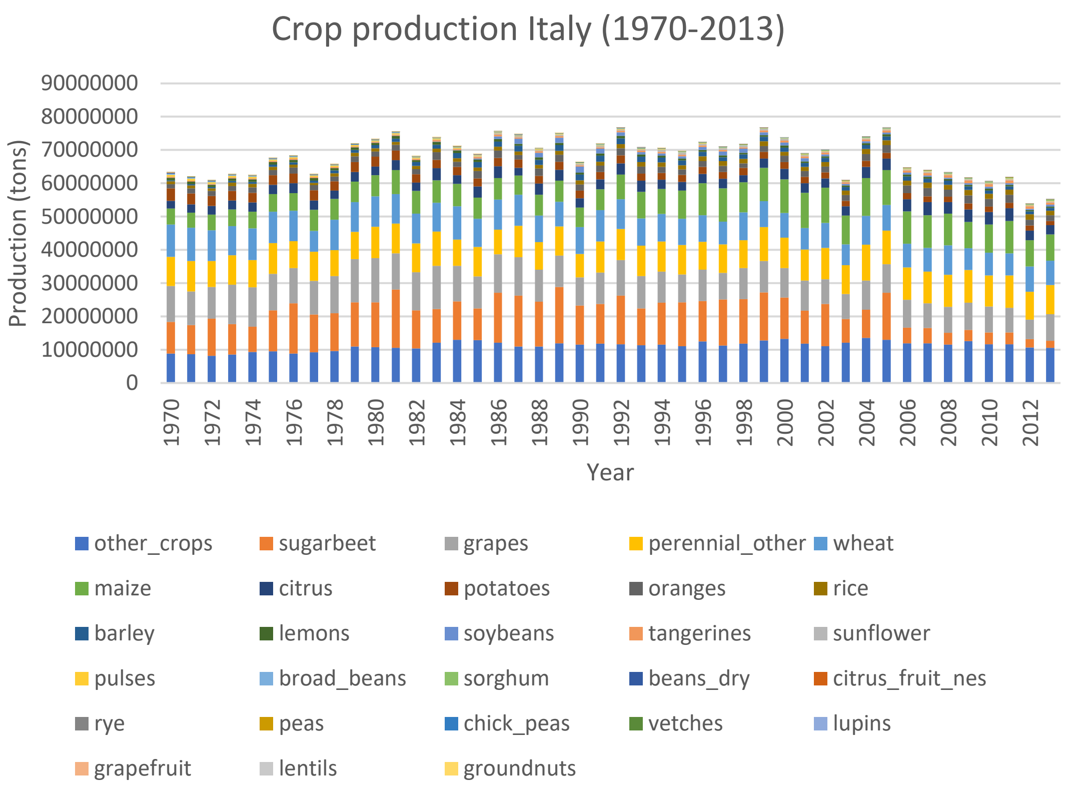
Appendix B

Overview of the ten most important crops produced per country (1000 tonnes), based on FAO (2016a):

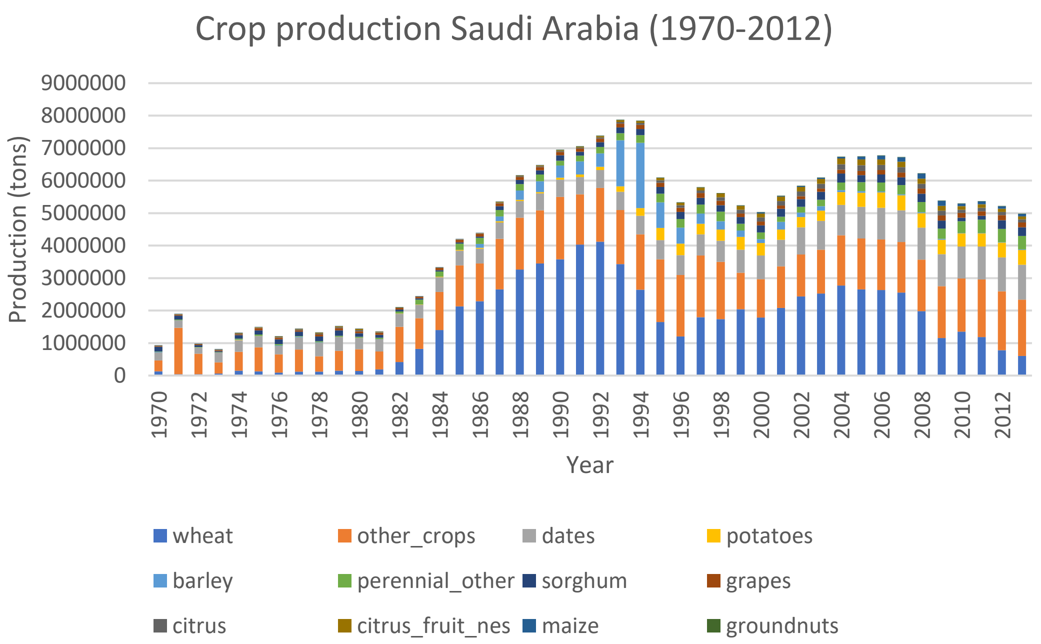
China		Egypt		India		Iran		Italy		Mexico	
rice	7618477	sugarcane	545520	sugarcane	10380218	wheat	389700	sugarbeet	469532	sugarcane	1908256
maize	4605872	maize	218993	rice	4883753	sugarbeet	195320	grapes	423516	maize	701844
wheat	3885583	wheat	209482	wheat	2488556	potatoes	119337	wheat	369367	sorghum	235927
sugarcane	2816625	rice	182485	potatoes	851666	sugarcane	118492	maize	342143	citrus	193877
potatoes	2117499	sugarbeet	99347	pulses	549034	barley	105994	citrus	132437	wheat	152455
soybeans	532829	citrus	91411	maize	499044	citrus	95793	potatoes	102576	oranges	124752
groundnu	385108	potatoes	87927	millet	455181	rice	89777	oranges	81200	pulses	61312
sugarbeet	383230	oranges	65160	sorghum	409950	grapes	75516	rice	54770	potatoes	53152
citrus	383085	sorghum	33757	groundnu	303164	oranges	52789	barley	50979	lemons	48573
pulses	234736	dates	33282	chick_pea	246636	maize	33766	lemons	28103	beans_dry	47558
Pakistan		**Saudi Arabia**		**South Africa**		**Spain**		**Turkey**		**USA**	
sugarcane	1818223	wheat	*71039*	sugarcane	830753	barley	353128	wheat	807912	maize	9939061
wheat	694647	dates	*26722*	maize	420585	sugarbeet	305093	sugarbeet	567777	soybeans	2807977
rice	260722	potatoes	*8827*	wheat	90526	grapes	242389	barley	296971	wheat	2638283
maize	80514	barley	*8657*	potatoes	59500	wheat	235746	potatoes	178128	sugarcane	1224835
citrus	66531	sorghum	*7282*	grapes	57379	citrus	196454	grapes	157945	sugarbeet	1156796
cotton	61513	grapes	*4158*	citrus	55294	potatoes	188185	maize	108172	potatoes	819369
potatoes	56996	citrus	*2979*	oranges	39360	maize	141687	citrus	81887	sorghum	695640
oranges	46634	citrus_frui	*2979*	sunflower	21763	oranges	105938	pulses	60013	citrus	537170
pulses	33327	maize	*1375*	sorghum	16776	tangerine	63106	oranges	41563	oranges	386555
chick_pea	24529	groundnut	*99*	grapefruit	8131	sunflower	34926	sunflower	38275	barley	351470

Overview of crop production of India, Italy, Saudi Arabia, Spain and Turkey, based on FAO (2016a):

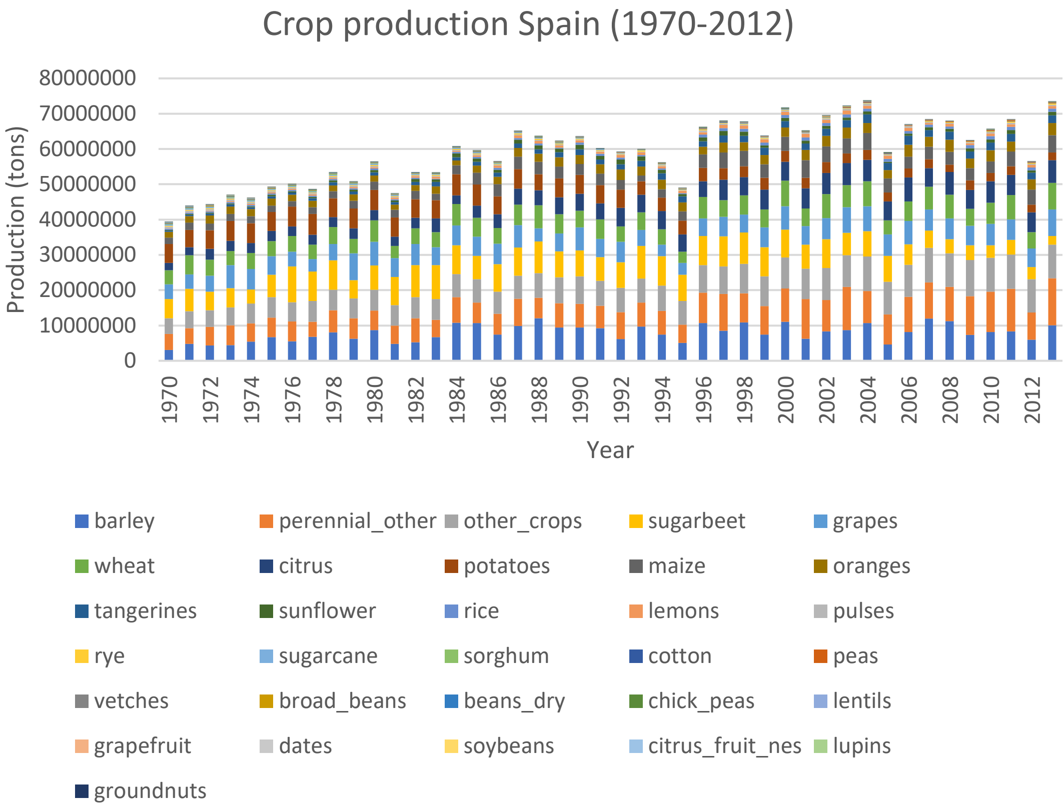


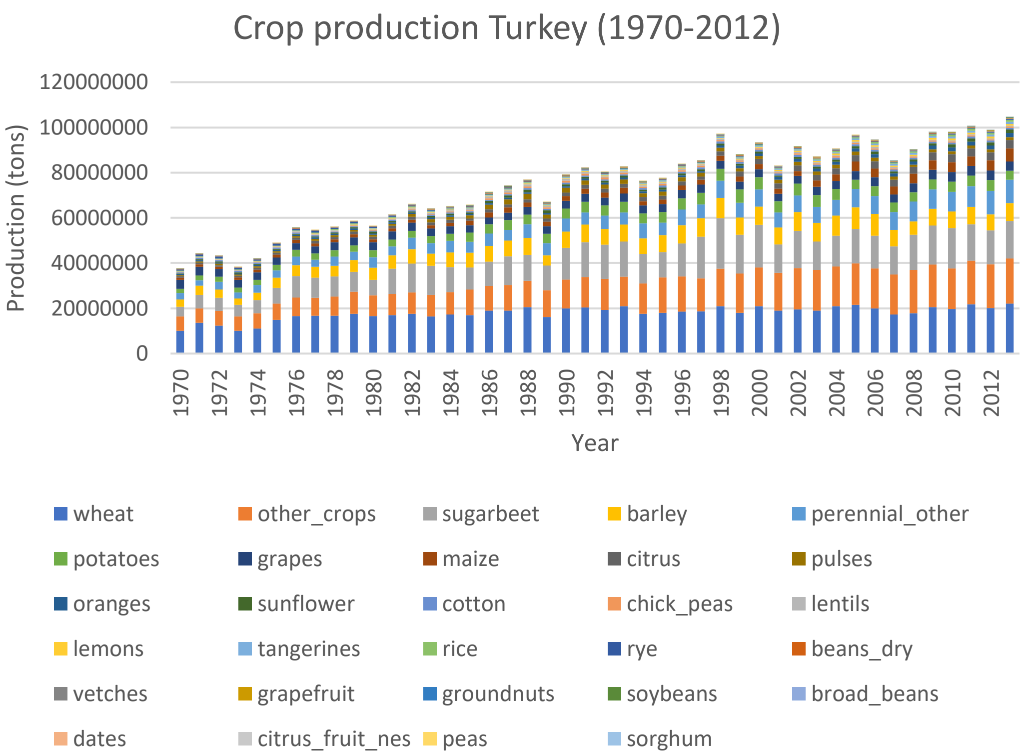


Crop production Italy (1970-2013)
90000000
80000000
70000000
60000000
50000000
40000000
30000000
20000000
10000000
0
Production (tons)
1970
1972
1974
1976
1978
1980
1982
1984
1986
1988
1990
1992
1994
1996
1998
2000
2002
2004
2006
2008
2010
2012
Year
other_crops
sugarbeet
grapes
perennial_other
wheat
maize
citrus
potatoes
oranges
rice
barley
lemons
soybeans
tangerines
sunflower
pulses
broad_beans
sorghum
beans_dry
citrus_fruit_nes
rye
peas
chick_peas
vetches
lupins
grapefruit
lentils
groundnuts



Crop production Saudi Arabia (1970-2012)
9000000
8000000
7000000
6000000
5000000
4000000
3000000
2000000
1000000
0
Production (tons)
1970
1972
1974
1976
1978
1980
1982
1984
1986
1988
1990
1992
1994
1996
1998
2000
2002
2004
2006
2008
2010
2012
Year
wheat
other_crops
dates
potatoes
barley
perennial_other
sorghum
grapes
citrus
citrus_fruit_nes
maize
groundnuts


Crop production Spain (1970-2012)
Production (tons)
80000000
70000000
60000000
50000000
40000000
30000000
20000000
10000000
0
1970
1972
1974
1976
1978
1980
1982
1984
1986
1988
1990
1992
1994
1996
1998
2000
2002
2004
2006
2008
2010
2012
Year
barley
perennial_other
other_crops
sugarbeet
grapes
wheat
citrus
potatoes
maize
oranges
tangerines
sunflower
rice
lemons
pulses
rye
sugarcane
sorghum
cotton
peas
vetches
broad_beans
beans_dry
chick_peas
lentils
grapefruit
dates
soybeans
citrus_fruit_nes
lupins
groundnuts


Crop production Turkey (1970-2012)
Production (tons)
120000000
100000000
80000000
60000000
40000000
20000000
0
1970
1972
1974
1976
1978
1980
1982
1984
1986
1988
1990
1992
1994
1996
1998
2000
2002
2004
2006
2008
2010
2012
Year
wheat
other_crops
sugarbeet
barley
perennial_other
potatoes
grapes
maize
citrus
pulses
oranges
sunflower
cotton
chick_peas
lentils
lemons
tangerines
rice
rye
beans_dry
vetches
grapefruit
groundnuts
soybeans
broad_beans
dates
citrus_fruit_nes
peas
sorghum

Appendix C

This appendix contains panel graphs and panel unit root tests for the variables of citrus, maize and sugarcane. The panel unit root test is shown for citrus production and performed in the same way for the other variables. The table below gives a summary of the outcomes: *yes* means that the data are stationary and *no* means that the data are nonstationary.

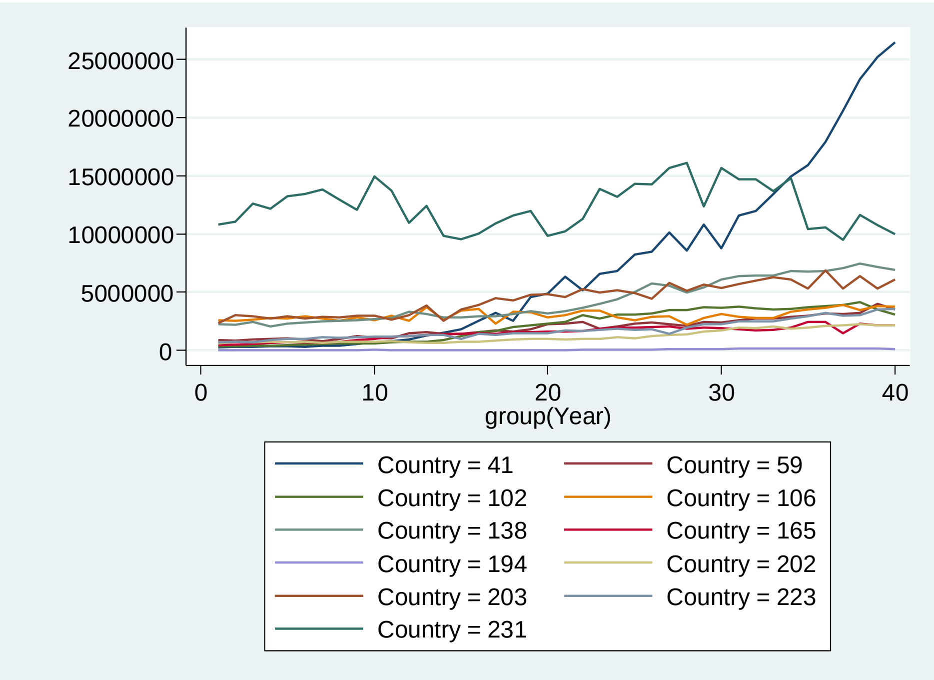
	Citrus		**Maize**		**Sugarcane**	
Variables	*Original*	*Ln*	*Original*	*Ln*	*Original*	*Ln*
Production	No	Yes	No	No	Yes/No*	Yes
Yield	No	Yes	No	Yes	Yes	Yes
Green water	No	Yes	Yes	Yes	Yes/No*	Yes
Blue water	No	Yes	No	Yes	No	No
Non-renewable groundwater	No	Yes	Yes/No*	Yes	Yes/No*	No

*Yes/No: Dependent on including a trend in the test or not. May be caused by country 100 (India) which deviates from rest of the countries in case of sugarcane.

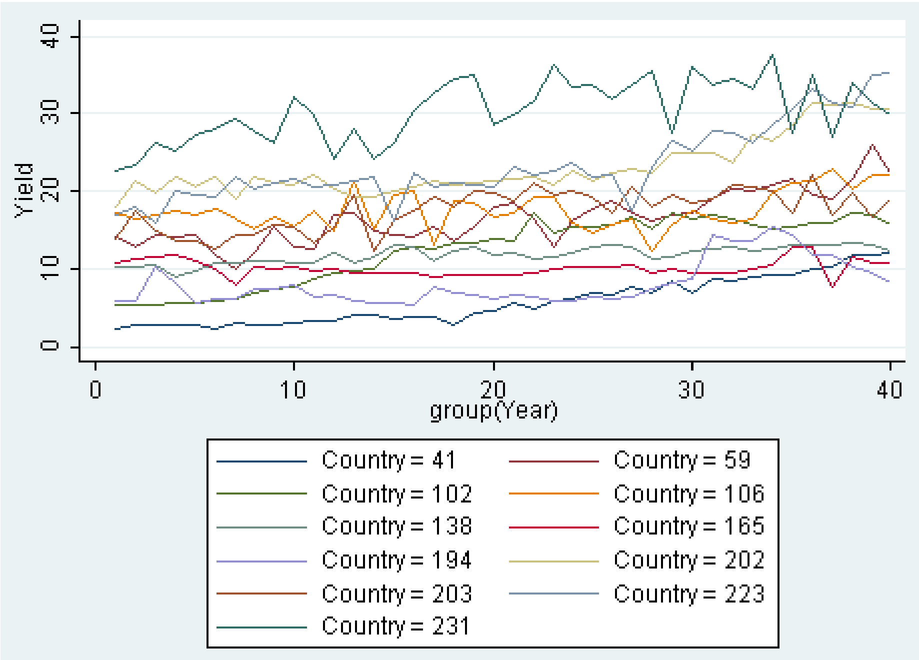
In the graphs, the countries are represented by numbers:

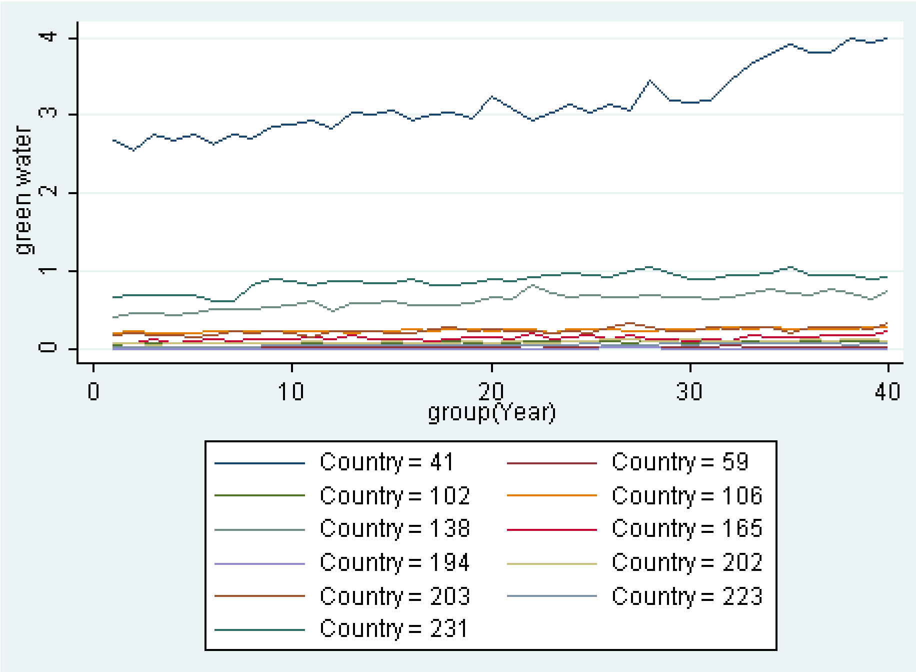
41	China	165	Pakistan
59	Egypt	194	Saudi Arabia
100	India	202	South Africa
102	Iran	203	Spain
106	Italy	223	Turkey
138	Mexico	231	USA

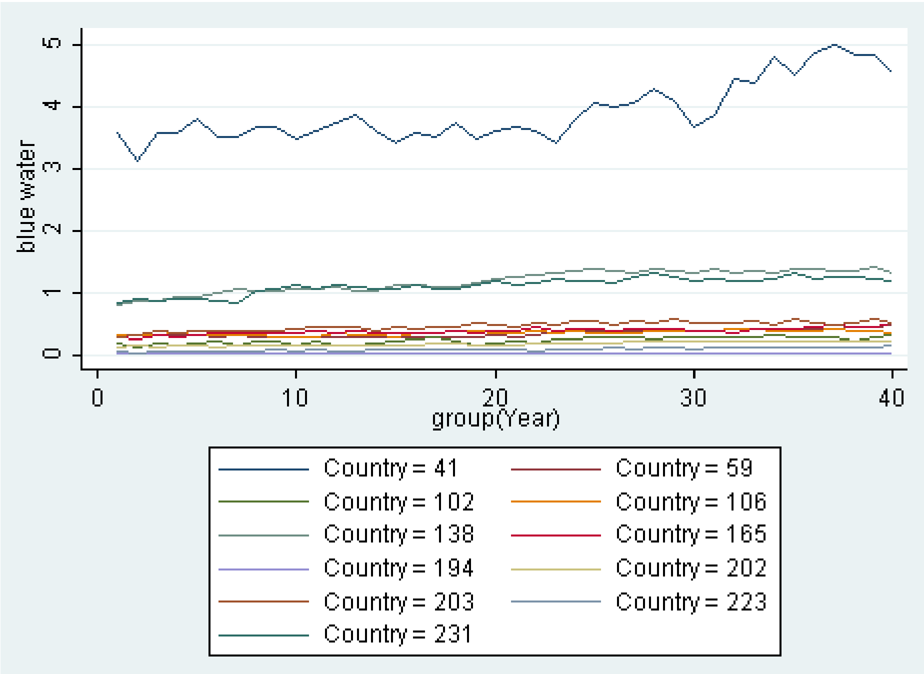
Citrus

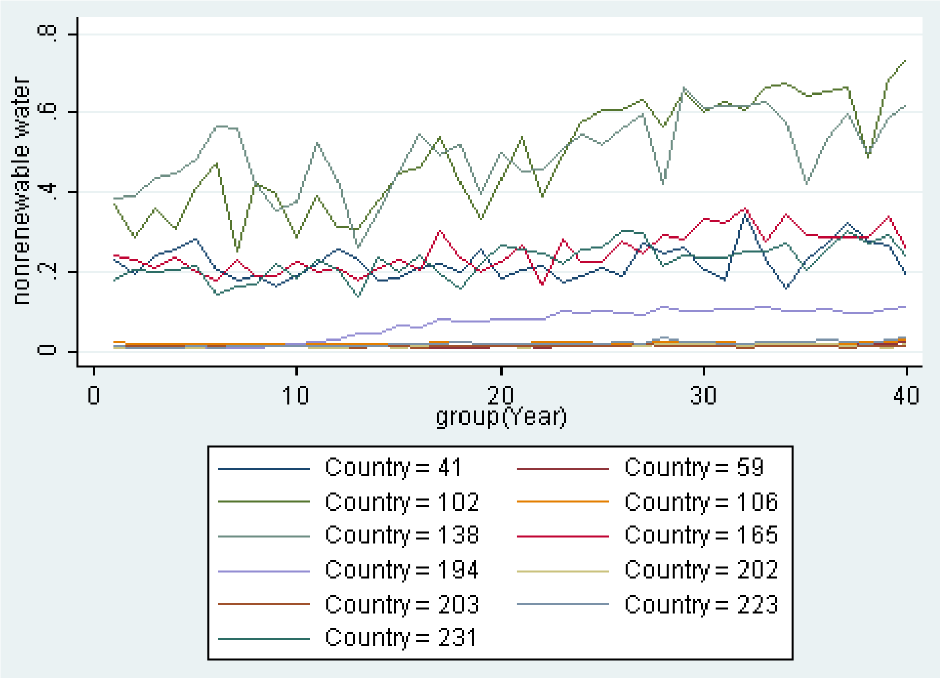


```
. xtunitroot llc Production, trend

Levin-Lin-Chu unit-root test for Production
-------------------------------------------
Ho: Panels contain unit roots                  Number of panels  =     11
Ha: Panels are stationary                      Number of periods =     40

AR parameter: Common                           Asymptotics: N/T -> 0
Panel means:  Included
Time trend:   Included

ADF regressions: 1 lag
LR variance:     Bartlett kernel, 10.00 lags average (chosen by LLC)
------------------------------------------------------------------------------
                    Statistic      p-value
------------------------------------------------------------------------------
 Unadjusted t        -2.9799
 Adjusted t*          2.9231        0.9983
------------------------------------------------------------------------------
```



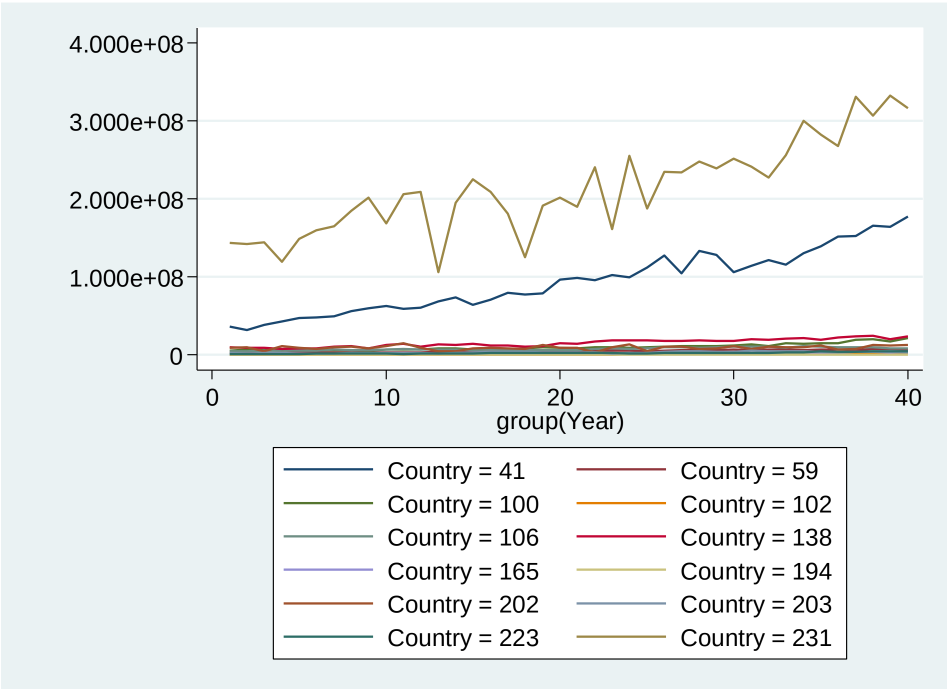

green water
0
1
2
3
4
0
10
20
30
40
group(Year)
Country = 41
Country = 59
Country = 102
Country = 106
Country = 138
Country = 165
Country = 194
Country = 202
Country = 203
Country = 223
Country = 231


blue water
0
1
2
3
4
5
0
10
20
30
40
group(Year)
Country = 41
Country = 59
Country = 102
Country = 106
Country = 138
Country = 165
Country = 194
Country = 202
Country = 203
Country = 223
Country = 231

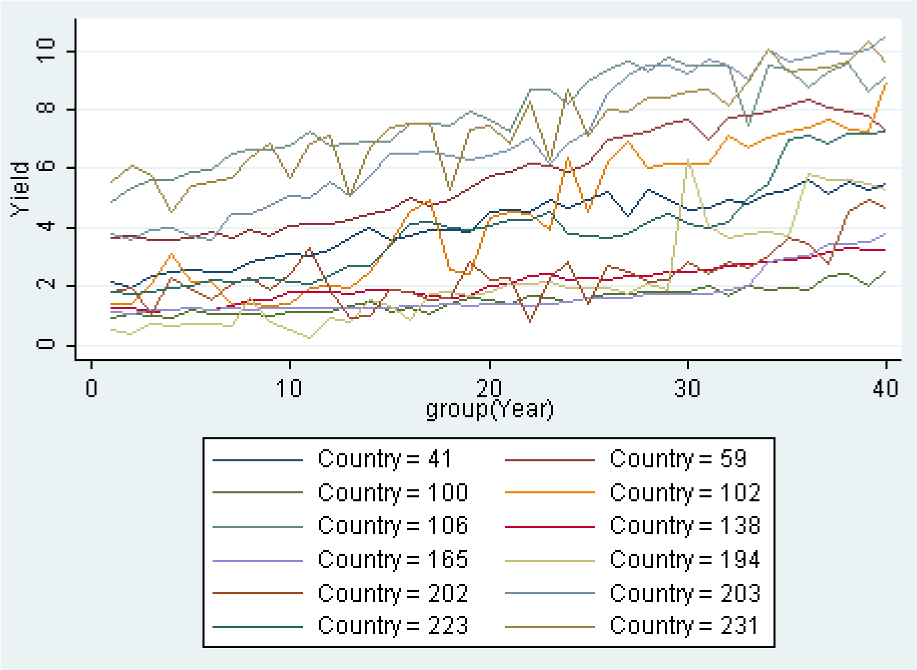


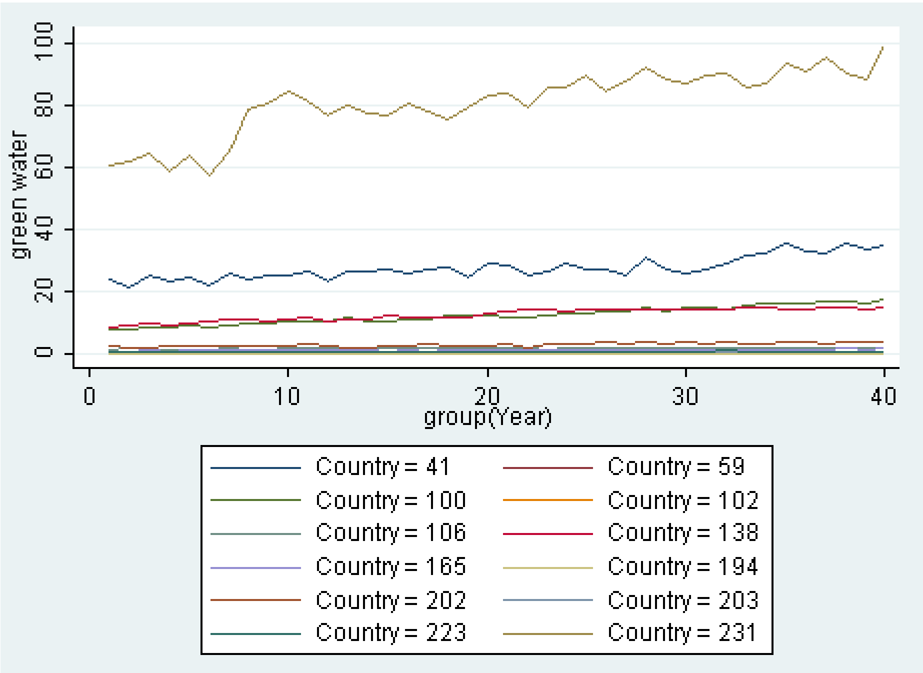
nonrenewable water
0
.2
.4
.6
.8
0
10
20
30
40
group(Year)
Country = 41
Country = 59
Country = 102
Country = 106
Country = 138
Country = 165
Country = 194
Country = 202
Country = 203
Country = 223
Country = 231

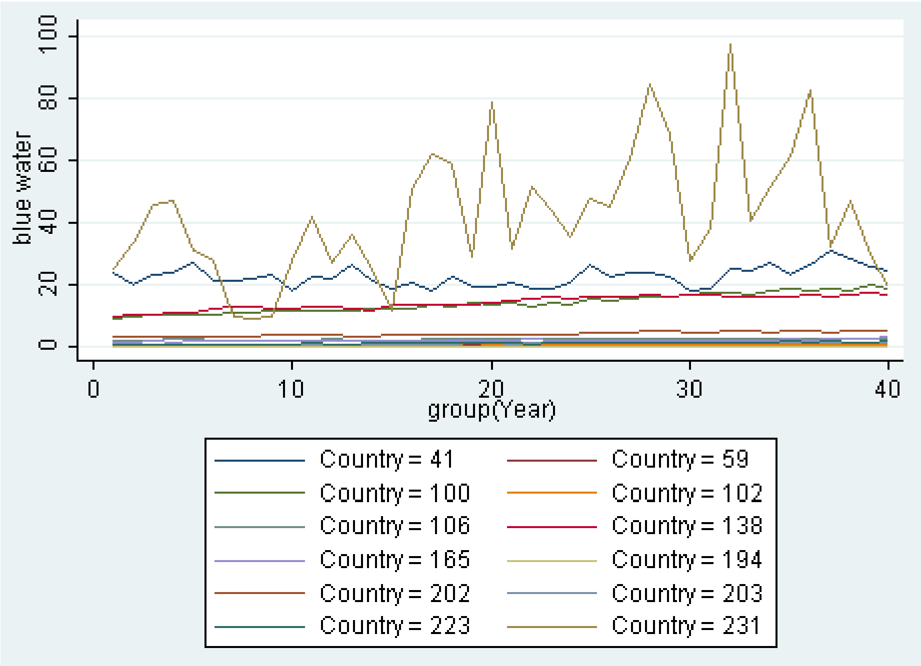
Maize

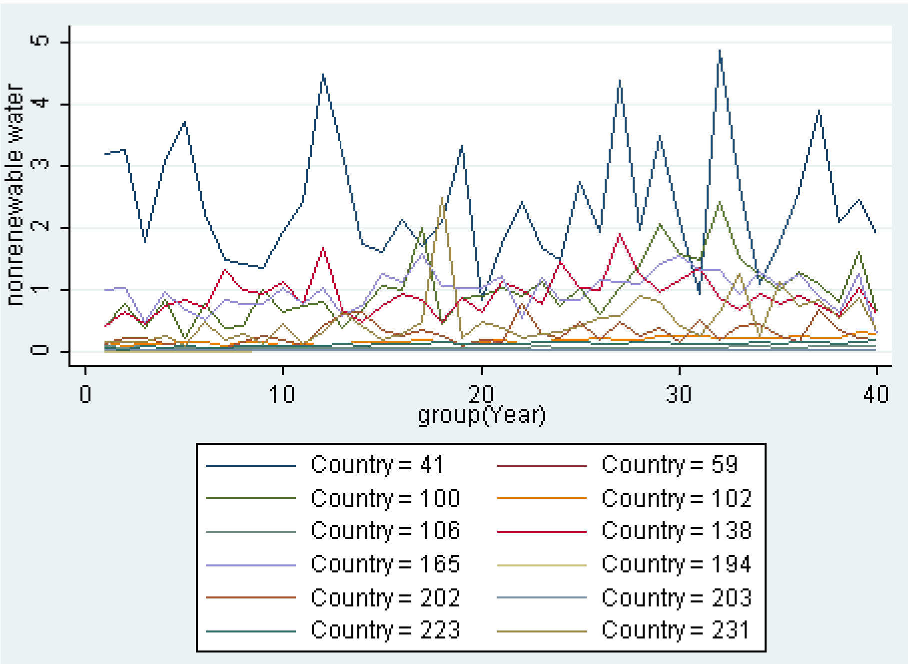


4.000e+08
3.000e+08
2.000e+08
1.000e+08
0
0
10
20
30
40
group(Year)
Country = 41
Country = 59
Country = 100
Country = 102
Country = 106
Country = 138
Country = 165
Country = 194
Country = 202
Country = 203
Country = 223
Country = 231

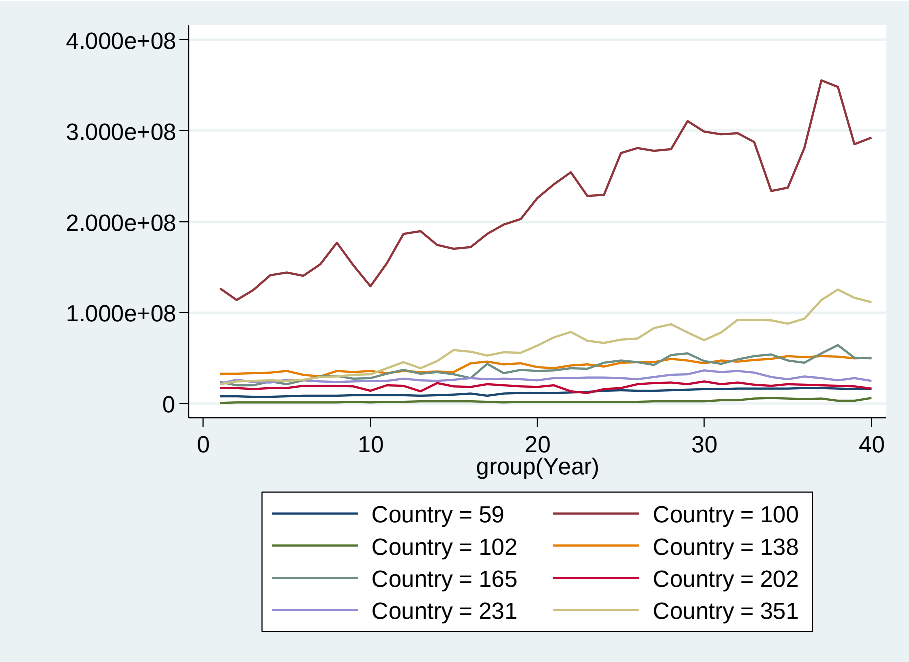

Yield
0
2
4
6
8
10
0
10
20
30
40
group(Year)
Country = 41
Country = 59
Country = 100
Country = 102
Country = 106
Country = 138
Country = 165
Country = 194
Country = 202
Country = 203
Country = 223
Country = 231

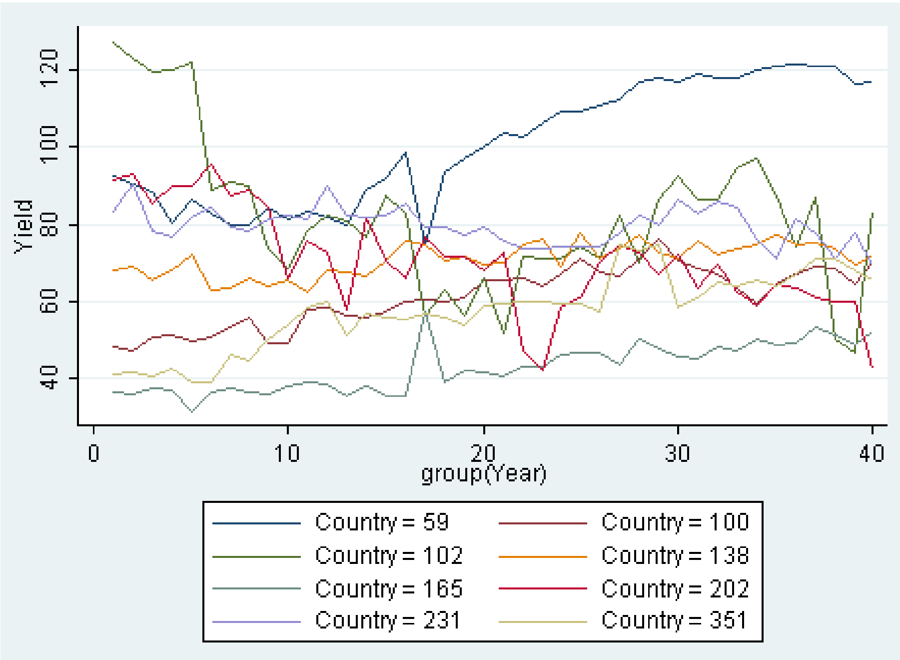

green water
0
20
40
60
80
100
0
10
20
30
40
group(Year)
Country = 41
Country = 59
Country = 100
Country = 102
Country = 106
Country = 138
Country = 165
Country = 194
Country = 202
Country = 203
Country = 223
Country = 231


0
20
40
60
80
100
blue water
0
10
20
30
40
group(Year)
Country = 41
Country = 59
Country = 100
Country = 102
Country = 106
Country = 138
Country = 165
Country = 194
Country = 202
Country = 203
Country = 223
Country = 231


0
1
2
3
4
5
nonrenewable water
0
10
20
30
40
group(Year)
Country = 41
Country = 59
Country = 100
Country = 102
Country = 106
Country = 138
Country = 165
Country = 194
Country = 202
Country = 203
Country = 223
Country = 231

Sugarcane


4.000e+08
3.000e+08
2.000e+08
1.000e+08
0
0
10
20
30
40
group(Year)
Country = 59
Country = 100
Country = 102
Country = 138
Country = 165
Country = 202
Country = 231
Country = 351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100
80
60
40
0
10
20
30
40
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Country = 231
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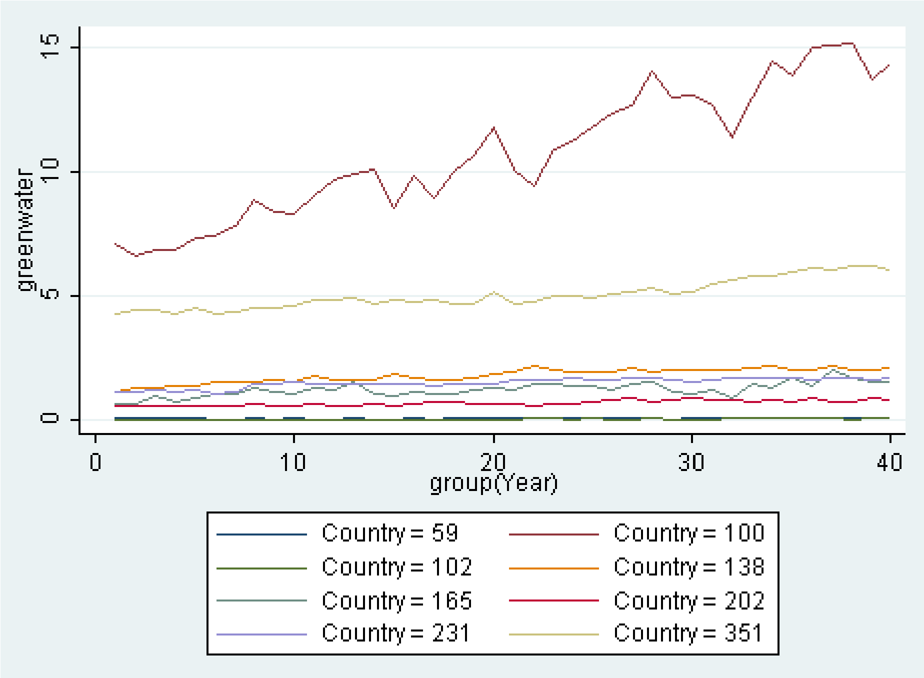
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0
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10
15
0
10
20
30
40
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Country = 138
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Country = 202
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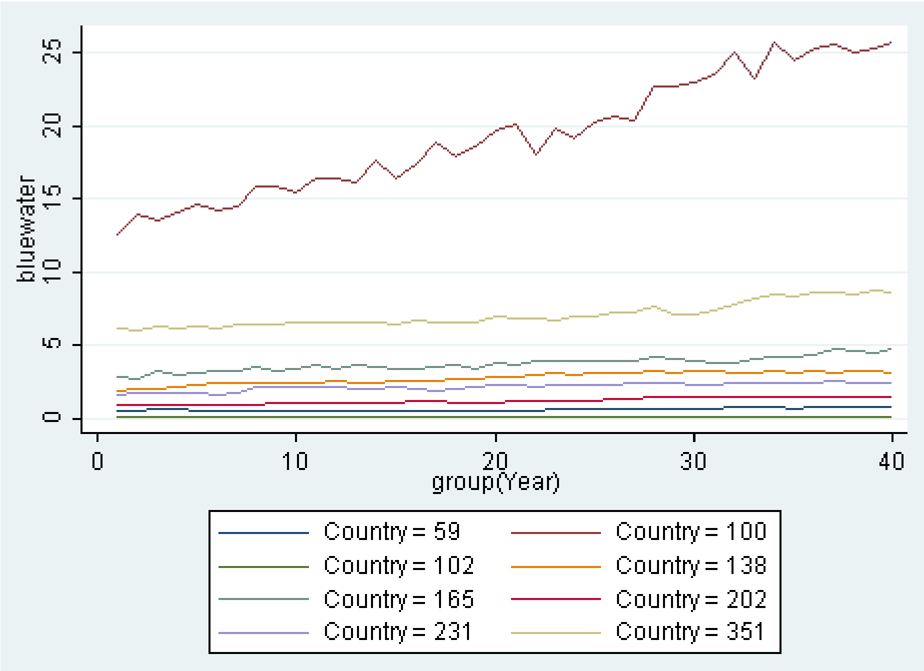
Country = 351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10
15
20
25
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20
30
40
group(Year)
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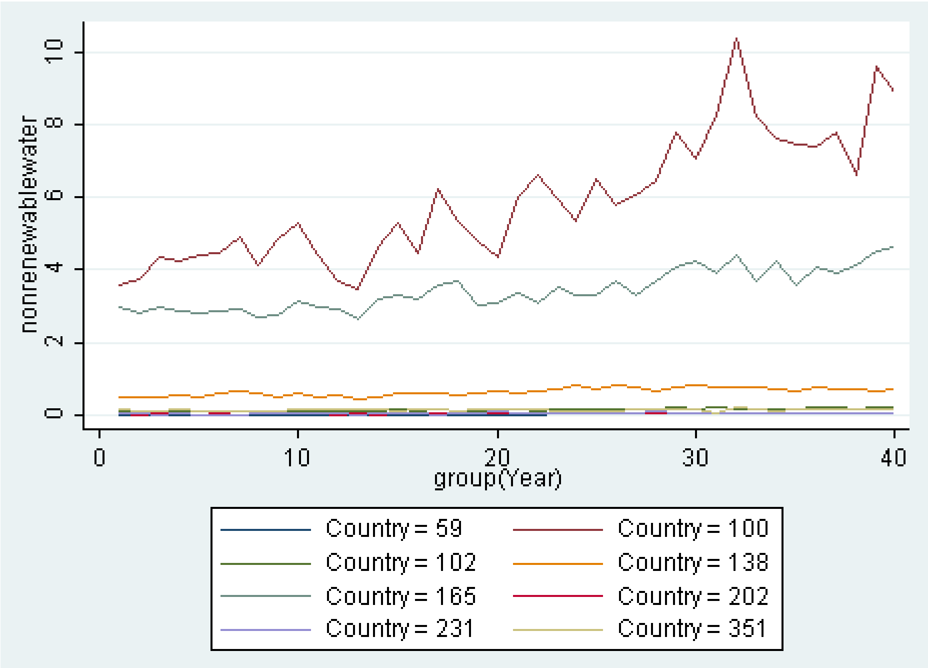
Country = 138
Country = 165
Country = 202
Country = 231
Country = 351



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6
8
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10
20
30
40
group(Year)
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Country = 102
Country = 138
Country = 165
Country = 202
Country = 231
Country = 351

Appendix D

This appendix contains the correlation coefficient tables, including the quadratic terms and cross terms, for the variables of citrus, maize and sugarcane.

Citrus

	Produc~n	Area	GW	BW	NRGW	Area2	GW2	BW2	NRGW2	Area_GW	Area_BW	Area_N~W
Production	1.0000											
Area	0.7705	1.0000										
GW	0.5346	0.8271	1.0000									
BW	0.5289	0.8264	0.9907	1.0000								
NRGW	0.2208	0.2712	0.2092	0.2668	1.0000							
Area2	0.6558	0.9287	0.7475	0.7329	0.1311	1.0000						
GW2	0.4571	0.8319	0.9663	0.9480	0.1223	0.8297	1.0000					
BW2	0.4521	0.8232	0.9694	0.9629	0.1557	0.8132	0.9924	1.0000				
NRGW2	0.1185	0.1615	0.0546	0.1170	0.9449	0.0389	-0.0108	0.0227	1.0000			
Area_GW	0.6153	0.9417	0.8305	0.8108	0.1229	0.9820	0.9030	0.8843	0.0145	1.0000		
Area_BW	0.6210	0.9480	0.8310	0.8172	0.1435	0.9817	0.8993	0.8871	0.0366	0.9981	1.0000	
Area_NRGW	0.6575	0.8640	0.6842	0.7174	0.6303	0.7746	0.6588	0.6781	0.5583	0.7664	0.7878	1.0000
GW_BW	0.4553	0.8282	0.9694	0.9562	0.1362	0.8228	0.9982	0.9979	0.0026	0.8954	0.8948	0.6671
GW_NRGW	0.5496	0.8276	0.9409	0.9595	0.4094	0.7379	0.8912	0.9154	0.2696	0.7976	0.8105	0.8351
BW_NRGW	0.5085	0.7742	0.8583	0.8990	0.5554	0.6622	0.7900	0.8282	0.4356	0.7084	0.7292	0.8771

	GW_BW	GW_NRGW	BW_NRGW
GW_BW	1.0000		
GW_NRGW	0.9034	1.0000	
BW_NRGW	0.8079	0.9747	1.0000

Maize

	Produc~n	Area	GW	BW	NRGW	Area2	GW2	BW2	NRGW2	Area_GW	Area_BW	Area_N~W
Production	1.0000											
Area	0.9249	1.0000										
GW	0.9591	0.9190	1.0000									
BW	0.8207	0.8530	0.8784	1.0000								
NRGW	0.2832	0.5172	0.2740	0.4350	1.0000							
Area2	0.9716	0.9686	0.9312	0.8036	0.3935	1.0000						
GW2	0.9307	0.7963	0.9618	0.7938	0.0808	0.8591	1.0000					
BW2	0.6831	0.6112	0.7239	0.8892	0.1797	0.6228	0.7332	1.0000				
NRGW2	0.2221	0.4169	0.1807	0.3056	0.8997	0.3343	0.0247	0.1122	1.0000			
Area_GW	0.9760	0.8837	0.9829	0.8169	0.1874	0.9381	0.9820	0.7079	0.1277	1.0000		
Area_BW	0.8908	0.8454	0.9005	0.9564	0.3104	0.8627	0.8700	0.9194	0.2394	0.8895	1.0000	
Area_NRGW	0.4868	0.6711	0.4123	0.5151	0.8709	0.6053	0.2390	0.2907	0.8977	0.3669	0.4779	1.0000
GW_BW	0.8353	0.7300	0.8735	0.9162	0.1483	0.7640	0.8957	0.9504	0.0810	0.8709	0.9703	0.2908
GW_NRGW	0.6573	0.7751	0.6277	0.7106	0.7936	0.7231	0.4932	0.5146	0.7669	0.5811	0.6783	0.9203
BW_NRGW	0.5061	0.6731	0.4935	0.6692	0.8643	0.5886	0.3355	0.4895	0.8477	0.4253	0.5979	0.9323

	GW_BW	GW_NRGW	BW_NRGW
GW_BW	1.0000		
GW_NRGW	0.5454	1.0000	
BW_NRGW	0.4582	0.9636	1.0000

Sugarcane

	Produc~n	Area	GW	BW	NRGW	Area2	GW2	BW2	NRGW2	Area_GW	Area_BW	Area_N~W
Production	**1.0000**											
Area	**0.9861**	**1.0000**										
GW	**0.9607**	**0.9607**	**1.0000**									
BW	**0.9756**	**0.9863**	**0.9857**	**1.0000**								
NRGW	**0.8387**	**0.8774**	**0.7515**	**0.8424**	**1.0000**							
Area2	**0.9727**	**0.9585**	**0.9161**	**0.9440**	**0.8480**	**1.0000**						
GW2	**0.9589**	**0.9370**	**0.9492**	**0.9524**	**0.7891**	**0.9694**	**1.0000**					
BW2	**0.9607**	**0.9458**	**0.9322**	**0.9578**	**0.8424**	**0.9798**	**0.9861**	**1.0000**				
NRGW2	**0.8663**	**0.8661**	**0.7815**	**0.8555**	**0.9363**	**0.8988**	**0.8549**	**0.9131**	**1.0000**			
Area_GW	**0.9726**	**0.9531**	**0.9367**	**0.9524**	**0.8218**	**0.9926**	**0.9916**	**0.9900**	**0.8817**	**1.0000**		
Area_BW	**0.9718**	**0.9569**	**0.9279**	**0.9550**	**0.8492**	**0.9951**	**0.9822**	**0.9947**	**0.9106**	**0.9963**	**1.0000**	
Area_NRGW	**0.9359**	**0.9257**	**0.8616**	**0.9147**	**0.9058**	**0.9736**	**0.9348**	**0.9724**	**0.9713**	**0.9612**	**0.9781**	**1.0000**
GW_BW	**0.9625**	**0.9437**	**0.9431**	**0.9574**	**0.8173**	**0.9778**	**0.9966**	**0.9963**	**0.8859**	**0.9943**	**0.9917**	**0.9565**
GW_NRGW	**0.9348**	**0.9161**	**0.8783**	**0.9188**	**0.8698**	**0.9710**	**0.9614**	**0.9874**	**0.9498**	**0.9739**	**0.9842**	**0.9905**
BW_NRGW	**0.9264**	**0.9138**	**0.8638**	**0.9148**	**0.8927**	**0.9614**	**0.9402**	**0.9793**	**0.9711**	**0.9578**	**0.9753**	**0.9950**

	GW_BW	GW_NRGW	BW_NRGW
GW_BW	**1.0000**		
GW_NRGW	**0.9779**	**1.0000**	
BW_NRGW	**0.9627**	**0.9956**	**1.0000**

Appendix E

This appendix contains the OLS regression results for citrus and maize of the four countries together.

The estimations include the proxy variables for some inputs (mentioned in Chapter 4).

Citrus

Source	SS	df	MS
Model	12.9166828	28	.461310101
Residual	.032376996	3	.010792332
Total	12.9490598	31	.417711608

Number of obs =	32
F(28, 3) =	42.74
Prob > F =	0.0050
R-squared =	0.9975
Adj R-squared =	0.9742
Root MSE =	.10389

lnProduction	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnArea	39.33984	55.72374	0.71	0.531	-137.998	216.6777
ln_emplinagr	8.997509	56.42223	0.16	0.883	-170.5632	188.5582
ln_agr_value_added	1.031908	2.671699	0.39	0.725	-7.470633	9.534448
lnGW	-6.537321	30.46461	-0.21	0.844	-103.4893	90.41465
lnWaterInput	51.78025	73.51217	0.70	0.532	-182.1683	285.7288
ln_fertiliser	-9.447922	31.10683	-0.30	0.781	-108.4437	89.54789
lnArea2	-.4442653	4.093267	-0.11	0.920	-13.47087	12.58234
ln_emplinagr2	2.018851	3.525293	0.57	0.607	-9.200204	13.23791
ln_agr_value_added2	-.0058761	.0095641	-0.61	0.582	-.0363132	.024561
lnGW2	1.163787	3.075752	0.38	0.730	-8.624628	10.9522
lnWaterInput2	-5.837225	13.99373	-0.42	0.705	-50.37153	38.69708
ln_fertiliser2	2.652065	2.29783	1.15	0.332	-4.660656	9.964787
lnArea_ln_emplinagr	.4694469	4.026341	0.12	0.915	-12.34417	13.28306
lnArea_ln_agr_value_added	-.039693	.1571996	-0.25	0.817	-.5399722	.4605862
lnArea_lnGW	-3.821445	3.867263	-0.99	0.396	-16.1288	8.485913
lnArea_lnWaterInput	-1.120856	6.236937	-0.18	0.869	-20.96957	18.72786
lnArea_ln_fertiliser	1.590933	1.584455	1.00	0.389	-3.451511	6.633376
ln_emplinagr_ln_agr_value_added	.0876239	.2761744	0.32	0.772	-.7912862	.9665341
ln_emplinagr_lnGW	-6.278329	4.349798	-1.44	0.245	-20.12133	7.564668
ln_emplinagr_lnWaterInput	2.937461	7.095182	0.41	0.707	-19.64258	25.5175
ln_emplinagr_ln_fertiliser	3.800528	3.235017	1.17	0.325	-6.49474	14.0958
ln_agr_value_added_lnGW	.029647	.204585	0.14	0.894	-.6214338	.6807278
ln_agr_value_added_lnWaterInput	-.0961888	.5104009	-0.19	0.863	-1.720512	1.528135
ln_agr_value_added_ln_fertiliser	.1009089	.119142	0.85	0.459	-.2782542	.4800721
lnGW_lnWaterInput	2.669644	6.37145	0.42	0.703	-17.60715	22.94644
ln_fertiliser_lnGW	-1.764975	2.924756	-0.60	0.589	-11.07285	7.542904
ln_fertiliser_lnWaterInput	1.124822	3.320793	0.34	0.757	-9.443423	11.69307
ln_t	-.0846566	.1136709	-0.74	0.510	-.4464081	.277095
_cons	-379.6589	436.9596	-0.87	0.449	-1770.259	1010.941

Maize

Source	SS	df	MS
Model	89.1490543	28	3.1838948
Residual	.002038805	3	.000679602
Total	89.1510931	31	2.87584171

Number of obs =	32
F(28, 3) =	4684.94
Prob > F =	0.0000
R-squared =	1.0000
Adj R-squared =	0.9998
Root MSE =	.02607

lnProduction	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnArea	.4891046	2.928863	0.17	0.878	-8.831845	9.810055
ln_emplinagr	-3.461112	2.209156	-1.57	0.215	-10.49163	3.569408
ln_agr_value_added	-.27423	.4585036	-0.60	0.592	-1.733393	1.184933
lnGW	4.911709	9.738766	0.50	0.649	-26.08139	35.90481
lnWaterInput	-5.304454	4.508094	-1.18	0.324	-19.65122	9.042312
ln_fertiliser	-7.937891	9.560066	-0.83	0.467	-38.36229	22.4865
lnArea2	.1452807	.2979515	0.49	0.659	-.8029339	1.093495
ln_emplinagr2	.4392862	.1582037	2.78	0.069	-.0641884	.9427609
ln_agr_value_added2	-.0001277	.0025178	-0.05	0.963	-.0081406	.0078853
lnGW2	-1.489703	1.321931	-1.13	0.342	-5.696679	2.717273
lnWaterInput2	-.3136025	.5454263	-0.57	0.606	-2.049392	1.422187
ln_fertiliser2	-.3146994	.4618224	-0.68	0.544	-1.784424	1.155025
lnArea_ln_emplinagr	.4024228	.1135444	3.54	0.038	.0410738	.7637718
lnArea_ln_agr_value_added	.0074928	.0099839	0.75	0.507	-.0242805	.039266
lnArea_lnGW	.0610039	.3814133	0.16	0.883	-1.152824	1.274831
lnArea_lnWaterInput	.0233494	.1521644	0.15	0.888	-.4609056	.5076044
lnArea_ln_fertiliser	.0277648	.3151514	0.09	0.935	-.9751877	1.030717
ln_emplinagr_ln_agr_value_added	.0058502	.0056314	1.04	0.375	-.0120713	.0237716
ln_emplinagr_lnGW	-.2193164	.150851	-1.45	0.242	-.6993915	.2607587
ln_emplinagr_lnWaterInput	.230428	.1471744	1.57	0.215	-.2379465	.6988026
ln_emplinagr_ln_fertiliser	-.0278575	.1589484	-0.18	0.872	-.5337023	.4779874
ln_agr_value_added_lnGW	-.012969	.0154389	-0.84	0.463	-.0621023	.0361643
ln_agr_value_added_lnWaterInput	.0292192	.0467895	0.62	0.577	-.1196858	.1781242
ln_agr_value_added_ln_fertiliser	.014748	.0149042	0.99	0.395	-.0326839	.0621798
lnGW_lnWaterInput	.4520429	.7024539	0.64	0.566	-1.783479	2.687565
ln_fertiliser_lnGW	.2422576	.5140055	0.47	0.670	-1.393537	1.878053
ln_fertiliser_lnWaterInput	.9981089	.8561449	1.17	0.328	-1.726526	3.722744
ln_t	.0312339	.0586504	0.53	0.631	-.155418	.2178858
_cons	13.8649	47.94605	0.29	0.791	-138.7208	166.4506

Sugarcane

Italy and Spain do not produce sugarcane, so the estimation could include only South Africa and the USA. Due to insufficient observations, no estimation for sugarcane can be performed.

Appendix F

This appendix contains the OLS regression results of the twelve countries together. The estimations include two water inputs (GW, BW+NRGW) and country dummy variables. The USA is used as reference country.

Citrus

Source	SS	df	MS
Model	997.812929	20	49.8906464
Residual	11.8843633	419	.028363636
Total	1009.69729	439	2.29999383

Number of obs	440
F(20, 419)	1758.97
Prob > F	0.0000
R-squared	0.9882
Adj R-squared	0.9877
Root MSE	.16842

lnProduction	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnArea	-1.799487	.7028642	-2.56	0.011	-3.181066	-.4179076
lnGW	.597821	.6092026	0.98	0.327	-.5996531	1.795295
lnWaterInput	-.617642	1.285734	-0.48	0.631	-3.144934	1.90965
lnArea2	.2257586	.0349543	6.46	0.000	.1570509	.2944663
lnGW2	.1632848	.0462367	3.53	0.000	.0724	.2541696
lnWaterInput2	.0194989	.1158789	0.17	0.866	-.2082775	.2472754
lnArea_lnGW	-.0573943	.0323182	-1.78	0.076	-.1209202	.0061316
lnArea_lnWaterInput	.1398414	.0556331	2.51	0.012	.0304866	.2491962
lnGW_lnWaterInput	-.1179104	.0547638	-2.15	0.032	-.2255565	-.0102643
ln_t	.0198084	.0176532	1.12	0.262	-.0148915	.0545083
Egypt	.3193593	.2368901	1.35	0.178	-.1462818	.7850003
China	-2.633203	.1557672	-16.90	0.000	-2.939386	-2.327021
Iran	-.2998252	.1726361	-1.74	0.083	-.6391659	.0395155
Italy	.3008504	.1323389	2.27	0.024	.0407196	.5609813
Mexico	-.9551809	.0630533	-15.15	0.000	-1.079121	-.8312408
Pakistan	-.3654802	.1454536	-2.51	0.012	-.6513898	-.0795705
SaudiArabia	.2856228	.3354786	0.85	0.395	-.373808	.9450535
SouthAfrica	.9553802	.1997321	4.78	0.000	.5627785	1.347982
Spain	.1717446	.1237548	1.39	0.166	-.071513	.4150022
Turkey	1.261777	.235897	5.35	0.000	.798088	1.725466
_cons	14.04001	7.59327	1.85	0.065	-.8856387	28.96566

Maize

Source	SS	df	MS
Model	3444.47367	21	164.022556
Residual	19.8672974	458	.043378379
Total	3464.34097	479	7.23244461

Number of obs	=	480
F(21, 458)	=	3781.21
Prob > F	=	0.0000
R-squared	=	0.9943
Adj R-squared	=	0.9940
Root MSE	=	.20827

lnProduction	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnArea	2.972598	.4456002	6.67	0.000	2.096924	3.848273
lnGW	-.9627583	.6363474	-1.51	0.131	-2.213281	.2877644
lnWaterInput	2.756633	1.054254	2.61	0.009	.6848581	4.828408
lnArea2	-.0304644	.0239399	-1.27	0.204	-.0775101	.0165814
lnGW2	.118384	.0539117	2.20	0.029	.0124391	.224329
lnWaterInput2	-.0842359	.1174039	-0.72	0.473	-.3149531	.1464813
lnArea_lnGW	.0623735	.0326594	1.91	0.057	-.0018074	.1265544
lnArea_lnWaterInput	-.1199838	.045567	-2.63	0.009	-.2095301	-.0304376
lnGW_lnWaterInput	-.0211987	.0708128	-0.30	0.765	-.1603571	.1179596
ln_t	.152234	.0181178	8.40	0.000	.1166297	.1878383
Egypt	6.320775	.676671	9.34	0.000	4.99101	7.65054
China	.3296226	.1156219	2.85	0.005	.1024074	.5568378
India	.3227219	.2100028	1.54	0.125	-.0899666	.7354103
Iran	6.551001	.653204	10.03	0.000	5.267352	7.834649
Italy	4.104362	.4061528	10.11	0.000	3.306208	4.902516
Mexico	.5884495	.2039895	2.88	0.004	.187578	.989321
Pakistan	2.780267	.4312048	6.45	0.000	1.932882	3.627652
SaudiArabia	8.948104	.8309426	10.77	0.000	7.315171	10.58104
SouthAfrica	2.022753	.3299675	6.13	0.000	1.374315	2.671191
Spain	5.243697	.5059338	10.36	0.000	4.249458	6.237936
Turkey	4.409207	.4908238	8.98	0.000	3.444661	5.373753
_cons	-34.00518	4.954544	-6.86	0.000	-43.74164	-24.26872

Sugarcane

Source	SS	df	MS
Model	544.110348	17	32.006491
Residual	4.22242213	302	.01398153
Total	548.33277	319	1.7189115

Number of obs	=	320
F(17, 302)	=	2289.20
Prob > F	=	0.0000
R-squared	=	0.9923
Adj R-squared	=	0.9919
Root MSE	=	.11824

lnProduction	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnArea	-1.190268	.6306215	-1.89	0.060	-2.431237	.0507006
lnGW	8.463173	1.016558	8.33	0.000	6.46274	10.46361
lnWaterInput	-11.39492	2.426813	-4.70	0.000	-16.17053	-6.619316
lnArea2	.1461541	.0244928	5.97	0.000	.0979559	.1943524
lnGW2	.4970019	.0785401	6.33	0.000	.3424468	.651557
lnWaterInput2	1.549321	.2778074	5.58	0.000	1.002637	2.096004
lnArea_lnGW	-.2949095	.0362318	-8.14	0.000	-.3662082	-.2236108
lnArea_lnWaterInput	.3346555	.0565954	5.91	0.000	.2232842	.4460269
lnGW_lnWaterInput	-.9026392	.1197215	-7.54	0.000	-1.138233	-.6670452
ln_t	-.01088	.0159762	-0.68	0.496	-.0423187	.0205587
Egypt	2.007959	.237899	8.44	0.000	1.53981	2.476109
China	-.6003137	.1010678	-5.94	0.000	-.7992001	-.4014274
India	-.9349831	.2132611	-4.38	0.000	-1.354649	-.5153172
Iran	1.881182	.2764543	6.80	0.000	1.337162	2.425203
Mexico	-.031721	.0547512	-0.58	0.563	-.1394631	.0760211
Pakistan	-.4932701	.1466657	-3.36	0.001	-.7818863	-.204654
SouthAfrica	.0489262	.0655874	0.75	0.456	-.08014	.1779923
_cons	32.87065	11.70898	2.81	0.005	9.829134	55.91217

Appendix G

This appendix contains the panel estimation results by including two water inputs (GW, BW+NRGW) for production and yield estimation of citrus, maize and sugarcane.

Citrus

Production

```
. xtreg lnProduction lnArea lnGW lnWaterInput lnArea2 lnGW2 lnWaterInput2 lnWaterInput_lnArea lnWaterInput_lnGW lnArea_lnGW ln_t, fe

Fixed-effects (within) regression               Number of obs      =       440
Group variable: Country                         Number of groups   =        11

R-sq:  within  = 0.9431                         Obs per group: min =        40
       between = 0.7316                                        avg =      40.0
       overall = 0.7506                                        max =        40

                                                F(10,419)          =    694.38
corr(u_i, Xb)  = -0.6666                        Prob > F           =    0.0000

------------------------------------------------------------------------------------
       lnProduction |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------------+---------------------------------------------------------------
             lnArea |  -1.779706   .6832716    -2.60   0.010    -3.122774   -.4366391
               lnGW |   .5978407    .609203     0.98   0.327    -.5996343    1.795316
       lnWaterInput |  -.6176183   1.285729    -0.48   0.631      -3.1449    1.909664
            lnArea2 |   .0078294    .048607     0.16   0.872    -.0877146    .1033733
              lnGW2 |    .163288    .046237     3.53   0.000     .0724027    .2541734
      lnWaterInput2 |    .019497   .1158784     0.17   0.866    -.2082784    .2472724
lnWaterInput_lnArea |    .238257   .0661015     3.60   0.000     .1083251    .3681889
  lnWaterInput_lnGW |  -.1179123    .054764    -2.15   0.032    -.2255587   -.0102659
        lnArea_lnGW |  -.1027722   .0395076    -2.60   0.010    -.1804299   -.0251144
               ln_t |   .0198085   .0176532     1.12   0.262    -.0148914    .0545084
              _cons |   13.95266   7.614814     1.83   0.068    -1.015336    28.92066
--------------------+---------------------------------------------------------------
            sigma_u |  1.0389606
            sigma_e |  .16841499
                rho |  .97439652   (fraction of variance due to u_i)
------------------------------------------------------------------------------------
F test that all u_i=0:     F(10, 419) =    132.83            Prob > F = 0.0000
```

Yield

```
. xtreg Yield lnArea lnGW_ha lnWI_ha lnArea2 lnGW_lnArea lnWI_lnArea lnGW_ha2 lnWI_ha2 lnGW_lnWI ln_t, fe

Fixed-effects (within) regression               Number of obs      =       440
Group variable: Country                         Number of groups   =        11

R-sq:  within  = 0.3601                         Obs per group: min =        40
       between = 0.5157                                        avg =      40.0
       overall = 0.2803                                        max =        40

                                                F(10,419)          =     23.58
corr(u_i, Xb)  = -0.8148                        Prob > F           =    0.0000

------------------------------------------------------------------------------
       Yield |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lnArea |  -.0198313   .2271882    -0.09   0.930    -.4664019    .4267393
     lnGW_ha |   1.067155   1.061305     1.01   0.315    -1.018991    3.153301
     lnWI_ha |   2.222894   1.761701     1.26   0.208    -1.239981    5.685768
     lnArea2 |   .0076552   .0044637     1.71   0.087    -.0011189    .0164292
 lnGW_lnArea |  -.1018892   .0506258    -2.01   0.045    -.2014014   -.0023771
 lnWI_lnArea |   .0219352   .0727347     0.30   0.763    -.1210352    .1649055
    lnGW_ha2 |    .846671   .2014242     4.20   0.000     .4507432    1.242599
    lnWI_ha2 |   .0391193   .3470151     0.11   0.910     -.642988    .7212267
   lnGW_lnWI |   -1.48011   .4557277    -3.25   0.001    -2.375908   -.5843128
        ln_t |    .004617   .0015304     3.02   0.003     .0016088    .0076252
       _cons |  -1.888258    2.81985    -0.67   0.503    -7.431074    3.654557
-------------+----------------------------------------------------------------
     sigma_u |  .07068426
     sigma_e |  .01508583
         rho |  .95643394   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0:     F(10, 419) =   105.00             Prob > F = 0.0000
```

Maize

Production

```
. xtreg lnProduction lnArea lnGW lnWaterInput lnArea2 lnGW2 lnWaterInput2 lnWaterInput_lnArea lnWaterInput_lnGW lnArea_lnGW ln_t, fe

Fixed-effects (within) regression               Number of obs      =       480
Group variable: Country                         Number of groups   =        12

R-sq:  within  = 0.9294                         Obs per group: min =        40
       between = 0.9242                                        avg =      40.0
       overall = 0.9043                                        max =        40

                                                F(10,458)          =    602.47
corr(u_i, Xb)  = -0.9580                        Prob > F           =    0.0000

-------------------------------------------------------------------------------------
       lnProduction |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------------+----------------------------------------------------------------
             lnArea |   1.178742   .5039103     2.34   0.020     .1884792    2.169005
               lnGW |  -.9628167   .6363511    -1.51   0.131    -2.213347    .2877133
       lnWaterInput |   2.756712   1.054259     2.61   0.009     .6849284    4.828496
            lnArea2 |   .0765066   .0220572     3.47   0.001     .0331609    .1198524
              lnGW2 |   .1183785   .0539117     2.20   0.029     .0124336    .2243234
      lnWaterInput2 |   -.084245   .1174043    -0.72   0.473     -.314963    .1464729
lnWaterInput_lnArea |  -.0145513   .0546279    -0.27   0.790    -.1219038    .0928012
  lnWaterInput_lnGW |  -.0211917   .0708131    -0.30   0.765    -.1603506    .1179672
        lnArea_lnGW |  -.0348103   .0331407    -1.05   0.294    -.0999369    .0303164
               ln_t |    .152234   .0181178     8.40   0.000     .1166297    .1878384
              _cons |  -30.53713    4.90905    -6.22   0.000    -40.18419   -20.89008
--------------------+----------------------------------------------------------------
            sigma_u |  2.9347677
            sigma_e |  .20827493
                rho |  .99498877   (fraction of variance due to u_i)
-------------------------------------------------------------------------------------
F test that all u_i=0:     F(11, 458) =   213.27             Prob > F = 0.0000
```

Yield

```
. xtreg Yield lnArea lnGW_ha lnWI_ha lnArea2 lnGW_lnArea lnWI_lnArea lnGW_ha2 lnWI_ha2 lnGW_lnWI ln_t, fe

Fixed-effects (within) regression               Number of obs      =       480
Group variable: Country                         Number of groups   =        12

R-sq:  within  = 0.7381                         Obs per group: min =        40
       between = 0.0131                                        avg =      40.0
       overall = 0.0000                                        max =        40

                                                F(10,458)          =    129.08
corr(u_i, Xb)  = -0.9686                        Prob > F           =    0.0000
```

Yield	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnArea	.6726952	.080002	8.41	0.000	.5154788	.8299117
lnGW_ha	-1.501689	.8168214	-1.84	0.067	-3.106872	.1034929
lnWI_ha	4.737456	1.058027	4.48	0.000	2.658267	6.816645
lnArea2	-.0148454	.0018449	-8.05	0.000	-.018471	-.0112198
lnGW_lnArea	.0442534	.043555	1.02	0.310	-.041339	.1298458
lnWI_lnArea	-.1479591	.0489108	-3.03	0.003	-.2440764	-.0518417
lnGW_ha2	.9995294	.2532125	3.95	0.000	.501927	1.497132
lnWI_ha2	-.2967913	.3595597	-0.83	0.410	-1.003383	.4098
lnGW_lnWI	-.974846	.5849735	-1.67	0.096	-2.124411	.1747189
ln_t	.0116793	.0016193	7.21	0.000	.0084971	.0148616
_cons	-7.466971	.9257219	-8.07	0.000	-9.28616	-5.647782
sigma_u	.21847949					
sigma_e	.01877441					
rho	.9926698	(fraction of variance due to u_i)				

F test that all u_i=0:   F(11, 458) =   150.89   Prob > F = 0.0000

Sugarcane

Production

```
. xtreg lnProduction lnArea lnGW lnWaterInput lnArea2 lnGW2 lnWaterInput2 lnWaterInput_lnArea lnWaterInput_lnGW lnArea_lnGW ln_t, fe

Fixed-effects (within) regression               Number of obs      =       320
Group variable: Country                         Number of groups   =         8

R-sq:  within  = 0.8871                         Obs per group: min =        40
       between = 0.9473                                        avg =      40.0
       overall = 0.9314                                        max =        40

                                                F(10,302)          =    237.22
corr(u_i, Xb)  = -0.9503                        Prob > F           =    0.0000
```

lnProduction	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnArea	1.741415	1.479578	1.18	0.240	-1.170173	4.653004
lnGW	8.463237	1.016577	8.33	0.000	6.462767	10.46371
lnWaterInput	-11.39493	2.426872	-4.70	0.000	-16.17065	-6.619208
lnArea2	.3076932	.1079923	2.85	0.005	.0951805	.5202059
lnGW2	.4970094	.0785408	6.33	0.000	.3424529	.651566
lnWaterInput2	1.549327	.2778136	5.58	0.000	1.002632	2.096023
lnWaterInput_lnArea	-.3120182	.1549441	-2.01	0.045	-.616925	-.0071113
lnWaterInput_lnGW	-.9026507	.1197238	-7.54	0.000	-1.138249	-.6670522
lnArea_lnGW	.1107306	.0691697	1.60	0.110	-.0253851	.2468462
ln_t	-.0108791	.0159763	-0.68	0.496	-.0423179	.0205598
_cons	33.10521	11.70863	2.83	0.005	10.06439	56.14603
sigma_u	1.1091352					
sigma_e	.11824359					
rho	.98876228	(fraction of variance due to u_i)				

F test that all u_i=0:   F(7, 302) =   49.97   Prob > F = 0.0000

Yield

```
. xtreg Yield lnArea lnGW_ha lnWI_ha lnArea2 lnGW_lnArea lnWI_lnArea lnGW_ha2 lnWI_ha2 lnGW_lnWI ln_t, fe

Fixed-effects (within) regression               Number of obs      =       320
Group variable: Country                         Number of groups   =         8

R-sq:  within  = 0.7639                         Obs per group: min =        40
       between = 0.3975                                        avg =      40.0
       overall = 0.1769                                        max =        40

                                                F(10,302)          =     97.73
corr(u_i, Xb)  = -0.7885                        Prob > F           =    0.0000
```

Yield	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnArea	-.2358028	.1986138	-1.19	0.236	-.626645	.1550394
lnGW_ha	16.13351	2.175238	7.42	0.000	11.85297	20.41405
lnWI_ha	-14.62755	2.843612	-5.14	0.000	-20.22335	-9.031748
lnArea2	.0097343	.0034505	2.82	0.005	.0029443	.0165243
lnGW_lnArea	-.6373112	.0757604	-8.41	0.000	-.7863963	-.488226
lnWI_lnArea	.5954164	.1013038	5.88	0.000	.3960657	.7947671
lnGW_ha2	3.108376	.4821881	6.45	0.000	2.159502	4.05725
lnWI_ha2	6.792666	.9375542	7.25	0.000	4.9477	8.637632
lnGW_lnWI	-10.27386	1.32876	-7.73	0.000	-12.88866	-7.659061
ln_t	-.0005367	.0013296	-0.40	0.687	-.0031532	.0020797
_cons	2.250908	2.889197	0.78	0.437	-3.434599	7.936414
sigma_u	.08953357					
sigma_e	.00976683					
rho	.98824025	(fraction of variance due to u_i)				

```
F test that all u_i=0:     F(7, 302) =     44.59             Prob > F = 0.0000
```

Cobb Douglas

```
. xtreg Yield lnArea lnGW_ha lnWI_ha ln_t, fe

Fixed-effects (within) regression               Number of obs      =       320
Group variable: Country                         Number of groups   =         8

R-sq:  within  = 0.6437                         Obs per group: min =        40
       between = 0.7100                                        avg =      40.0
       overall = 0.4391                                        max =        40

                                                F(4,308)           =    139.11
corr(u_i, Xb)  = -0.9015                        Prob > F           =    0.0000
```

Yield	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnArea	.0592832	.0095558	6.20	0.000	.0404804	.0780861
lnGW_ha	.3188772	.0683331	4.67	0.000	.1844184	.4533359
lnWI_ha	.3995615	.0669818	5.97	0.000	.2677617	.5313612
ln_t	-.0040371	.0015014	-2.69	0.008	-.0069915	-.0010828
_cons	-.6019108	.2071821	-2.91	0.004	-1.009582	-.1942394
sigma_u	.1028579					
sigma_e	.01188153					
rho	.98683222	(fraction of variance due to u_i)				

```
F test that all u_i=0:     F(7, 308) =     89.49             Prob > F = 0.0000
```

Appendix H

This appendix contains the calculated shadow prices per year for the countries included in the estimation of citrus, maize and sugarcane yield.

Citrus

	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001
Iran	0,678715	1,145815	0,128727	0,1418187	0,358392	0,469977	0,4538105	0,594121	0,887446	0,85213	0,840424
Italy	0,661861	0,567946	0,388126	0,3686698	0,402193	0,434209	0,3831434	0,362305	0,387411	0,307337	0,323632
Mexico	0,203355	0,191301	0,193511	0,1233311	0,089844	0,107091	0,1002737	0,125156	0,157455	0,132468	0,095894
Pakistan	0,104501	0,101088	0,129277	0,1451964	0,12747	0,11456	0,116057	0,114863	0,067366	0,099207	0,081982
Saudi Arabia									0,768866	0,711913	0,797343
South Afri	0,220348	0,242068	0,23792	0,2278053	0,325127	0,243541	0,196686	0,242287	0,225565	0,137097	0,164727
Spain	0,308215	0,262712	0,185368	0,261328	0,372941	0,42272	0,2910872	0,259563	0,272248	0,213062	0,22142
Turkey	0,329884	0,321137	0,339755	0,2776004	0,387099	0,401926	0,343936	0,336166	0,310479	0,305252	0,207955
USA	0,249595	0,22285	0,16287	0,1794977	0,170819	0,191379	0,1715958	0,118215	0,154873	0,114662	0,108144
China	0,068882	0,065811	0,05601	0,0475197	0,041523	0,0843	0,0218977	0,096728	0,134938	0,13472	0,122869
Egypt			0,11351	0,1155452	0,112645	0,127932	0,1344745	0,136487	0,136485	0,135539	0,116911

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Iran	0,30308	0,276793	0,206956	0,25188	0,307191	0,37885	0,396143	0,488574	0,537966	0,600141	0,935176	0,811308
Italy	0,367775	0,46751	0,488933	0,440581	0,44858	0,517156	0,442244	0,493536	0,464743	0,511121	0,458629	0,536529
Mexico	0,105171	0,114225	0,101887	0,094922	0,117933	0,137641	0,12938	0,114848	0,142619	0,166623	0,152591	0,148573
Pakistan	0,159772	0,190191	0,191802	0,188917	0,211241	0,209273	0,191299	0,191962	0,201755			
Saudi Arabia	0,711913	0,711913										
South Afri	0,145005	0,235703	0,30939	0,204457	0,222464	0,317044	0,32657	0,270175	0,434495	0,487713	0,437525	0,297762
Spain	0,23183	0,275274	0,305148	0,316889	0,238851	0,296029	0,416176	0,335821	0,367958	0,309194	0,265858	0,316204
Turkey	0,244284	0,336092	0,400936	0,472564	0,428539	0,558318	0,621452	0,486354	0,520909	0,471448	0,424748	0,354756
USA	0,128475	0,10817	0,113925	0,160291	0,194806	0,353178	0,220084	0,191151	0,233958	0,250868	0,381135	0,339301
China	0,129982	0,108871	0,119356	0,122658	0,162936	0,476663	0,648864	0,632894	0,538113	0,652762	0,613001	0,755788
Egypt	0,105348	0,081939	0,082285	0,09038	0,146855	0,197373	0,154367	0,286307	0,194937	0,192247	0,189297	0,167366

Maize

	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001
India	0,150624	0,133127	0,116694	0,12977	0,129984	0,118651	0,12228868	0,121135	0,12782	0,119692	0,107842
Iran		0,218946	0,191323	0,149014	0,184363	0,264377	0,26374327	0,337815	0,556439	0,540021	0,551066
Italy	0,327155	0,290649	0,232137	0,214883	0,254043	0,247059	0,18515155	0,174153	0,179486	0,141185	0,134456
Mexico	0,252951	0,265544	0,266205	0,209901	0,183707	0,203924	0,18466164	0,170926	0,164243	0,172232	0,16773
Pakistan	0,208222	0,196201	0,175282	0,200643	0,22614	0,21393	0,22480574	0,209051	0,177129	0,161362	0,14401
South Afri	0,139621	0,171153	0,13616	0,111011	0,171797	0,148702	0,13827443	0,11213	0,119139	0,08481	0,111266
Spain	0,284972	0,270462	0,241725	0,214346	0,239937	0,220171	0,17230931	0,165863	0,161996	0,142578	0,131814
Turkey	0,177582	0,216697	0,206458	0,169639	0,197802	0,227291	0,20827195	0,199577	0,184133	0,17791	0,149019
USA	0,100434	0,087475	0,105834	0,096114	0,138232	0,151191	0,10367403	0,082075	0,077756	0,078835	0,084235
China	0,087233	0,091258	0,104771	0,106005	0,15414	0,279266	0,22928016	0,202188	0,15785	0,443533	0,168311
Egypt	0,151769	0,141423	0,147534	0,152812	0,163636	0,170677	0,17591315	0,184558	0,192434	0,1888	0,166625

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
India	0,113747	0,116694	0,142219	0,138084	0,182808	0,210199	0,208515					
Iran	0,165189	0,158421	0,159956	0,172845	0,193735	0,262596	0,269145	0,263248	0,299017	0,430771	0,52182	0,518286
Italy	0,130501	0,165153	0,193885	0,169109	0,186317	0,268953	0,295661	0,196939	0,238581	0,34153	0,311521	0,323584
Mexico	0,167874	0,161955	0,16071	0,156433	0,199296	0,241343	0,273339	0,224321	0,240827	0,355717	0,329036	0,284737
Pakistan	0,151891	0,165024	0,187187	0,183537	0,197122	0,204474	0,180992	0,235661	0,247249			
South Afri	0,139849	0,133337	0,14016	0,107229	0,157561	0,222431	0,217786	0,168781	0,148473	0,229001	0,259765	0,225054
Spain	0,139242	0,180389	0,197376	0,181621	0,20598	0,302701	0,28791	0,216288	0,259753	0,325331	0,322597	0,285287
Turkey	0,181133	0,232237	0,266384	0,281372	0,272994	0,332792	0,360112	0,307956	0,336221	0,406535	0,34732	0,348133
USA	0,098274	0,102594	0,087475	0,085315	0,129593	0,17819	0,17279	0,151191	0,220307	0,264585	0,292663	0,190069
China	0,157875	0,230939	0,20485	0,204301	0,272261	0,208822	0,235767	0,262474	0,295109	0,347553	0,414176	0,528182
Egypt	0,150962	0,127912	0,180564	0,193612	0,203249	0,303933	0,281291	0,271739	0,361068	0,352573	0,387423	0,35129

Sugarcane

	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001
India	-0,04866	-0,06124	-0,06305	-0,06412	-0,06844	-0,05267	-0,054904199	-0,0379	-0,03866	-0,03928	-0,03898
Iran	0	0	0								
Mexico	-0,06979	-0,07957	-0,08285	-0,09406	-0,05731	-0,06926	-0,079881897	-0,07222	-0,07643	-0,08014	-0,09187
Pakistan	-0,04799	-0,04992	-0,04655	-0,04397	-0,04829	-0,04441	-0,043733161				
South Afri	-0,06124	-0,09883	-0,09079	-0,0869	-0,08589	-0,07522	-0,076619617	-0,06762	-0,05876	-0,056	-0,05514
Spain	-0,15247	-0,16229	-0,12076	-0,12181	-0,14039	-0,14078	-0,123609056	-0,12114	-0,11873	-0,10268	-0,10866
USA	-0,08604	-0,08307	-0,08604	-0,08604	-0,08901	-0,09197	-0,091973686	-0,08901	-0,08307	-0,08604	-0,09494
China	-0,07914	-0,06886	-0,06333	-0,05301	-0,07816	-0,09278	-0,090905608	-0,08171	-0,06559	-0,05806	-0,0681
Egypt	-0,05484	-0,05895	-0,0646	-0,07099	-0,07872	-0,08311	-0,083173691	-0,08319	-0,08301	-0,08118	-0,07094

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
India	-0,04242	-0,04649	-0,04879	-0,05108	-0,0526	-0,05823	-0,05524					
Iran												
Mexico	-0,09206	-0,08629	-0,08641	-0,09894	-0,10131	-0,10356	-0,10639	-0,08529	-0,1456	-0,14633	-0,14961	-0,1196459
Pakistan												
South Afri	-0,04841	-0,06628	-0,07324	-0,08089	-0,07942	-0,0826	-0,07578	-0,10091	-0,13353	-0,14465	-0,14092	-0,1208216
Spain	-0,10052	-0,13394	-0,1328	-0,13306	-0,1356	-0,14762	-0,15776					
USA	-0,09197	-0,09791	-0,09197	-0,09197	-0,10087	-0,09494	-0,09791	-0,11274	-0,13648	-0,15428	-0,13648	-0,1038413
China	-0,09571	-0,30468	-0,32261	-0,3766	-0,44283	-0,51104	-0,6063	-0,63856	-0,82828	-0,73483	-1,08143	-0,6225694
Egypt	-0,06923	-0,05324	-0,06225	-0,08215	-0,0828	-0,09582	-0,10923	-0,12585	-0,14782	-0,16761	-0,17625	-0,1555209