Development of a global economic-land use model (GTEM-AEZ) for analysis of climate change impact and agricultural productivity.

Abstract

With a vital role of agricultural sectors and associated land use in addressing climate change and food security, science-based research to raise awareness of the public and to inform policymakers become crucial. We extended our modelling GTEM (Global Trade Environmental Model) by incorporating the land use mechanism in GTAP-AEZ into GTEM, becoming the GTEM-AEZ model to evaluate the impact of economic and environmental issues. We also develop a data routine program to transform GTAP land use data to the data used for the GTEM-AEZ model. For such development, we identified several bugs and incomprehensive features in the database. We aim to document how to develop the land use mechanism in GTEM-AEZ model and how to develop program to transform GTAP land use to GTEM land use data, fix bugs. In the GTEM-AEZ model, 18 AEZs (Agro-Ecological Zones) land are substituted via CES (Constant Elasticity of Substitution) function in the production structure, and we constructed a three-level nested CET (Constant Elasticity of Transformation) functional form to allow land transformation in the land supply. For the database, all 141 regions and 65 sectors in GTEM data are aggregated into 22 regions and 43 industrial sectors, with disaggregated all land using sectors and food sectors. The baseline scenarios are built on the projection of GDP, population, and labour supply along with energy efficiency in agricultural sectors, transportation sectors and agricultural productivity forecasted by 2050. For the policy scenario, we aim to analyse the impact of climate change, along with agricultural productivity development. The results show that a higher agricultural productivity along with climate change (RCP2.6) leads to higher GDP growth rate and lower food price increase.

1. Introduction

Climate changes such as floods, droughts, heat waves, wildfire, and tornadoes, have recently occurred frequently and intensively in many countries. Human-induced activities releasing more GHG emissions are considered as a main reason for global warming. Global warming is expected to increase by an average of 1.3ºC by 2050 and 2.2ºC by 2100 (Pachauri & Meyer, 2014). Total net anthropogenic GHG emissions have continued to rise in recent years, in particular these emissions in 2019 were about 12% higher than in 2010 and 54% higher than in 1990. The annual average during the decade 2010-2019 was 56+_6.0 GtCO2-eq, 9.1 GtCO2 -eq higher than in 2000-2010. In 2019 GHG emissions sourced from the energy supply accounts for about 34%, compared to 24% from industry and 15% and 6% from transport and building, respectively. The agriculture, forestry, and other land use (AFOLU) account for 22% of the total emissions. The emissions growth in AFOFU is more uncertain than in other sectors. (Change, 2022).

Agriculture is most affected by climate change however agriculture is an optimum option to reduce carbon emissions in a cost- effective way. GHG emissions released from agriculture include methane (CH4) from livestock and rice paddy, nitrous oxide (N2O) from fertilizer application, CO2 from decomposition or burning crop residues, and use of fossil fuels. Agricultural GHG emissions could be reduced thanks to production management and land change use. Wang et al. (2022) estimated that to achieve a net zero-emissions target, the agricultural sector plays an important role in GHG emissions reduction. For instance, inclusion of the agricultural sectors leads to 4.4 times, compared to the case of exclusion of agricultural sector, equivalence to gross emissions reduces by 22% for the former, compared with 5.3% for the later.

In 2019, agriculture accounts for 7.21 GtCO2e of emissions from existing agricultural production and another 3.5 GtCO2e in net emissions from land use change. If global cropland increases by 6% (about 95 million hectares) from 2017 levels, agriculture releases a total of 272.5 GtCO2e from land use change and existing agricultural production by 2050. Meanwhile, global cropland decreases by 5% in carbon-rich areas; it reduces agricultural emissions by 29.7 GtCO2e (Fuglie et al., 2022). Increasing agricultural productivity is highly recommended to address both issues of food security by lowering food prices and GHG emissions reduction via land use change and production change. There is a connection between agricultural productivity growth, global food security and the cost of environmental policy. Fuglie et al. (2022) stated that increased 1.65 billion R &D spending reduce food price, reduce agricultural emissions by 46.7 GtCO2e, it also indicated that increase $0.61 billion R&D spending in developing countries leads to lower food price and reduce number of under nourish persons.

A general equilibrium (CGE) model has been widely used to evaluate various aspects of climate change on agriculture (Fabregat-Aibar et al., 2022; van Tongeren et al., 2021). However, they have been differences in various land covers or in addressing the land heterogeneity with various construction of land transformation in the land supply.

In this study, we aim to document how we develop the land use mechanism by incorporating Agro-Ecological Zones (AEZ) land uses into the GTEM model to create the GTEM-AEZ version. We also detail how we develop a program to transform GTAP land use to GTEM land use data, fix bugs. For the database, all 141 regions and 65 sectors in GTAP data are aggregated into 22 regions and 43 industrial sectors, in which all 8 crop sectors, 4 livestock sectors and food sectors in the GTAP database are disaggregated sectors in the GTEM-AEZ database. The baseline scenarios are formed from the projections of GDP and population, along with projection of labour supply, energy efficiency in agricultural and transportation sectors and climate change. We also calibrated the agricultural productivity data by region by 2050, based on our forecast data come from our econometric model with agricultural total factor productivity (TFP) index in a period of 60 years between 1961 and 2020. For the policy scenario, we analyse the impact of three scenarios of agricultural productivity development. The result indicated that climate change result in reductions in GDP growth rate in most regions at various degree. However, productivity leads to the increase in prices of foods caused by climate change become lower.

This paper is organized as follows. Section 2 overviews literature review and section 3 describes the GTEM- AEZ model with its modelling framework, AEZ land data compilation, and baseline & policy scenarios. The results are presented in section 4 and section 5 outlines some conclusions and suggestions.

2. Literature Review

There have been many studies employing a partial equilibrium model or a general equilibrium model to evaluate the impact of climate change on agricultural production, food consumption, trade, carbon emissions as well as land change. A partial equilibrium model includes MAgPIE model (Dietrich et al., 2019; Schmitz et al., 2012), GLOBIOM model (Havlík et al., 2018; Havlík et al., 2013) incorporate spatially explicit land use as part of the model solution, GCAM model (Kyle et al., 2011), and IMPACT model (Ignaciuk & Mason-D'Croz, 2014; Robinson et al., 2015) link to grid-based models. A general equilibrium (CGE) model, based on the GTAP database, include FARM model (Darwin, 1995; Darwin et al., 1996), GTAP-AEZ model, GTAP-BIO model (Golub & Hertel, 2012),GDyn-BIO model (Golub et al., 2017), GTEM model (Ahammad & Mi, 2005), MAGNET model (Woltjer et al., 2014) and ENVISAGE model. These models include land types including cropland, pastureland, managed forest land, unmanaged forest land, other natural vegetation, and urban land with different land status of dynamic and static (Schmitz et al., 2014).

There has been land heterogeneity in land rental across alternative uses (Hertel et al., 2008; Sands & Leimbach, 2003). However, the land heterogeneity is handled in various methods of representation of land mobility across uses and accessing new lands. To deal with the land heterogeneity, when modelling land supply, some CGE models such as FARM, GTEM, MAGNET, and ENVISAGE employ Constant Elasticity of Transformation (CET) approach, AIM model use logit functions rather than constant elasticities to model the competition between different land types, or EPPA model based on the average return to cropland to allocate land between crops and livestock or crops and forestland. For partial equilibrium models, the IMPACT model is based on given own- and cross- price elasticity of supply to specify harvested area for crop. With GLOBIOM and MAgPIE, the allocation of land to different crops is based on the relative profitability of crops with minimization of production costs for MAgPIE model and maximization of profitability for GLOBIOM model (Schmitz et al., 2014). There are many approaches employed to handle the land heterogeneity. An approach that takes into account the explicit cost of land preparation and land conversion will effectively address the land heterogeneity (Taheripour et al., 2020). Zhao et al (2020) indicated that land use modelling approach differ not only by the extent of parameter uses, but also more importantly, by the consideration of land heterogeneity and conversion cost, the definition and the treatment of land conversion cost. Land conversion could be classified into an intermediate service employed to transform land from one to another, or a maintenance cost materialized in production; or costs implied by landowner’s preference. It is hard to account exactly the conversion cost to transform land from one to another, thus there are differences in land cost definition among land use models. The CET approach accounts for conversion cost at expense of physical land, in which landowner maximizes the aggregate land rent revenue subject to total land constraint. CGE modes employ the CET function to allow the imperfect transformation of land endowment across alternative uses (Darwin, 1995; Hertel & Tsigas, 1988). The CET approach may be explained as effectively accounting for land heterogeneity and conversion cost in a way of sacrificing resource constraint and the CET function is easy to model in the CGE model.

The limitation of the CET approach is symmetric to all changes, indicating that the conversion cost from forest land to agricultural land is the same as that from agricultural land to forest land. Moreover, the CET approach fails to maintain the physical area of land in balance across agricultural activities (Schmitz et al., 2014; Zhao et al., 2017). The CGE models operate based on I-O tables that represent monetary values of sales and purchases, not physical quantities. Thus, the CET approach is used to track the percentage change in land allocation among alternative uses and land price varies across uses. Total physical area of land can not remain fixed in moving from one equilibrium to another, leading to an imbalance in physical area of land. Taheripour et al. (2020) illustrates that the curvature of the CET function has minor impact on the size of imbalance and the heterogeneity in land price is the main source of imbalance. To maintain balance in physical area of land, there have been some approaches recommended such as an Additive Constant Elasticity of Transformation (ACET) (van der Mensbrugghe & Peters, 2016), logit function or Fretche-based approach (Fujimori et al., 2014; Sands & Leimbach, 2003; Wise et al., 2014).

Taheripour et al. (2020) proposed that to maintain physical area of land in balance, one can use either ex post or ex ante scaling approaches. The ex post approach converts a given solution obtained from the CET approach to the physical area of land by adding an endogenous slack variable in the equation of dollar value of land and physical area of land. The ex ante approach actively makes the adjustments during the simulation process doing swap physical area of land to dollar value of land, in which dollar value of land becomes endogenous variable and physical area of land is an exogenous variable.

Comparing results from these approaches, van de Mensbrugghe & Peters (2016) studied the CET and ACET approaches and concluded that the differences at the global level are relative small, within 1 percent, while there are greater variations across regions, in which wheat production is almost 2.5 percent higher in developing countries, a reduction of over 1.5 percent for developed countries and an average increase of about 1 percent at the global level with the

ACET approach. For the price impact of the ACET and CET approaches, it is higher 4% to 5% for developing countries, and lower 1% for developed countries. For land use, at the global level, the ACET increased aggregate land use in 2050 by nearly 3%, there has been various changes at the regional level, from negative to non- change in high income countries. Taheripour et al. (2020) compared all these approaches and found out that the imbalance issue still exists in the CET approach, while other approaches show zero imbalance. The CET approach and logit function have the same change to price, quantity crop and the same change in welfare. But they have differences for change in land use, land rent and yield. The logit functions require equalization of land rents across uses in the benchmark data, however this requirement is not in line with real observation.

The CET approach has been widely used in most CGE models to allocate land across alternative use. The data source that most CGE model use is the GTAP database with the FAO data, in which land is categorized by 7 land cover and 18 AEZs (Agro-Ecological Zones). Seven land covers include cropland, pastureland, forestland, shrubland, savanna grassland, built-up land, and other land. 18 AEZs land types are classified by 3 temperate zones (tropical, temperate, and boreal) combined with 6 lengths of growing period (6* 60 interval days). Land is transformed across alternative use with the different stage nest CET functional form. With the GTAP-BIO model and GTAP-DynBIO model, land is allocated to alternative use by a three-stage nested CET function. The first level is a CET function of agricultural land and forest land, then agricultural land is allocated to cropland and pastureland, based on the land returns. The third level shows the land allocation among crop sectors and the land allocation among livestock sectors. The value of CET represents the land transformation capability and the higher value of land transformation elasticity the easier land transformation capability among land uses. When CET tends to infinity it represents a perfect transformation among land uses. Different CET values and different nested CET function in the land supply leads to the different effects of climate change to agriculture. With a land expansion, these GTAP models include a parameter represented the relationship between the land expansion with the yield, named ETA parameter.

Woltjer et al. (2014) constructed land supply with three stage-nested CET functional form, land can be transferred between forest land and agricultural land, then agricultural land is allocated to cropland and pastureland. While cropland is supplied to crop sectors, pastureland is supplied to livestock sectors such as cattle and milk sectors. Due to the transformation capability between land uses that determines the value of transformation elasticity. The elasticity of transformation among crop sectors and livestock sectors are higher than that among cropland

and pastureland, as well as higher than forest land and agricultural land. This trend has been recognised in most agricultural land use modelling.

Most recent studies agreed that most economies have been negatively affected by climate change, including a fall in GDP, a reduction in agricultural production, higher prices of agricultural goods, and land use change. For a fall in GDP, climate change is predicted to the average annual losses from 0.4% to 1.8% of Brazilian GDP until the end of century (Souza & Haddad, 2022), while it results in decrease in GDP fall by up tp 2/6%, 7.2%, 8.9%, and 7.8% in India, Pakistan, Bangladesh, and Sri Lanka in 2050 compared to 2015 (Yan & Alvi, 2022). For decreased agricultural production, climate change is estimated to be the median losses of 15% in the production of maize in the US by 2050 (Burke & Emerick, 2016). Climate change is expected to make agricultural loss of 18% between 2030 and 2049 in Brazil (Assunção & Chein, 2016). With prices of agricultural goods, when climate change effects were included into the model prices of major grains such as maize, wheat, rice are on average increase between 5% and 30%, while prices of beef and poultry are projected to increase by 3% and 5% (Ignaciuk & Mason-D'Croz, 2014). Regarding land use change, Alexandratos and Bruinsma (2012) concluded that cropland will be increased by some 70 million hectares by 2050, while developing countries have 132 million ha expansion, at expense of 63 million hectares contraction in developed countries.

Increased agricultural productivity and further land expansion are ways to increase agricultural production. Alexandratos and Bruinsma (2012) represented that the contribution of further land expansion to crop production growth is estimated to be very small, around 4% while the intensification (higher yields, and more intensive use of land) is seen to contribute over 90% of the growth in crop production. In addition, further cropland expansion will generate more GHG emissions. Therefore, expanding cropland to increase food supply is not a good choice. Increasing agricultural productivity via higher Research and Development (R&D) spending on agriculture is recommended to increase the quantity of foods and it also reduces GHG emissions and lower agricultural goods prices. Additional $225 billion investment results in 61 Mha less conversion of cropland and reduce 15 GtCO2e emissions by 2050 (Lobell et al., 2013), Spending $1.65 trillion on R& D will reduce agricultural emissions by 46.7 GtCO2e by 2050. Higher agricultural productivity results in saving in cropland necessary for meeting a higher food demand (Fuglie et al., 2022). Villoria (2019) concluded that during ten-year period between 2000 and 2010, without total factor productivity (TFP) growth, we need 173 Mha of additional cropland, accounting for one-third of the Brazilian Amazon or 10% of the extant tropical forests to satisfy observed demand.

3. GTEM-AEZ model description

3.1.GTEM-AEZ modelling framework

We use the GTEM-C model with the disaggregation of land input into 18 Agro-Ecological Zones (AEZ), based on the GTAP AEZ database (Baldos & Corong, 2020), to construct the GTEM AEZ model. The GTEM-C model constructs differentially the production function of a technology bundle and that of a non- technology bundle. Figure 1 outlines the production structure of a technology bundle industry in the GTEM -C model provided in Cai et al (2015). and originally in Pant (2007). There have been three technology bundle industries, including electricity, land transportation, and steel manufacturing sectors. There are 15 technologies in the electricity generation sector and 5 technologies in the land transportation sector, and 2 technologies in the steel manufacturing sector. Even they have different technologies in their processes, they only produce unique commodities, such as electricity, land transportation service and steel, respectively.

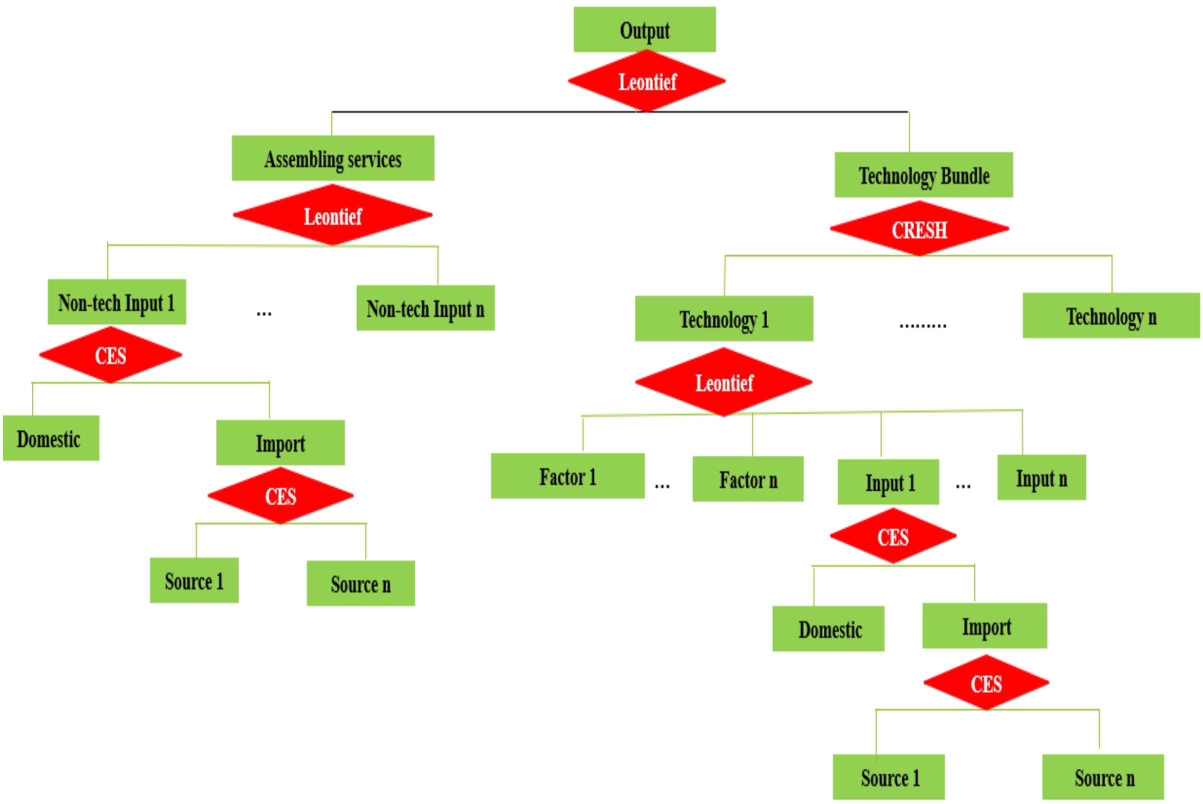

Figure 1: Production structure of a technology bundle industry in GTEM -C

At the top level, the industrial output is a Leontief function of technology bundle and assembling services. Technology bundle is a CRESH function of all technology inputs, while assembling services consist of all non-technology inputs, those are combined with a Leontief function. At the lower level, each technology-specific input is a Leontief function of intermediate inputs and endowment factors that include labour, capital, AEZs land, and natural resources. Each intermediate input sourced from domestic and imported or sourced from any foreign markets, those are substituted via a CES function. Technology industry does not use land in their production, so values of all 18 AEZs in all these industries are equal 0.

For a non-technology bundle, these include other industries such as manufacturing, agriculture, food processing, service sectors. The production structure of these industries in the GTEM -C model is shown in Figure 2. At the top level, industrial output is a Leontief function of all non-energy inputs and a composite of energy and factor inputs, indicating that all these inputs are used in proportion to output level. For each non-energy input, it is sourced from domestic and imported or its import is sourced from overseas markets are combined with each other by a CES function. Energy-factor composite is a CES function of energy composite and input factor composite. At a lower level, energy composite is a CRESH function of coal, gas, petrol, and electricity. This indicates as percentage change of petrol price increases, relative to percentage change of gas price, demand for petrol will decrease compared to that for gas. Each energy input is a CES function of domestic and imported ones, as well as imported energy input is a CES function of one sourced from different regions. Factor composite is formed by the CES function of all four endowments, including land, labour, capital, and natural resources. An aggregate land is combined by the CES function of 18 Agro-Ecological Zones (AEZ) land types.

Except for agricultural and forestry sectors, all other sectors do not use land in their production structure. All agricultural products and forestry products could be planted or raised from AEZ1 to AEZ18, depending on where they are located and the length of their growing period. In the GTEM-AEZ database, there are four land covers, including cropland, pastureland, forestland, and other land, in which other land are combined from last 4 out of 7 land covers in the GTAP AEZ data that include shrubland, savanna grassland, built-up land and other land. In this study, cropland, pastureland, and forestland can be converted to each other, depending on their conversion cost. Agricultural products could be produced in almost or some AEZs. For example, paddy rices that has been harvested in various AEZs from AEZ1 to AEZ18 at the difference in the length of growing period. These seven land covers located in each AEZ in which three of them include cropland, pastureland, and forestland that could be converted to each other. Therefore, land using sectors could substitute AEZs land in their production structure with a CES function of 18 AEZs. In this study, we assigned 18 AEZs substitution elasticity of 20, indicating a high level of substitution.

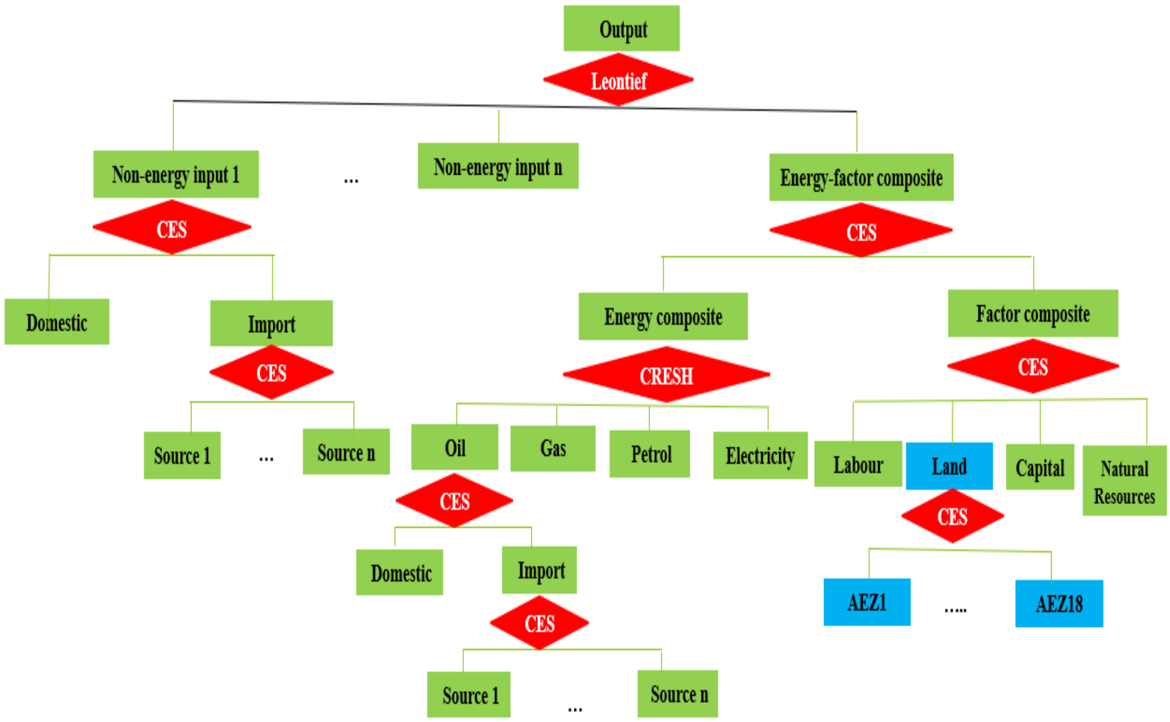

Figure 2: Production structure of a non- technology bundle industry in GTEM -C

There has been heterogeneity in land rent in the CGE models. To address this issue, there are many approaches to be recommended to allocate land uses across sectors. They consist of Constant Elasticity of Transformation (CET), Additive CET (ACET), logit approaches. CET may be explained as effectively accounting for land heterogeneity and/or conversion cost in a way sacrificing resource constraint. (Golub et al., 2009; van der Mensbrugghe & Peters, 2016; Zhao et al., 2020). The advantage of the CET approach is easily handled by modelling tools, and it traces the productivity of land use. The CET approach has been widely used in many CGE models, such as GTEM, GTAP AEZ GTAP-BIO, ENVIRAGE, MIRAGE, and MAGNET models (Zhao et al., 2017).

The CGE model applies the CET function to solve the heterogeneity in land rent, however the CET approach fails to maintain the physical area of land in balance. To maintain the physical area of land in balance, we can use either ex post or ex ante scaling approaches. The ex post approach to convert a given solution obtained from the CET solution to physical area of land by adding an endogenous slack variable to the equation showed the connection between physical area of land and productivity adjusted land. The ex ante approach maintains physical area of land in balance by swap productivity adjusted land to be endogenous variable and physical area of land to be exogenous variable. (Taheripour et al., 2020).

We apply the CET function in the allocation of AEZ land types across sectors with the ex post approach to maintain physical area of land in balance. In the GTEM AEZ model, we assume that land located in a specific AEZ can move only between land using sectors sectors, thus each AEZ land is transformable between crop, livestock, and forestry sectors, but the land is not cross AEZs land. Therefore, we demonstrated the allocation of AEZs land uses across sectors by a three -level nested CET functional form as shown in Figure 3. The top nest differentiates AEZ land use for agricultural land and forest land with a relatively low transformation of elasticity of 0.2. Agricultural land was divided into cropland and pastureland with elasticity transformation of 0.5 in the second stage. On the top, cropland was transformed to 8 crop sectors under the transformation of elasticity of 1, meanwhile pastureland was supplied to cattle, other animal products, raw milk and wool sectors with a relatively high transformation of elasticity of 10. The higher value of CET the easier transformation land use among the land using sectors. It is harder to transform land use among agricultural land and forest land, but it is easier to transform land use between crop sectors or transform land use between grazing sectors (Hertel et al., 2009).

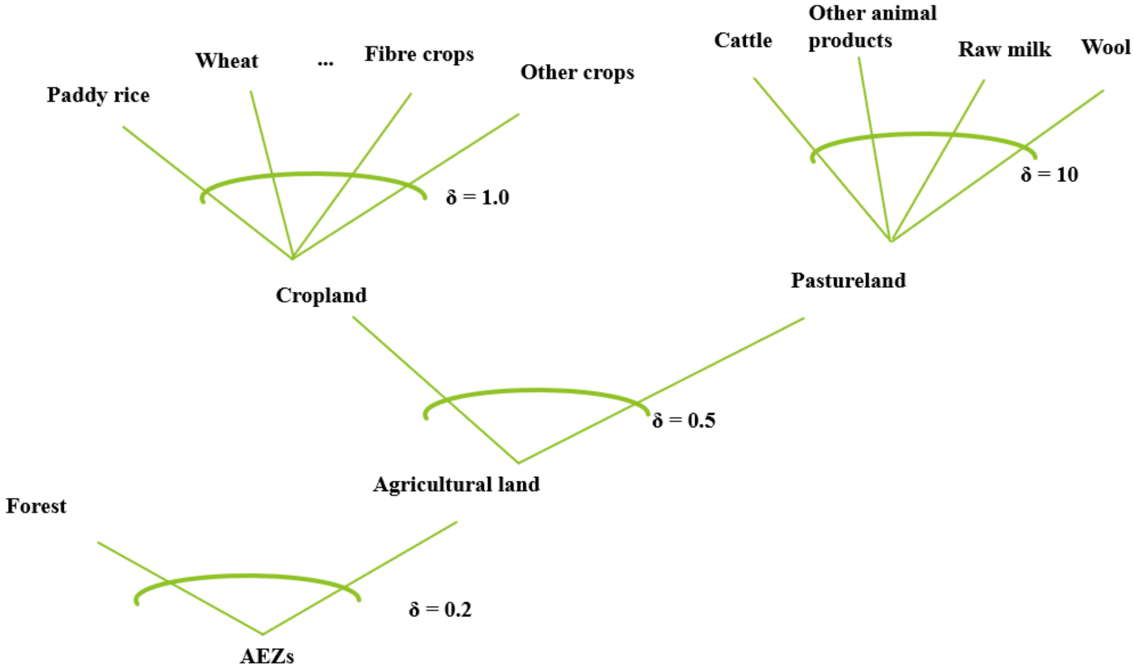

Figure 3: AEZs land supply.

Figure 4 outlines the preference of the representative household in the GTEM–C model. The Cobb-Douglas function illustrates the preference of households to saving, private consumption, and public consumption to maximize household utility, as well as the preference of households to various goods to their public consumption. Regarding private consumption, this consists of non-energy goods and energy composite that are combined with a CDE (Constant Difference in Elasticity) function. This is a non-homothetic function, accounting for the possible change in income elasticities for various energy and non-energy consumption. At a lower level, coal, gas, petrol, and electricity can be substitutable with a CRESH function, in which their sources from domestic and imported or sources imported from different foreign markets are substituted with a CES function.

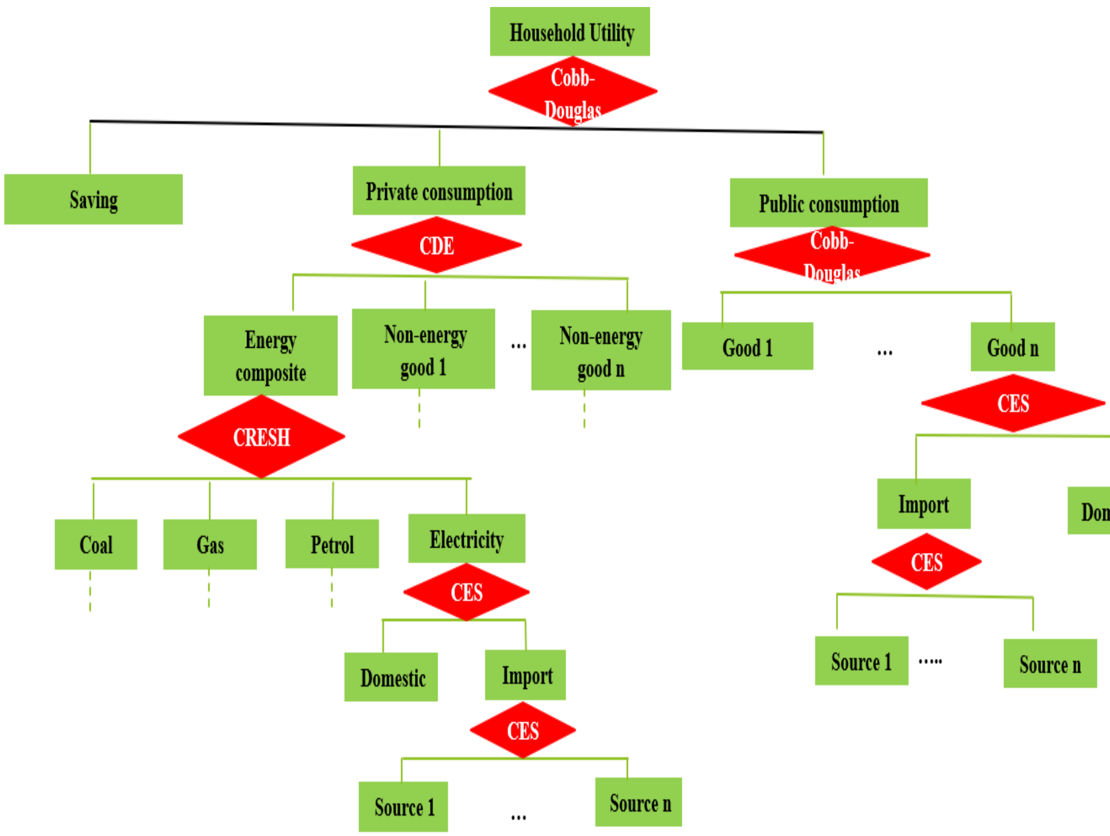

Figure 4: Preference of the representative household in GTEM-C

3.2 Data description

We mostly compile data from the GTAP v10 (Aguiar et al., 2019) and GTAP AEZ v10(Baldos & Corong, 2020) data, in which GTAP database has been adjusted with the GTEM data routine to get original GTEM data of 141 countries and 65 sectors. There have been the data of CO2 and non-CO2 emissions (N2O, CH4, FGAS) in the original GTEM data with only one land endowment. In GTEM-AEZ, there are 18 AEZs land types that are identified by a combination of three climatic zones (tropical, temperate, and boreal) and six lengths of growing period. Length of growing period refers to the number of days when both soil moisture and temperature of above 5^0C are considered adequate to crop growth and development. Six lengths of growing period range from 1 to over 300 days, by every 60 days intervals. The data of 18 AEZs in GTEM-AEZ are split up from the land data in GTEM with the AEZ rental shares calculated from the GTAP AEZ data.

However, there has been differences between GTEM data and GTAP AEZ data in land use. In particular, land rents have just been accounted for all agricultural sectors in GTEM data. The forestry sector does not have land rent, but it does incur natural resource rent. Meanwhile GTAP AEZ data does not have AEZ land rentals in the other animal products, and this data provides AEZ land rentals instead of natural resource rent in the forestry sector. According to (Lee, 2005) Natural resource that is used in the forestry sector in GTAP data is moved to AEZ rentals in GTAP AEZ. Moreover, there are a few small countries such as Hong King, Singapore, Malta, Bahrain, Qatar, Mauritius, rest of North America, and rest of the world that do not have AEZ rentals in all agricultural sectors, but they have land rent in the GTEM data. In addition, in a few countries and in a few agricultural sectors that have land use in the GTEM data, but they have not used AEZs in the GTAP AEZ data. Therefore, we did adjustment in these two sectors consistent with GTEM data and GTAP AEZ data.

In the GTAP AEZ data, there has also been inconsistencies between land rental and land covers in the agricultural and forestry sectors, between land rental and harvested area, as well as between harvested area and production yield in crop sectors. In practice, agricultural and forestry sector in a country that have AEZ rentals should have AEZ land cover or vice versa. Crop sectors have AEZ rentals should have AEZ harvested area or vice versa, and these sectors have AEZ harvested area should have production yield or vice versa. To make the data consistent, we based on the world average land rental per hectare of each AEZ land type in each land cover or in unit of harvested area or the world average yield per hectar of each AEZ in each crop sector to calculate the missing values of land covers, harvested area and production yield.

For CO2 and non-CO2 emissions, we copied these data from GTEM data (Aguiar et al., 2019) for CO2 emissions and non-CO2 emissions (Chepeliev, 2020). GHG emissions that generated from agricultural and forestry sectors from land use are split into 18 AEZs, based on the AEZ rental shares of a specific sector in the GTAP AEZ data.

3.3 Baseline and Policy scenarios

For baseline scenarios, we apply the projections of real GDP, population, and labour supply, in which real GDP projection was adjusted with negative growth rate in most regions due to the Covid-19 pandemic impact, and population and labour supply projections are followed the Shared Socioeconomic Pathway (SSP2). Second, for energy efficiency assumption, we apply exogenous shocks to energy efficiency in agricultural sectors and land transportation. Third, we added the climate change simulation of RCP 4.5 in the baseline. Fourth, we calibrated the agricultural productivity forecast by 2050 by region based on the data come from our econometric model with the agricultural total factor productivity index in a period of 60 years from 1961 to 2020 that was collected from (USDA, 2022).

There are three policy scenarios that reflect climate change of RCP 2.6 with changes in agricultural productivity development. We assumed that agricultural productivity increases 1.0 percent, 1.5 percent, and 2.0 percent yearly in all regions by 2050.

REFERENCE

Aguiar, A., Chepeliev, M., Corong, E. L., McDougall, R., & Van Der Mensbrugghe, D. (2019). The GTAP data base: version 10. *Journal of Global Economic Analysis*, *4*(1), 1-27.

Ahammad, H., & Mi, R. (2005). *Land use change modeling in GTEM accounting for forest sinks*. Australian Bureau of Agricultural and resource Economics.

Alexandratos, N., & Bruinsma, J. (2012). World agriculture towards 2030/2050: the 2012 revision.

Assunção, J., & Chein, F. (2016). Climate change and agricultural productivity in Brazil: future perspectives. *Environment and Development Economics*, *21*(5), 581-602.

Baldos, U. L., & Corong, E. (2020). *Development of GTAP 10 Land Use and Land Cover Data Base for years 2004, 2007, 2011 and 2014* [GTAP Research Memorandum](36). https://www.gtap.agecon.purdue.edu/resources/res_display.asp?RecordID=6187

Burke, M., & Emerick, K. (2016). Adaptation to climate change: Evidence from US agriculture. *American Economic Journal: Economic Policy*, *8*(3), 106-140.

Cai, Y., Newth, D., Finnigan, J., & Gunasekera, D. (2015). A hybrid energy-economy model for global integrated assessment of climate change, carbon mitigation and energy transformation. *Applied Energy*, *148*, 381-395.

Change, I. P. o. C. (2022). *Climate Change 2022 Mitigation of Climate Change* (Working Group III contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, Issue.

Chepeliev, M. (2020). *Development of the Non-CO2 GHG Emissions Database for the GTAP 10A Data Base* [GTAP Research Memorandum](32). https://www.gtap.agecon.purdue.edu/resources/res_display.asp?RecordID=5993

Darwin, R. (1995). *World agriculture and climate change: economic adaptations*. US Department of Agriculture, Economic Research Service.

Darwin, R., Tsigas, M., Lewandrowski, J., & Raneses, A. (1996). Land use and cover in ecological economics. *Ecological Economics*, *17*(3), 157-181.

Dietrich, J. P., Bodirsky, B. L., Humpenöder, F., Weindl, I., Stevanović, M., Karstens, K., Kreidenweis, U., Wang, X., Mishra, A., & Klein, D. (2019). MAgPIE 4–a modular open-source framework for modeling global land systems. *Geoscientific Model Development*, *12*(4), 1299-1317.

Fabregat-Aibar, L., Niñerola, A., & Pié, L. (2022). Computable general equilibrium models for sustainable development: past and future. *Environmental Science and Pollution Research*, 1-13.

Fuglie, K., Ray, S., Baldos, U. L. C., & Hertel, T. W. (2022). The R&D cost of climate mitigation in agriculture. *Applied Economic Perspectives and Policy*.

Fujimori, S., Hasegawa, T., Masui, T., & Takahashi, K. (2014). Land use representation in a global CGE model for long-term simulation: CET vs. logit functions. *Food Security*, *6*(5), 685-699.

Golub, A., Hertel, T. W., & Sohngen, B. (2009). Land use modelling in a recursively dynamic GTAP framework. In *Economic analysis of land use in global climate change policy* (pp. 255-298). Routledge.

Golub, A. A., & Hertel, T. W. (2012). Modeling land-use change impacts of biofuels in the GTAP-BIO framework. *Climate Change Economics*, *3*(03), 1250015.

Golub, A. A., Hertel, T. W., & Rose, S. K. (2017). Global land use impacts of US ethanol: revised analysis using GDyn-BIO framework. In *Handbook of Bioenergy Economics and Policy: Volume II* (pp. 183-212). Springer.

Havlík, P., Valin, H., Mosnier, A., Frank, S., Lauri, P., Leclère, D., Palazzo, A., Batka, M., Boere, E., & Brouwer, A. (2018). GLOBIOM documentation. *International Institute for Applied Systems Analysis, Laxenburg, Austria*.

Havlík, P., Valin, H., Mosnier, A., Obersteiner, M., Baker, J. S., Herrero, M., Rufino, M. C., & Schmid, E. (2013). Crop productivity and the global livestock sector: Implications for land use change and greenhouse gas emissions. *American Journal of Agricultural Economics*, *95*(2), 442-448.
Hertel, T. W., Lee, H.-L., Rose, S., & Sohngen, B. (2009). Modeling land-use related greenhouse gas sources and sinks and their mitigation potential. *Economic analysis of land use in global climate change policy*, 123-153.
Hertel, T. W., Rose, S., & Tol, R. S. (2008). Land use in computable general equilibrium models: an overview.
Hertel, T. W., & Tsigas, M. E. (1988). Tax policy and US agriculture: a general equilibrium analysis. *American Journal of Agricultural Economics*, *70*(2), 289-302.
Ignaciuk, A., & Mason-D'Croz, D. (2014). Modelling adaptation to climate change in agriculture.
Kyle, G. P., Luckow, P., Calvin, K. V., Emanuel, W. R., Nathan, M., & Zhou, Y. (2011). *GCAM 3.0 agriculture and land use: data sources and methods*.
Lee, H.-L. (2005). Incorporating agro-ecologically zoned land use data and land-based greenhouse gases emissions into the GTAP framework. 8th annual conference on Global Economic Analysis, Lübeck, Germany,
Lobell, D. B., Baldos, U. L. C., & Hertel, T. W. (2013). Climate adaptation as mitigation: the case of agricultural investments. *Environmental Research Letters*, *8*(1), 015012.
Pachauri, R., & Meyer, L. (2014). Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.
Pant, H. (2007). Global Trade and Environment Model (GTEM)(Australian Bureau of Agricultural and Resource Economics and Sciences, Canberra).
Robinson, S., Mason-D'Croz, D., Sulser, T., Islam, S., Robertson, R., Zhu, T., Gueneau, A., Pitois, G., & Rosegrant, M. W. (2015). The international model for policy analysis of agricultural commodities and trade (IMPACT): model description for version 3.
Sands, R. D., & Leimbach, M. (2003). Modeling agriculture and land use in an integrated assessment framework. *Climatic Change*, *56*(1), 185-210.
Schmitz, C., Biewald, A., Lotze-Campen, H., Popp, A., Dietrich, J. P., Bodirsky, B., Krause, M., & Weindl, I. (2012). Trading more food: Implications for land use, greenhouse gas emissions, and the food system. *Global Environmental Change*, *22*(1), 189-209.
Schmitz, C., Van Meijl, H., Kyle, P., Nelson, G. C., Fujimori, S., Gurgel, A., Havlik, P., Heyhoe, E., d'Croz, D. M., & Popp, A. (2014). Land-use change trajectories up to 2050: insights from a global agro-economic model comparison. *Agricultural economics*, *45*(1), 69-84.
Souza, B., & Haddad, E. (2022). Climate change in Brazil: dealing with uncertainty in agricultural productivity models and the implications for economy-wide impacts. *Spatial Economic Analysis*, *17*(1), 83-100.
Taheripour, F., Zhao, X., Horridge, M., Farrokhi, F., & Tyner, W. (2020). Land Use in Computable General Equilibrium Models. *Journal of Global Economic Analysis*, *5*(2), 63-109.
USDA, U. S. D. o. A. (2022). *International Agricultural Productivity*
van der Mensbrugghe, D., & Peters, J. C. (2016). Volume preserving CES and CET formulations.
van Tongeren, F., Koopman, R., Karingi, S., Reilly, J., & Francois, J. (2021). Back to the Future: A 25-year Retrospective on GTAP and the Shaping of a New Agenda. In *Policy Analysis And Modeling Of The Global Economy: A Festschrift Celebrating Thomas Hertel* (pp. 41-93). World Scientific.
Villoria, N. B. (2019). Technology spillovers and land use change: empirical evidence from global agriculture. *American Journal of Agricultural Economics*, *101*(3), 870-893.
Wang, Y., Sharp, B., Poletti, S., & Nam, K.-M. (2022). Economic and land use impacts of net zero-emission target in New Zealand. *International Journal of Urban Sciences*, *26*(2), 291-308.

Wise, M., Calvin, K., Kyle, P., Luckow, P., & Edmonds, J. (2014). Economic and physical modeling of land use in GCAM 3.0 and an application to agricultural productivity, land, and terrestrial carbon. *Climate Change Economics*, *5*(02), 1450003.

Woltjer, G. B., Kuiper, M., Kavallari, A., van Meijl, H., Powell, J., Rutten, M., Shutes, L., & Tabeau, A. (2014). *The MAGNET model: Module description*.

Yan, S., & Alvi, S. (2022). Food security in South Asia under climate change and economic policies. *International Journal of Climate Change Strategies and Management*(ahead-of-print).

Zhao, X., Calvin, K. V., & Wise, M. A. (2020). The critical role of conversion cost and comparative advantage in modeling agricultural land use change. *Climate Change Economics*, *11*(01), 2050004.

Zhao, X., Van Der Mensbrugghe, D., & Tyner, W. (2017). Modeling land physically in CGE models: new insights on intensive and extensive margins.