The Decomposition Model of the World Agricultural Production and Consumption

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Abstract

This paper presents a core that will be used for the construction of the model proper for the analysis of the dynamics of the world agricultural production and consumption. First, the paper overviews the index decomposition analysis (hereafter, IDA). The IDA is a commonly adopted tool for determination of the impact of indicators such as population, economic activity, its structure, technology and possibly other factors on a chosen variable. In this paper, the IDA is applied on data provided by the World Bank for the last 20 years. The IDA splits observed changes in investigated variables into level, intensity, and structural indicators: changes in the world agricultural production are divided between changes in the total population (scale effect) and its regional composition (structural effect), and in employment and capital effects (intensity effects). The evolution of world food consumption can be decomposed to changes in total population (scale effect), its composition over the world (structural effect), changes in GDP per capita and structure of consumption (intensity effects). Our results suggest that structural effects are relatively small in comparison with intensity effects. The structural effects are manifested by a rapid growth of agricultural production and consumption in Asia. The results will be used for specification and estimation of food demand function and agricultural production function. The estimates will be combined in a small simulation model, which will link the agriculture production and food consumption via prices. The final model will be able to project food prices based on assumptions about population growth and technology improvements. All the computations are/will be done in Matlab.

1 Introduction

The dynamics of the agricultural production and food consumption interests researchers, policy-makers, or planners around the world for a variety of reasons. The main reason is the assessment of the world's ability to feed itself (Islam, 1995), but other reasons like impacts of agricultural production on composition of land or regional relationships between agricultural supply and demand are important too. The goal of this paper is to contribute to this research agenda by analysis of regional and intensity shifts in agricultural production and consumption around the world and its consequences on food demand function and world agricultural production function.

For the determination of the main impacts, the index decomposition analysis (hereafter, IDA) is used. The IDA is a commonly adopted tool for determination of the effects of indicators such as population, economic activity and its structure, technology and possibly other factors on a chosen indicator (Ang [2]). Nevertheless, alternative approaches, such as econometric decomposition analysis (Stern [9]) or structural decomposition analysis (Hoekstra & van der Bergh [6]) have been proposed too. Each approach has different data requirements and provides different pieces of information but there can also been found several common features[1]. This paper primarily uses the IDA to isolate the impacts of changes in labor productivity, capital formation, technology and composition of population on world food production and impacts of shifts in GDP, its structure and population on world agricultural consumption. Namely, logarithmic mean Divisia index method II (hereafter LMDI II) proposed by Ang and Choi [1] or Ang [4] is chosen as appropriate tool for the analysis.

Based on these results, we will propose a demand function for food and an agricultural production function and estimate them. The two estimates will be then combined in a small simulation model, which links the agriculture production and food consumption via prices.

The rest of the paper is organized as follows: Section 2 describes the main stylized facts for the food production and consumption in past years. Section 3 describes the methodology behind the IDA and section 4 shows the results of agricultural production and consumption decomposition analysis. Section 5 summarizes the results and describes implications for further work on this research.

2 Data and stylized facts

The data for the analysis come mainly from the World Bank website.[2] The world has been divided among seven aggregated regions: Europe, non-European developed countries, Middle East, rest of the former USSR, the rest of Asia, Africa, and Latin America. Grouping of the region respect preferentially economic structures of particular states and their location.

For the purpose of the analysis, we use the value added in agricultural sector measured in 2000 US dollars as variable expressing regional agricultural production. The real agricultural value added increased about 42 % between the year 1990 and 2007. The growth can be split into two periods: the years (1990 - 1995) witnessed moderate increase oscillating around 1 % per year. Moreover a very negligible drops in real value added were recorded in the years 1991 and 1995. Since the year 1996 the total real value added in agriculture has permanently been increasing with annual growths oscillating around 2 % and ranging from 1,6 % to 4,8 %.

Food consumption in the selected regions is computed as the real value added created in the

[1] For example, structural decomposition analysis is often cited together with IDA (eg. Hoekstra & van der Bergh [6]). In both methods, Laspeyeres (weighting by base year), Paasche (weighting by target year) and Marshall-Edgeworth (weighting by the mean of base and target year) indices can be applied. However, only in IDA approach, different types of Divisia indices can further be employed.

[2] World Development Indicators & Global Development Finance downloadable at: *http://databank.worldbank.org.*

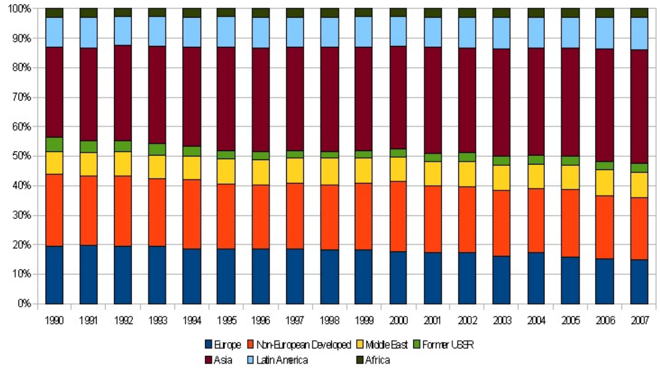

Figure 1: Composition of World Agricultural Production

agriculture minus the real value of net agricultural exports. It increased about the same amount as world agricultural production in inspected period. The total indicator of food consumption in selected regions grew annually about 2 % on average. Real agricultural consumption increased the most in Asian, African and Middle East countries (around 3 % a year on average). A relatively high annual growth in real consumption was also indicated in the case of non European developed countries (1.47 %). Looking at regional composition of overall food consumption, Asian countries increased their share from 30 % to 37 % in the analyzed period while African countries raised their share from 2.7 % to 3.1 %. The share of European countries on overall food consumption declined by approximatively 4 % from 20.6 % to 16.4 %.

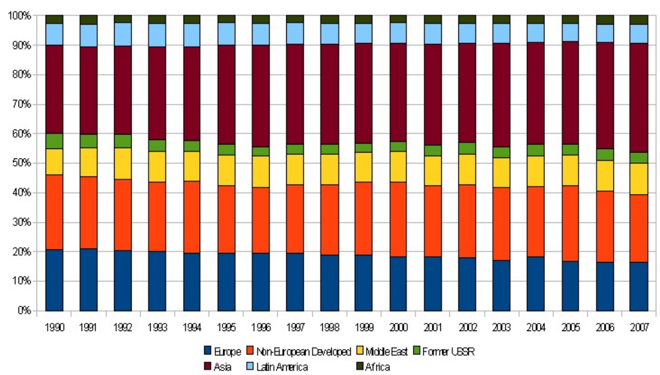

Figure 2: Composition of World Food Consumption

3 The index decomposition analysis

3.1 General theory

The goal of the IDA is to understand historical changes in a social, economic, environmental, or agricultural indicator, and to gauge the driving forces or determinants that underlie these changes. The application of the IDA to agricultural indicators has been used especially in assessing the influence of the population size, the amount of arable land, sectoral shifts, capital formation, or technology changes.

Let us consider the indicator Φ, which is given as:

$$\Phi_t = \Upsilon_t \sum_i \phi_{1it} \dots \phi_{Mit}, \tag{1}$$

where Υ_t is the scale measure[3], and the summation runs over countries, commodities, or another interesting dimension. The goal is to decompose the change in the indicator into a number of determinants.

If observations were available in continuous time, the decomposition would be straightforward: the percentage change in the indicator $\dot{\Phi}_t/\Phi_t$ could be written as follows:

$$\frac{\dot{\Phi}_t}{\Phi_t} = \frac{\dot{\Upsilon}_t}{\Upsilon_t} + \frac{\sum_i \frac{\dot{\phi}_{1it}}{\phi_{1it}}\phi_{1it}\dots\phi_{Mit}}{\sum_i \phi_{1it}\dots\phi_{Mit}} + \dots + \frac{\sum_i \frac{\dot{\phi}_{Mit}}{\phi_{Mit}}\phi_{1it}\dots\phi_{Mit}}{\sum_i \phi_{1it}\dots\phi_{Mit}} \tag{2}$$

where $\frac{\dot{\Upsilon}_t}{\Upsilon_t}$ is the growth in the scale measure, and the expression $\frac{\sum_i \frac{\dot{\phi}_{mit}}{\phi_{mit}}\phi_{1it}\dots\phi_{Mit}}{\sum_i \phi_{1it}\dots\phi_{Mit}}$ could be interpreted as the weighted percentage change in the factors ϕ_{mit}. The problem is that observations are not available in continuous time, and therefore discrete-time approximations should be used.

A discrete-time decomposition approximation can adopt an additive or a multiplicative mathematical form. The additive form decomposes the difference in the indicator Φ between times t_1 and t_2 into the sum of determinants D_i and a residual term $\tilde{R}$:

$$\Phi_{t_2} - \Phi_{t_1} = D_1 + D_2 + \dots + D_N + \tilde{R}. \tag{3}$$

The multiplicative form decomposes the relative growth of the indicator into the product of determinant effects:

$$\frac{\Phi_{t_2}}{\Phi_{t_1}} = D_1 \times D_2 \times \dots \times D_N \times \tilde{R} \tag{4}$$

A number of mathematical forms for the additive as well as multiplicative decomposition forms has been proposed. Ang[2], [4] provide useful overviews of mathematical forms and their useful properties. The following four properties are particularly relevant to the index decomposition analysis:

Exactness: an exact decomposition has no residual; in the additive case this means that the residual equals 0, while it equals 1 in the multiplicative case.

Time reversal: the decomposition satisfies this property whenever the decomposition yields the reciprocal results after the reversal of the time periods.

Factor reversal: concerns the invariance with respect to the permutation of determinants.

Robustness: a decomposition is robust if it does not fail when it comes across zero (or even negative) values in the dataset.

3.2 LMDI II

This paper applies the LMDI II suggested by Ang and Choi [1] or Ang [4] as the preferred method under a wide range of circumstances: the LMDI II satisfies the four requirements mentioned above and has no residual (i.e. $\tilde{R} = 0$ in the additive case and $\tilde{R} = 1$ in the multiplicative case.[4]) While LMDI II has both a multiplicative and an additive form the multiplicative form will be applied for subsequent analysis.

[3]Such as the total population if the aggregate food consumption is investigated, or the total agricultural land if the production is investigated, but it may represent also the real GDP if the relation between wealth and food production/consumption is investigated

[4]This is advantage since decomposition based on Laspeyres indices could suffer from large unexplained residuals in some cases.

The multiplicative LMDI II is defined as follows:

$$D_j^{t_2,t_1} \equiv \exp\left(\sum_i \frac{\mathcal{L}(\Phi_{it_2},\Phi_{it_1})}{\mathcal{L}(\Phi_{t_2},\Phi_{t_1})}\log\left(\frac{\phi_{jit_2}}{\phi_{jit_1}}\right)\right), \tag{5}$$

where $\Phi_{it} \equiv \prod_{j=1}^{m}\phi_{jit}$ and $\mathcal{L}$ is so-called logarithmic average:

$$\mathcal{L}(x_1,x_2) \equiv \begin{cases} \frac{x_1-x_2}{\log x_1-\log x_2} & \text{if } x_1 \neq x_2 \\ x_1 & \text{otherwise.} \end{cases}$$

The residual term satisfies $R = 1$, since the *LMDI II* is an exact approach.

The *intensity effect* is than given as:

$$D_a^{t_2,t_1} = \exp\left(\sum_i \frac{\mathcal{L}(a_{it_2}s_{it_2},a_{it_1}s_{it_1})}{\mathcal{L}(\sum_j a_{jt_2}s_{jt_2},\sum_j a_{jt_1}s_{jt_1})}\log\left(\frac{a_{it_2}}{a_{it_1}}\right)\right),$$

and the *structure* effect is given as follows:

$$D_s^{t_2,t_1} = \exp\left(\sum_i \frac{\mathcal{L}(a_{it_2}s_{it_2},a_{it_1}s_{it_1})}{\mathcal{L}(\sum_j a_{jt_2}s_{jt_2},\sum_j a_{jt_1}s_{jt_1})}\log\left(\frac{s_{it_2}}{s_{it_1}}\right)\right).$$

4 Empirical Results

The decomposition is provided both for agricultural production and agricultural consumption for seventeen year period 1991-2007.[5] The explanations of changes in both indicators are, however, different.

4.1 The Agricultural Production

In the case of agricultural production, the *scale effect* explains the changes in real production in agriculture as a result of changes in total population over the world L. The assumption is that growing population results in growing needs and higher production. Further, the *structural effect* D_s is the result of changes in composition of population over the world.The *structural effect* is assumed to be rather negative since agricultural production often moves to less productive world regions with higher population growths. The *intensity effect* is in the case of agricultural production consequently decomposed into following sub-effects:

Intensity effect of employment D_a: reflects changes in number of employees in agriculture per total population, the assumption is that the effect is rather adverse since the number of people employed in agricultural sector declines compared to total population of selected region.

Intensity effect of capital D_b: are changes in value added per employee in agriculture, the effect is expected to be positive since better capital equipment leads to higher productivity.

Equations (1), (4), and from the common known approximation $\log(\frac{X_2}{X_1}) \cong \frac{X_2}{X_1} - 1)$ imply:

$$\frac{A_{t2}^s - A_{t1}^s}{A_{t1}^s} = \frac{L_{t2} - L_{t1}}{L_{t1}} + \log D_a + \log D_b + \log D_s, \tag{6}$$

[5]With utilization of new dataset, we expect to have the time period for last 20 years.

where A^s stands for real agricultural value added, L is total population and whole fraction addresses scale effect, logarithms of D_a, D_b are particular intensity effects, and the logarithm of D_s shows structure effect.

The lower subfigure of Figure (3) shows the decomposition of changes in the real value added (production). The increases in value added are mainly driven by the scale effect of population and capital effect. The employment intensity effect adversely affects changes in the value added during the whole analyzed period. The structural effect rather shows that the agricultural production is indeed moved to poorer countries. The structural effect is weakened by the fact, that the value added in agriculture naturally increases also in developed countries as a result of production of 'more luxurious' agricultural products.

A deeper analysis of the regions shows that the value added per square kilometer of agricultural land favorably developed mainly in Asian countries which supported growths in total agricultural value added. Growing productivity was also possible to see in the European region up to the year 2003, than after a relatively high improvement in the year 2004, continuous drops were observed in the years 2005, 2006 and 2007. In Europe, the main driver for the highest agricultural production increase in observed period was a relatively large improvement in value added per agricultural land and a large decrease in employees.

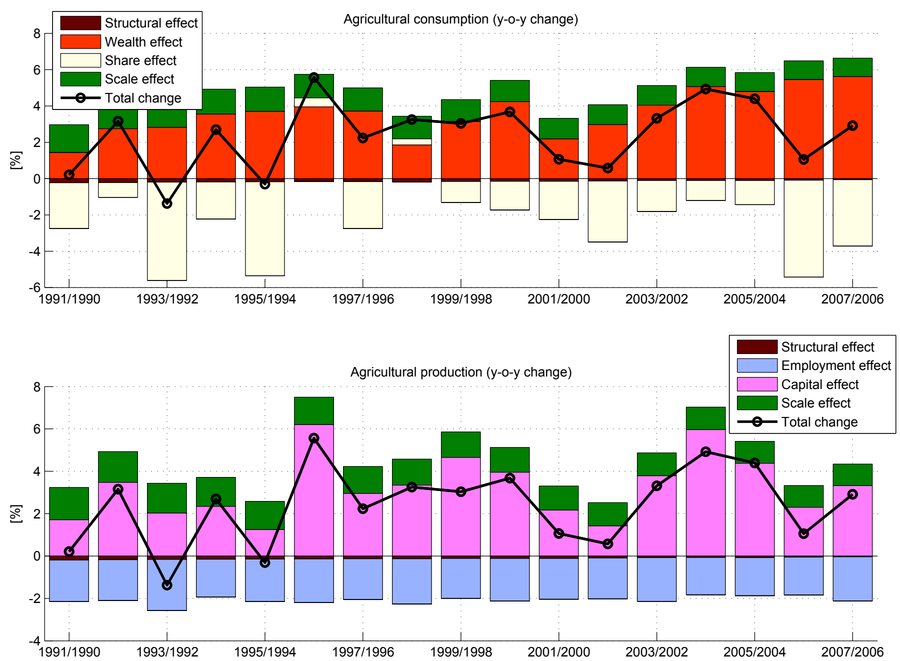

Figure 3: Results

4.2 The Real Agricultural Consumption

In the case of agricultural consumption, the *scale effect* explains the changes in real consumption of agricultural goods as a result of changes in total population L with an expectation of positive relationship since more people are assumed to consume more food. Furthermore, the *structural effect* reflects changes in composition people in the world. The idea of this effect is that negative effect shows growing number of people in poorer regions with smaller demand on food. The *intensity effect* is in the case of real agricultural consumption split into two sub-effects:

Intensity effect of GDP D_a: is measured by changes in ratio of GDP per capita, it is assumed a positive impact on consumption since higher income usually leads to higher consumption,

Intensity effect of agricultural consumption share D_b: reflects changes in share of consumption of food in GDP, the effect should be negative since food is a basic commodity and the share of expenditure on food in total income declines as the society becomes richer.

Again, using the same approximation we get following formula:

$$\frac{A^d_{t2} - A^d_{t1}}{A^d_{t1}} = \frac{L_{t2} - L_{t1}}{L_{t1}} + \log D_a + \log D_b + \log D_s, \tag{7}$$

where A^d stands for agricultural demand/consumption, L expresses population, D_a intensity effect of GDP, D_b intensity effect of agricultural consumption share and D_s structural effect.

The upper subfigure of Figure (3) shows the decomposition of changes in real agricultural consumption. It can be seen that annual changes in world agricultural consumption range from approximately - 2 % to 4.7 %. The growths are mainly driven by intensity effect of GDP. In addition, the growing population also significantly contributed to increases in agricultural demand. On the contrary, the share of consumption in GDP mainly hampered the growth (the only exception are the years 1996 and 1998). The structural effect is relatively small but its negative direction occurred as expected.

Inspecting the data more deeply, it can be seen that the share of people with lesser food demand (i.e. in the rest of Africa and Latin America) was gradually increasing causing the structural effect to be negative. Intensity effect of GDP was mainly driven by Asian, non European developed and European countries.

For the completeness, we show basic formulas programmed in Matlab in the Appendix of this paper.

5 Conclusion

This paper attempts at explaining the changes in the world agricultural demand and supply by changes of other relevant socioeconomic and agricultural indicators. For the analysis, IDA was chosen as appropriate tool with LMDI II as flagship to this approach. The changes in both variables were described by changes in level, intensity and structural effects. The world agricultural production is explained by changes in total population (scale effect) and its regional composition (structural effect), employment and capital intensity effects. In addition, evolution of world food consumption can be described by changes of total population (scale effect) and its composition over the world (structural effect), changes in GDP per capita and structure of consumption (intensity effects). The structural effects are relatively negligible compared to intensity and scale effects. Based on these results, we will propose a demand function for food and an agricultural production function and will estimate them. In the estimation, we will have to use computationally-intensive Bayesian techniques (MCMC algorithms) to deal with missing data implied by incomplete dataset. The two estimates will then combined in a small simulation model, which will link the agriculture production and food consumption via prices. The model will be able to project food prices based on assumptions about population growth and technology improvements. Estimations and model simulations will be done in Matlab.

Acknowledgements

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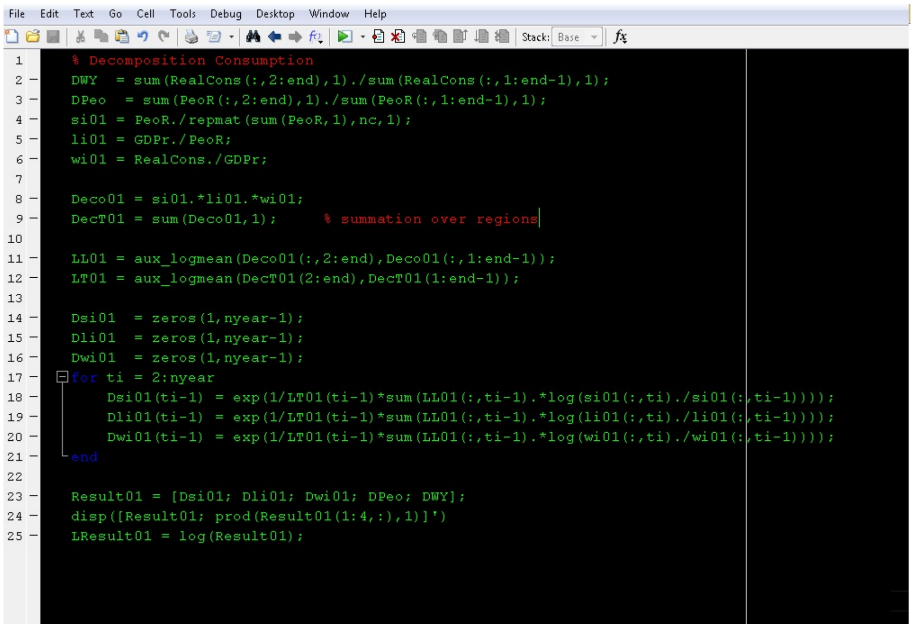
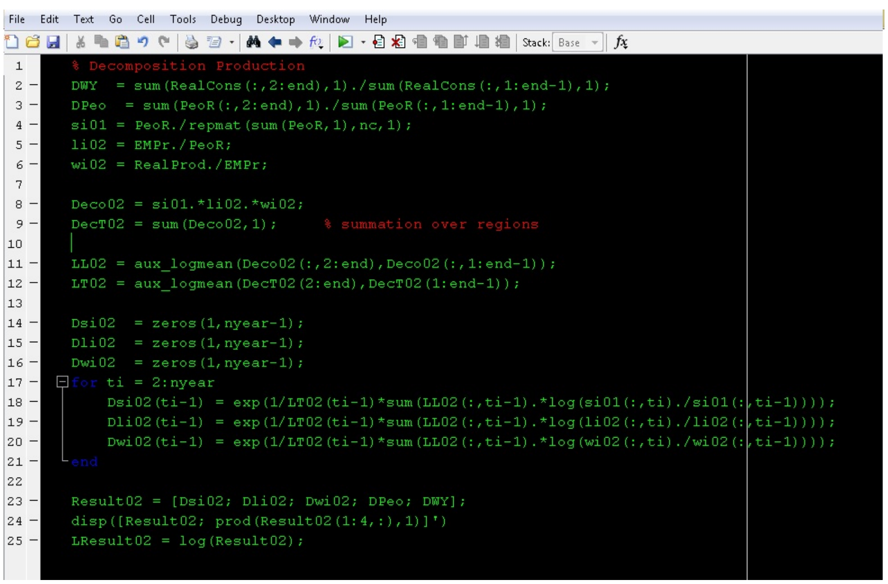
Appendix



```
% Decomposition Consumption
DWY  = sum(RealCons(:,2:end),1)./sum(RealCons(:,1:end-1),1);
DPeo  = sum(PeoR(:,2:end),1)./sum(PeoR(:,1:end-1),1);
si01 = PeoR./repmat(sum(PeoR,1),nc,1);
li01 = GDPr./PeoR;
wi01 = RealCons./GDPr;

Deco01 = si01.*li01.*wi01;
DecT01 = sum(Deco01,1);      % summation over regions

LL01 = aux_logmean(Deco01(:,2:end),Deco01(:,1:end-1));
LT01 = aux_logmean(DecT01(2:end),DecT01(1:end-1));

Dsi01  = zeros(1,nyear-1);
Dli01  = zeros(1,nyear-1);
Dwi01  = zeros(1,nyear-1);
for ti = 2:nyear
    Dsi01(ti-1) = exp(1/LT01(ti-1)*sum(LL01(:,ti-1).*log(si01(:,ti)./si01(:,ti-1))));
    Dli01(ti-1) = exp(1/LT01(ti-1)*sum(LL01(:,ti-1).*log(li01(:,ti)./li01(:,ti-1))));
    Dwi01(ti-1) = exp(1/LT01(ti-1)*sum(LL01(:,ti-1).*log(wi01(:,ti)./wi01(:,ti-1))));
end

Result01 = [Dsi01; Dli01; Dwi01; DPeo; DWY];
disp([Result01; prod(Result01(1:4,:),1)]')
LResult01 = log(Result01);
```

Figure 4: Decomposition code - Food Consumption



```
% Decomposition Production
DWY  = sum(RealCons(:,2:end),1)./sum(RealCons(:,1:end-1),1);
DPeo  = sum(PeoR(:,2:end),1)./sum(PeoR(:,1:end-1),1);
si01 = PeoR./repmat(sum(PeoR,1),nc,1);
li02 = EMPr./PeoR;
wi02 = RealProd./EMPr;

Deco02 = si01.*li02.*wi02;
DecT02 = sum(Deco02,1);      % summation over regions

LL02 = aux_logmean(Deco02(:,2:end),Deco02(:,1:end-1));
LT02 = aux_logmean(DecT02(2:end),DecT02(1:end-1));

Dsi02  = zeros(1,nyear-1);
Dli02  = zeros(1,nyear-1);
Dwi02  = zeros(1,nyear-1);
for ti = 2:nyear
    Dsi02(ti-1) = exp(1/LT02(ti-1)*sum(LL02(:,ti-1).*log(si01(:,ti)./si01(:,ti-1))));
    Dli02(ti-1) = exp(1/LT02(ti-1)*sum(LL02(:,ti-1).*log(li02(:,ti)./li02(:,ti-1))));
    Dwi02(ti-1) = exp(1/LT02(ti-1)*sum(LL02(:,ti-1).*log(wi02(:,ti)./wi02(:,ti-1))));
end

Result02 = [Dsi02; Dli02; Dwi02; DPeo; DWY];
disp([Result02; prod(Result02(1:4,:),1)]')
LResult02 = log(Result02);
```

Figure 5: Decomposition code - Agricultural Production