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Improving the way land use change is handled in economic models

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A B S T R A C T

Sound economic modelling of land use in global economic models is critical for evaluating agricultural, biofuel, and climate policies. Current approaches do not preserve physical land area, do not account for the fact that land is of different qualities, or do not explicitly include the cost of converting land from one use to another. This study proposes a land use modelling framework building on the additive form of the constant elasticity of transformation (ACET) approach. We demonstrated that the framework could (1) directly provide traceable physical land use results, (2) flexibly handle land productivity differences based on biophysical information, (3) explicitly introduce land conversion cost, and (4) provide welfare decomposition in light of land heterogeneity and conversion cost. An experiment of mandating a 10 percent increase in grain consumption in the US food sector showed that ignoring land heterogeneity and conversion cost would underestimate the welfare loss by 28 percent.

1. Introduction

The economic modelling of land plays a central role in global economic and integrated assessment models. Recent application of these models include, for example, developing Shared Socioeconomic Pathways (SSPs) and Representative Concentration Pathways (RCPs) to evaluate future climate impacts and challenges of mitigation and adaption (Calvin et al., 2017; O'Neill et al., 2014; Riahi et al., 2017; Schmitz et al., 2014), estimating biofuels induced land use change emissions to be considered in biofuel policies (EPA, 2010; Taheripour et al., 2017a; Taheripour et al., 2017b; Valin et al., 2015), and studying policy impacts on agriculture, trade, and land use (Costinot et al., 2016; Dixon et al., 2016; Giesecke et al., 2013; Nassios et al., 2019; Wang et al., 2018). However, the difference in land use modelling theories was an important uncertainty factor in these empirical studies, and there have been important challenges for integrating physical data into economic analysis in a theoretically consistent way (van Tongeren et al., 2017). In particular, when facilitating the transformation of land from one use to another, three critical and related concerns are (1) how to preserve the physical land balance, (2) how to account for the land productivity differences during transformation, and (3) how to include land conversion costs (Golub and Hertel, 2012; Gurgel et al., 2016). Hertel et al. (2009) reviewed the literature of land use modelling in global economic models at the time and highlighted these issues as key for future research. Several recent studies discussed later in this article provided important insights. The puzzles, however, have not been completely solved. In this article, we are motivated to develop a consistent and communicable framework that addresses the three concerns of land use modelling on the basis of the existing literature.

Since being introduced into the standard Global Trade Analysis Project (GTAP) model for handling land heterogeneity (Hertel and Tsigas, 1996), the constant elasticity of transformation (CET) functional form has been a workhorse for modelling land transformation in computable general equilibrium (CGE) studies. Under the assumption that landowners maximize aggregate rental revenue subject to a CET technology for land transformation, the solution will be a set of sector-specific land supply equations (Hertel and Tsigas, 1988). While parsimonious, one drawback of the CET approach is that physical land cannot be traced. That is, the direct land use results from a simulation would not sum up the total physical land data. This is because the CET approach transforms land on a value basis rather than by physical area. Nevertheless, it was claimed that CET effectively accounted for land productivity heterogeneity during transformation based on the assumption that land rental rate would represent land quality or productivity, and the results were thus in “productivity-weighted areas” or “effective land” (Golub et al., 2009; Hertel et al., 2009). In several studies, “ad hoc”

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adjustments were developed to translate the effective land to physical land (Golub and Hertel, 2012; Hertel et al., 2010; Taheripour et al., 2012b). However, the "ad hoc" treatment for preserving area balance was a compromise solution since it was implemented on ex post equilibrium values (Fujimori et al., 2014; Valin et al., 2013). That means that any endogenous price changes could not directly impact the physical land areas. Also, the land conversion cost was not interpreted or explicitly modeled in the CET approach. In a study focusing on land use change related issues, a model that can directly produce physical land use results and can be flexible on governing the extent of land productivity adjustment during transformation would be preferred. A consistent and traceable land use modelling framework also lays foundations for calibrating crop yield responses, decomposing welfare, and incorporating cropland intensification responses including multi-cropping practices and better use of existing unused cropland, both of which have been demonstrated to be very important in modelling agricultural land use (Keeney and Hertel, 2009; Ray and Foley, 2013; Taheripour et al., 2017a). More recently, van der Mensbrugghe and Peters (2016) developed the additive form of the CET function (ACET) for allocating land to different uses on a physical basis. It provides an opportunity to technically compare a physical land transformation approach (ACET) with the effective land transformation approach (CET) to illuminate the role of land mobility, land productivity heterogeneity, and land conversion cost in land use modelling.

The ACET approach was developed based on intuition provided by several previous studies in which the additive form of the constant elasticity of substitution (ACES) function and the additive form of the constant ratio of elasticity of transformation, homothetic (ACRETH) function[1] were created (Dixon and Rimmer, 2003; Giesecke et al., 2013; Mariano and Giesecke, 2014). The ACET land supply is derived from maximizing the CET aggregation of land revenues, which was defined as the utility of landowners, subject to the area-preserving constraint. It is also demonstrated that the initial prices do not affect the percentage change results from a model when using the standard CET formulation, while they do matter in the ACET approach since the initial land quantity is needed in the ACET formulation (van der Mensbrugghe and Peters, 2016). Other efforts had been made as well in the literature to developing physical land transformation methods. In the Agriculture and Land Use (AgLU) model, Sands and Leimbach (2003) developed a logit approach for land transformation, which was derived from the maximization of the economic return of land subject to explicitly defined joint probability distributions of crop yield. Wise et al. (2014) introduced a simplified version of the logit approach to the Global Change Assessment Model (GCAM) for studying agricultural production, land use, and terrestrial carbon. In empirical studies, it is difficult to match logit-sharing parameters with yield distributions that imply land quality. Thus, the idea of distributional representation of yield or land profitability serves more like an interpretation of the model specification than as an instrument for parameter calibration. Fujimori et al. (2014) compared the logit approach with the CET approach for modelling land supply in the Asia-Pacific Integrated Model (AIM) and concluded that the area balance violation for CET was small for the aggregated world total, but relatively large and heterogeneous across regions. There is a direct mapping between the ACET functional form and the logit sharing functional form presented in Fujimori et al. (2014) and Wise et al. (2014). In addition, several other studies attempted to preserve physical land with the standard CET approach through modifying the land rent database based on additional assumptions (Laborde and Valin, 2012; Sands et al., 2017). These studies of physical land transformation, however, provided minor implications for considering land productivity heterogeneity or conversion cost.

Ideas and intuition from several other important streams of studies also contributed to the analysis in this article. An approach for land use modelling is to incorporate land conversion costs by depicting a complete transformation process so that the value discrepancy generated by a physical land transformation approach can be explained by the cost of land conversion. This approach was introduced by Gurgel et al. (2007) to the MIT Emissions Prediction and Policy Analysis (EPPA) model, in which it assumed that the marginal conversion cost of converting land from one type to another equals to the difference in the value of the land types. It requires treatments to balance land conversion costs with capital, labor, and intermediate inputs. Furthermore, modellers have developed coupled approaches that link separate frameworks for modelling physical and effective land units in production. Ronneberger et al. (2009) introduced a coupling framework between a GTAP model and, KLUM, a global agricultural land use model. KLUM worked as the land supply module, and it provided feedback on crop yields to the economic model based on the biophysical information. A similar coupling framework between LEITAP and IMAGE was also tested (Verburg et al., 2009). It appears that the coupling frameworks link biophysical information to economic models consistently. However, the application of these coupling frameworks has not been updated in the literature, likely because of the complexity of the framework and the challenge of simulation convergence (Woltjer et al., 2014). A recent innovation from Costinot et al. (2016) and Sotelo (2017) applied the Ricardian trade model (Eaton and Kortum, 2002) to handling land heterogeneity. Agricultural production technology was defined at the plot level. Competitive farmers would choose crops that maximizing the rental rate on each plot, given the expected land quality distribution for each crop. The theory provides a tight connection between the micro-level land productivity data from agronomic models and the economic model. However, land conversion cost was not considered and, for maintaining traceability, the production function and the land quality distribution type under the Ricardian trade approach are fairly restrictive.

In the present article, our objective is to extend the existing literature to develop a consistent and communicable approach for modelling land in a global economic model, which addresses the three concerns mentioned above simultaneously in a theoretically consistent way. In particular, we propose to make use of the ACET approach for physical land transformation, incorporate biophysical information for adjusting land productivity change due to land heterogeneity from the land demand side, and also explicitly account for conversion cost. These changes allow us to maintain welfare traceability. In Section 2, we provide detailed illustrations for understanding effective land and physical land in land transformation, and the role of conversion cost as a complement to land heterogeneity in interpreting landowners' behavior. The illustrations in Section 2 pave the way for the theoretical framework presented in Section 3. In Section 4, we build a GTAP-based CGE model with three regions and seven industries and design experiments to compare the standard CET approach with the approach we proposed in this study. Results are explained and discussed in Sections 5 and 6. A discussion of policy implications and future development is also provided in Section 6. Finally, Section 7 concludes the study.

2. Theoretical background

Understanding the two methods for land productivity adjustment in an economic equilibrium framework, shifting "effective land" supply and implementing land biased technical shocks, is important for reconciling effective land transformation and physical land transformation approaches. The discussions in this section show that both land productivity adjustment approaches and land conversion cost are the keys for modelling land physically. Incorporating biophysical information for land productivity adjustment and land conversation cost permits consistently tracing both physical land and welfare.

[1] Constant ratio of elasticity of transformation, homothetic (CRETH) is a generalized functional form of CET.

2.1. Reconciling physical land transformation and effective land transformation approaches

The CET approach is an effective land transformation approach since it transforms land based on rent revenue. The ACET approach is a physical land transformation approach in which land transformation is by physical area. Fig. 1 illustratively compares the two approaches. In both cases, low rental rate land (with subscript l) is converted to the high rental rate land (with subscript h) driven by a shock shifting land demand from D_h^0 to D_h^*. Land supply curves also shift in response to the shock. With the effective land transformation approach (Fig. 1A), two shaded areas are equal in size as rent revenue is preserved during the transformation, though it loses track of physical land ($q_h^1 < q_l^1$). Additional treatment is needed to convert the effective land to physical land. With the physical land transformation approach (Fig. 1B), physical land is preserved as $q_h^2 = q_l^2$. However, there is apparently a welfare gain as the land rent increase for high rent land outweighs the land rent decrease for low rent land. ACET does not account for land productivity heterogeneity while CET effectively accounts for land productivity heterogeneity based on the assumption that land rent reflects land productivity (Ricardian rent) by shifting land supply (Golub et al., 2009).

As illustrated in Appendix A, in an economic equilibrium framework, a factor productivity change can be imposed by shifting the “effective factor” supply or, alternatively, implemented from factor demand side as a factor biased technical shock. For adjusting land productivity, the difference is that the land market equilibrium is in “effective land” in the traditional method while the alternative method provides physical land. Echoing the explanation from Golub et al. (2009), if we adjust land productivity through the method of shifting effective land supply curves (S_h^2 and S_l^2) to the extent implied by the effective land transformation approach, Fig. 1B can become identical to Fig. 1A. Furthermore, following the intuition from Appendix A, instead of applying the land productivity adjustments from the land supply side, implementing equivalent land productivity adjustments as technical shocks from land demand side in Fig. 1B would provide the same non-land market results as Fig. 1A but physical land use results. In other words, effective land transformation is equivalent to physical land transformation plus proper land productivity adjustments, and both physical land and welfare can be traced by implementing the productivity adjustments from the land demand side in the latter approach. This was tested with experiments conducted in section 5, in which, taking advantage of the ACET approach, the land productivity adjustments were disaggregated from the CET approach and implemented from the land demand side in the ACET approach.

2.2. Land productivity heterogeneity and conversion cost in land transformation

Golub et al. (2009) suggested that the welfare discrepancy in the physical land transformation approach was entirely attributed to land heterogeneity. However, an important issue was the assumption that land rental rates imply land productivity might not hold in reality given that land productivity differences may not be the only reason why land rental rates are different. On the other extreme, Gurgel et al. (2007) ascribed the rental rate difference entirely to land conversion cost while land heterogeneity was overlooked. We argue that the truth lies in between. That is, the welfare discrepancy in the physical land transformation approach should be compensated by both land productivity change and conversion cost. Instead of relying on land rental rates, biophysical information or agronomic models may provide more reliable implications for land productivity change after conversions. For example, Costinot et al. (2016) employed the potential yield data predicted at high-resolution grid cell level by the Food and Agriculture Organization's Global Agro-Ecological Zones (GAEZ) dataset to calibrate the distribution parameters for land productivity. Also, in GTAP models, an elasticity of effective cropland with respect to cropland expansion parameter was introduced to govern the productivity of new cropland relative to the existing cropland. The parameter, though used in the ex post “ad hoc” adjustments, was derived using the net primary production (NPP) data from the Terrestrial Ecosystem Model (TEM) for each agro-ecological zone (AEZ) in a region (Taheripour et al., 2012b). If land productivity and rental rate of the converted land are adjusted based on the information from agronomic models, the remaining rental rate difference can be allocated to land conversion cost (Lubowski et al., 2008; Rashford et al., 2011).

By way of illustration, in the U.S., the average rental rate for cropland ($336 per ha) has been more than ten times higher than pastureland ($31 per ha) (USDA, 2018). If land rental rates imply land productivity, with no consideration of land conversion cost, converting one hectare of pastureland to one hectare of cropland would imply that the land productivity of converted cropland from pastureland is less than one-tenth of existing cropland. Conversely, assuming that biophysical information implies cropland converted from pastureland has two-thirds the productivity of the existing cropland (Hertel et al., 2010), the newly converted cropland would have a marginal rental rate of $224 per ha. It implies a marginal land conversion cost of at least $193 per ha per annum, which is equivalent to $1930 per ha assuming a 10% discount rate. The conversion cost explains why pastureland has not been converted to the more profitable cropland. The landowner may spend

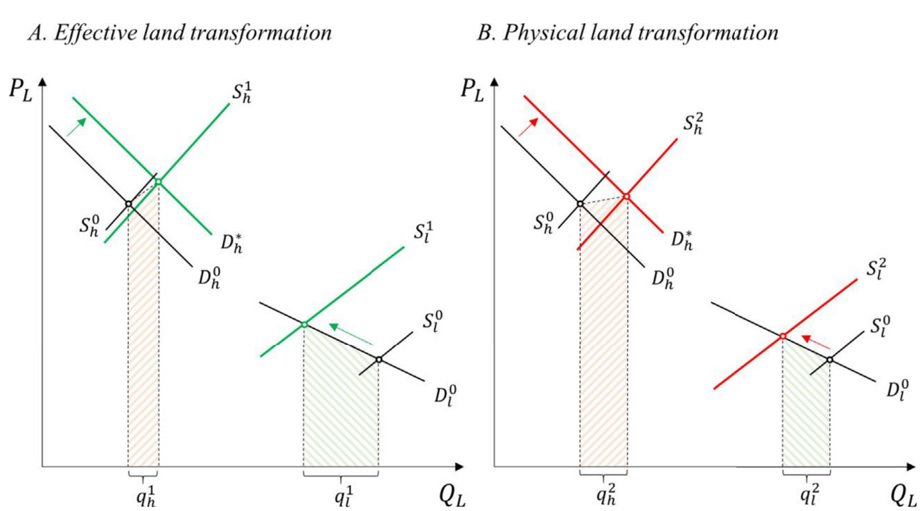

Fig. 1. Comparison of effective and physical land transformation due to a model shock. Land transformation from low rental rate land (q_l) to high rental rate land (q_h) due to a shock shifting land demand from D_h^0 to D_h^* using effective land transformation (A) and physical land transformation (B) approaches.

capital, labor, and other intermediate inputs for land conversion, the total expenses of which offset the land conversion cost. Thus, the landowner earns zero pure profit from the land transformation. In this study, we propose to, based on the physical land transformation approach, incorporate biophysical information for adjusting land productivity due to transformations through technical shifters on the land demand side. The welfare discrepancy due to physical land transformation is partly explained by the land productivity adjustment, and the rest is interpreted as the land conversion cost.

3. Theoretical model

3.1. Land demand

It is assumed that agricultural producers use a composite of non-land input (A) and land (X) to produce an output (Q), following the constant elasticity of substitution (CES) technology (Eq. (1)). β_i are CET parameters. ρ is the CES exponent. $\rho = 1 - 1/\sigma$ whereas σ is the elasticity of substitution. The production generates zero economic profits. The land biased technical shifter (λ) is introduced in the production function, which provides the channel for demand side land productivity adjustments (Costinot et al., 2016).

$$Q = [\beta_A A^\rho + \beta_X(\lambda X)^\rho]^{\frac{1}{\rho}} \tag{1}$$

Producers minimize the cost of production, $P_A A + P_X X$, where P_A is the producer price of A and P_X is the land rental rate paid by the producer. Eq. (2) presents the land demand derived in the linearized form.[2] Hat () denotes proportional change throughout this study ($\widehat{X} = \Delta X/X$). c_i denote input cost shares in production.

$$\widehat{X}^D = \widehat{Q} - \sigma(\widehat{P}_X - \widehat{\lambda}) + \sigma[c_A\widehat{P}_A + c_X(\widehat{P}_X - \widehat{\lambda})] - \widehat{\lambda} \tag{2}$$

The elasticity of substitution (σ) plays an important role in determining crop yield responses. $\widehat{\lambda}$ is the key variable for incorporating biophysical information for adjusting land productivity. For example, a -10% value for $\widehat{\lambda}$ indicates that it requires 10% more converted land to produce what can be produced on existing cropland.

3.2. ACET land supply and decomposition

The additive form of the CET function is derived from maximizing the utility which is a CET aggregation of land rental revenues (Eq. (3)), subject to the area-preserving condition (Eq. (4)) (van der Mensbrugghe and Peters, 2016). We modified the area-preserving condition to introduce CHF (φ). P_i are land rental rates faced by landowners and X_i are land areas. Y is the total land area. g_i are CET parameters. u is the CET exponent. $u = 1/\omega + 1$ whereas ω is the absolute value of the ACET exponent.

$$\max_{X_i} Utility = \left[\sum_i g_i (P_i X_i)^u\right]^{\frac{1}{u}} \tag{3}$$

$$s.t. \quad Y = \frac{1}{\varphi} \cdot \sum_i X_i \tag{4}$$

The CHF (φ) parameter becomes relevant only in the case of transformation between land cover and crop-harvested area. Otherwise, φ is set to one. Land supply can be derived through first order conditions (Eq. (5)) and the function is homogeneous of degree zero in rental rates. When nesting ACET, the price link can be derived using the zero-profit condition.

$$X_i = \frac{g_i^{1+\omega} \cdot P_i^\omega}{\sum_j g_j^{1+\omega} \cdot P_j^\omega} \cdot \varphi \cdot Y \tag{5}$$

The log-differentiation form of Eq. (5) can be derived as

$$\widehat{X}_i = \widehat{Y} + \omega\widehat{P}_i - \omega\sum_j (s_j\widehat{P}_j) + \widehat{\varphi} \tag{6}$$

whereas s_i denotes land area shares, $s_i = X_i/\sum_j X_j$.

Following the intuition provided in Section 2, we decompose CET into ACET and technical shifters. The technical shifters are interpreted as the implicit land productivity adjustments embedded in the standard CET approach. Denote θ_i as land rent shares, $\theta_i = P_i X_i/\sum_j P_j X_j$. Eq. (7) can be derived by introducing CET components into Eq. (6), whereas δ is the absolute value of the elasticity of transformation.

$$\widehat{X}_i = \widehat{Y} + \delta\widehat{P}_i - \delta\sum_j \theta_j\widehat{P}_j + (\omega - \delta)\widehat{P}_i - \sum_j [(\omega s_j - \delta\theta_j)\widehat{P}_j] + \widehat{\varphi} \tag{7}$$

Decomposing Eq. (7) with Eqs. (8) and (9),

$$\widehat{X}_i = \widehat{Y} + \delta\widehat{P}_i - \delta\sum_j \theta_j(\widehat{P}_j - \widehat{\alpha}_i) - (1+\delta)\widehat{\alpha}_i \tag{8}$$

$$\delta\sum_j (\theta_j\widehat{\alpha}_j) - (1+\delta)\widehat{\alpha}_i = (\omega - \delta)\widehat{P}_i - \sum_j [(\omega s_j - \delta\theta_j)\widehat{P}_j] + \widehat{\varphi} \tag{9}$$

Eq. (8) is the supply function derived from the standard CET approach with $\widehat{\alpha}_i$ being technical shifters. The decomposition demonstrates that the gap between ACET and CET can be explained by the technical shifters, $\widehat{\alpha}_i$, regardless of the parameters used. When nesting ACET land supply, the decomposition becomes more complex in the case that ω and δ are different, but land productivity adjustment is differentiated across sectors. Following the discussion in section 2.1, one hypothesis is that if implementing the decomposed technical shifters as land biased technical shifters from the land demand side in production (i.e., setting $\widehat{\lambda}_i = \widehat{\alpha}_i$ for all land associated with the transformation), the non-land market equilibria should remain unchanged. The hypothesis is verified with tests in Section 5. It contributes to the reconciliation of the physical and effective land transformation approaches. In practice, however, it is more promising to incorporate land productivity changes hinging on biophysical information.

3.3. Biophysical information for land productivity adjustment

Here, we link biophysical information to land biased technical shifters ($\widehat{\lambda}$) for endogenously adjusting land productivity due to land transformations. Denote X_i as the existing area for land i and $\Delta X_{i,j}$ as the increase in X_i converted from land j, where i and j are land categories (i.e., croplands, pasture, or forest). Define $\eta_{i,j}$ as a parameter the governing relative land productivity between land i and land j. For example, if $\eta_{i,j}$ has a value of 0.66 in a region, it takes three hectares of land i converted from land j to produce what two hectares of average existing cropland produce in the region. In other words, $(1/\eta_{i,j} - 1) \cdot 100\%$ more $\Delta X_{i,j}$ is needed to produce what X_i produces. The link between $\widehat{\lambda}$ and η can be constructed as

$$\widehat{\lambda}_i = -\frac{\sum_j [\Delta X_{i,j} \cdot (1/\eta_{i,j} - 1)]}{X_i} \tag{10}$$

That is, the demand side technical shifter, $\widehat{\lambda}$, is equal to the sum of the land use change share weighted land productivity change. $\eta_{i,j}$ can be calibrated based on biophysical information for each transition and region. Since the ACET approach only provides the net land use change rather than detailing the land transition matrix, additional assumptions may be necessary to infer the land source j in $\Delta X_{i,j}$. However, employing

[2] The log-differentiated forms are used in GEMPACK-based models.

the nesting structure for land transformation helps identify the most important land transition flows. Modelling land at finer spatial resolution also improves the results by strengthening the land transition estimation as well as making better use of high-resolution biophysical information.

In the tests conducted later in this article, for a simple demonstration, we make assumptions to simplify Eq. (10) for experiments leading to cropland expansion into pasture and forest. We assume that $\eta_{cropland,pasture} = \eta_{cropland,forest} = 0.66$ for each region and $\eta = 1$ for any other transitions. In other words, we concentrate on adjusting the productivity of cropland converted from pasture or forest while assuming no land productivity change due to crop switching. For experiments leading to cropland expansion into pasture and forest, the major land productivity changes are accounted, while land conversion and crop switching costs from all transitions are considered. Based on the assumptions, Eq. (10) can be simplified to Eq. (11).

$$\widehat{\lambda}_{cropland} = -\widehat{X}_{cropland} \cdot \left(\frac{1}{0.66} - 1\right) \tag{11}$$

The assumptions applied can be relaxed or altered conditional on land transitions and available biophysical information. We demonstrate tests of endogenizing biophysical information through Eq. (11) while applying the ACET approach for land transformation.

3.4. Land conversion cost and welfare decomposition

With the application of the ACET approach, equations for welfare decomposition become different from the conventional ones due to the change in landowner behavior. We make modifications based on the equivalent variation (EV) decomposition developed by Huff and Hertel (2000) for GTAP models. In particular, one condition used in the original derivation implied by the standard CET approach was that the market land rental rate index equals land rent share weighted land rental rates (Eq. (12))

$$\widehat{P} = \sum_i \theta_i \widehat{P}_i \tag{12}$$

This equation is the zero-profit condition under the standard CET approach in which landowners were modeled as revenue maximizers. However, it is not held with ACET in which land-owners are utility maximizers, and the complete zero-profit condition has to be applied. Thus, the derivation has to be reconsidered. It also helps understand the role of land conversion cost from the perspective of regional household income from which EV decomposition was derived. The welfare change due to physical land transformation compensated by welfare change due to land productivity heterogeneity adjustments, namely the annualized land conversion cost (C_1) in a region can be calculated as

$$C_1 = VOM^{land} \cdot \left(\widehat{P} + \widehat{Y}\right) - \sum_i \left(\widehat{P}_i \cdot VFM_i\right) + \sum_i \left(\widehat{\lambda}_i \cdot VFA_i\right) - \sum_i \left(\widehat{\lambda}_i \cdot ETAX_i\right) \tag{13}$$

VFM_i and VFA_i are the land rent expenditures for sector i valued at market prices and agent's prices, respectively. VOM is the total land rent valued at market prices, and $VOM^{land} = \sum_i VFM_i$. $ETAX_i$ is the tax on the land use for sector i. The first two terms of the right-hand side of the equation are the terms brought back which calculates the welfare change due to physical land transformations. The third term indicates welfare change due to land productivity adjustments and the fourth term is the welfare change due to land allocative efficiency changes. The calculation is in line with the literature that the annualized marginal cost of converting land from one use to another is equal to the rental rate difference between the two uses (Lubowski et al., 2008; Rashford et al., 2011).

In an economic equilibrium framework, it is challenging to explicitly model the costs of land conversion since the definition is abstract and they are usually not included in the equilibrium state database. Gurgel et al. (2016) depicted an approach in which the land conversion service is produced using capital, labor, and intermediate inputs. In the present study, for simplicity, we assume that the land conversion service is produced using only labor. It can be implemented via endogenously shifting the labor supply to the extent that labor expenses offset the land conversion costs. The welfare change due to labor endowment supply change (C_2) can be decomposed as

$$C_2 = \widehat{L} \cdot VOA^{labor} + \widehat{L} \cdot PTAX \tag{14}$$

where $\widehat{L}$ is the percentage change in labor supply. VOA^{labor} is the total wage revenue and $PTAX$ is the tax on wage. Thus, $\widehat{L}$ is endogenized to guarantee that the total labor expenses equals the land conversion cost, or $C_1 + C_2 = 0$. Even though only labor is used for producing the land conversion service in the base scenario, we also test an additional scenario of utilizing capital to supply land conversion cost following the same method. The revised EV decomposition equations in GEMPACK code are provided in Section S1 in Supplementary Online Material (SOM), along with which the land conversion cost is highlighted as well. The welfare decomposition results are discussed based on the designed experiments.

4. Modelling framework and experimental tests

To compare the different land modelling approaches, we develop a small-scale general equilibrium model with three regions and seven industries based on the standard GTAP framework and assumptions (Hertel and Tsigas, 1996). We employ the GTAP 9 database and the coupled land database (Aguiar et al., 2016; Baldos, 2017). The database represented an economic equilibrium in 2011. It is aggregated to three regions including the USA, EU, and rest of the world (ROW), and seven sectors including grain, other crops, livestock, food, manufacture, forestry, and service. Endowment commodities include capital, labor, land, and natural resources. Capital and labor are mobile goods that can freely move across sectors. The nesting structure used for the CES production function and CET or ACET land supply is presented in Fig. 2. Details about the model and parameters are presented in Appendix B. The model is also available in SOM.

For this study, we use a textbook style comparative-static test of mandating a 10% increase in grain consumption in the US food sector to study land use change impacts. A mandate on grain consumption encourages grain production and thus increases grain harvested area. The new grain land can only come from land being used by other crops, livestock (pasture), and forestry (accessible forest). The same simulation test is used to compare different land modelling approaches. We design four experiment scenarios, presented in Table 1, to test and compare land use modelling approaches proposed in section 3. The parameters in CET and ACET have different meanings since the derivation of own- and cross-price elasticity of land supply is different. As the decomposition in section 3.2 allows the parameters to be different between the two approaches, we calibrate ACET parameters (ω_i) to have similar cropland supply elasticity implied by the CET parameters (δ_i). The calibration of the parameters is discussed in more detail in Appendix B. Furthermore, on the basis of E4, the sensitivity of cropland intensification responses is tested and discussed.

5. Results

The economic results and land use change results for the US are presented in Tables 2 and 3, respectively. A complete set of results are provided in Section S2 in SOM. With a 10% mandate increasing US grain consumption in the food sector, total grain production expanded, and other lands were converted to producing grain. This encouraged an increase in crop prices and cropland rents. Note that pasture rent fell by

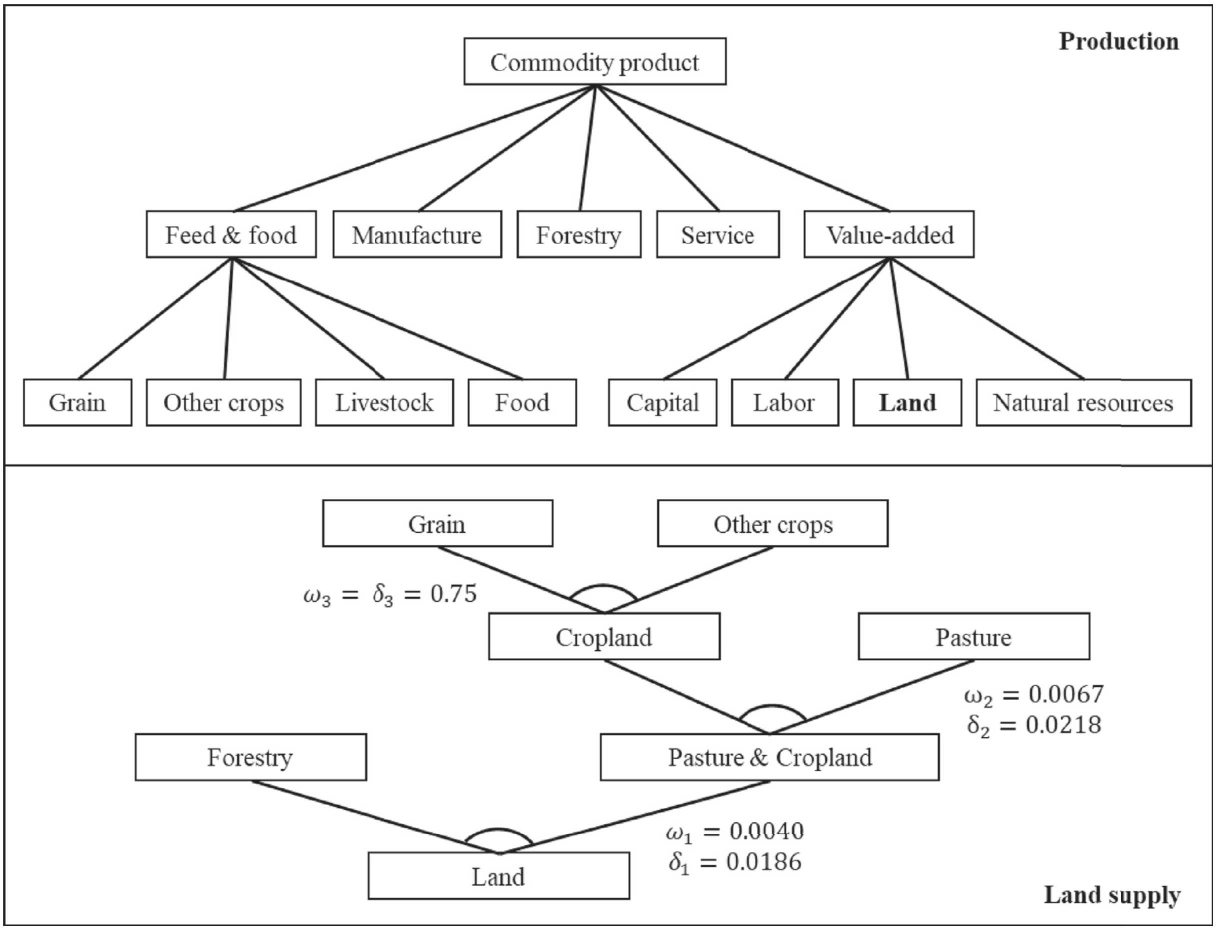

Fig. 2. The nesting structure for production (top panel) and land supply (bottom panel).

Table 1
Experimental design.

Scenario	Description
E1. CET	Standard CET, $\delta_1 = 0.0186$, $\delta_2 = 0.0218$, and $\delta_3 = 0.75$. The "ad hoc" adjustment is also tested.
E2. ACET	Replacing CET with ACET and different parameters are used. $\omega_1 = 0.004$, $\omega_2 = 0.0067$, and $\omega_3 = 0.75$. These transformation parameters provide the same cropland supply elasticity as CET.
E3. ACET & IMTECH	ACET plus implicit technical shifters (IMTECH) implied by CET for land productivity adjustment on the land demand side. That is, set $\hat{\lambda}_i = \hat{\alpha}_i$ for all land associated with the transformation.
E4. ACET & EXTECH & CC	ACET plus explicit technical shifters (EXTECH) based on biophysical information for land productivity (Eq. (11)) on land demand side and adjustments on land conversion cost (CC). Land conversion cost is entirely ascribed to labor expenses by endogenously shifting labor supply.

Table 2
Economic results for the USA due to the mandate.

Variable	Sector	E1. CET	E2. ACET	E3. IMTECH	E4. EXTECH & CC
Land rent change (%)	Grain	4.75	4.26	4.63	4.35
	Other crops	1.56	1.19	1.44	1.26
	Pasture	−2.07	−2.40	−2.14	−2.41
Production output change (%)	Grain	1.79	1.83	1.79	1.82
	Other crops	−0.64	−0.52	−0.64	−0.54
	Livestock	−0.38	−0.35	−0.38	−0.35
Market price change (%)	Grain	0.67	0.60	0.67	0.62
	Other crops	0.27	0.21	0.27	0.22
	Livestock	0.07	0.03	0.07	0.03
Yield change (%)	Grain	0.16	0.15	0.04	0.13
	Other crops	0.06	0.05	−0.05	0.03
Yield elasticity	Grain	0.24	0.24	0.07	0.20
	Other crops	0.24	0.24	−0.19	0.13

over 2% in the USA for all for scenarios. It was because the mandate led to a decline in grain consumption (accounting for 35% of cost share) in livestock production which in turn dampened the livestock sector production. Relative to land, other factor and intermediate inputs moved to other sectors at a faster speed so that pasture rent decreased. On the other hand, the production also fell significantly in the other crops sector. Factors moved mainly to the grain sector, but the land rent of other crops did not fall because of high land mobility or substitutability between other crops land to grain land.

Land use change results from the CET approach (E1 in Table 2) are in "effective land." There is a land cover loss of 257 thousand hectares if directly applying "effective land" percentage change to physical land base data due to the conversions from high-rental land to low-rental land. The change of crop harvest frequency (CHF) cannot be conjectured since it was not explicitly modeled. Based on the CET results, we applied the revised ex post "ad hoc" adjustments to translate the effective land to physical land shown in E1.1. In particular, the productivity adjustment parameter (0.66) is first employed to adjust the CET cropland area results. Two sets of slack variables are then applied to, respectively, (1) scale the CET-transformed forest and pasture areas to preserve the physical land cover area, and (2) adjust the CET-transformed crop harvested areas based on the assumption that the change in total harvested area equals the change in cropland cover. Even though, with the "ad hoc"

Table 3
Land use change results for the USA due to the mandate, in thousand hectares.

Land use change		E1. CET	E1.1 CET & "ad hoc"	E2. ACET	E3. IMTECH	E4. EXTECH & CC
Harvested area	Grain	604	648	625	648	630
	Other crops	−736	−616	−595	−617	−599
	Total	−131	32	31	31	31
Land cover	Cropland	23	32	33	34	34
	Pasture	−214	−24	−24	−23	−24
	Forest	−66	−8	−10	−11	−10
	Total	−257	0	0	0	0

adjustments used in this study, the adjusted-CET results were not too different from results from other scenarios, different assumptions used in the treatments may lead to very different results (see Section S2 in SOM for details). The approach of using ad hoc adjustments is a compromise solution that introduces uncertainties to the results.

E1 and E3 had identical economic results for non-land markets while E3 provided physical land use change results that preserve total land area. This verified the hypothesis described in section 3.2 that implementing a same land productivity change shock from either land supply side or land demand side would not affect non-land market equilibrium, and the effective land transformation is equivalent to the physical land transformation plus proper land productivity adjustments from the land demand side. In E3, the productivity of all land decreased due to the implicit adjustment since all land categories were assigned with the productivity adjustment shifter in the decomposition process implied by section 3.2. That is, for the US, $\widehat{\lambda}_{grain} = \widehat{\lambda}_{ocrops} = -0.115$; $\widehat{\lambda}_{livestock} = -0.076$; $\widehat{\lambda}_{forestry} = -0.025$. It implied that the average productivity of both the source and the sink of land transition might be changed due to the transition. The decomposition process could be more flexibly adjusted if more information were used. E4 applied biophysical information to adjust only cropland productivity, and it indicated a much smaller productivity decrease compared with E3 ($\widehat{\lambda}_{grain} = \widehat{\lambda}_{ocrops} = -0.011$ for the US). This explains why E4 had crop yield responses in-between of E2 and E3. E1 and E2 had the same yield elasticity of around 0.24 because the price yield response was endogenously calibrated through the elasticity of substitution among factor inputs in crop production (Keeney and Hertel, 2009). Note that the yield change and yield elasticity presented in Table 2 were results from both intensive and extensive yield responses. Implementing land productivity change from demand side permits consistently tracing yield responses with respect to both crop prices (intensive margin) and land heterogeneity (extensive margin). Furthermore, the inclusion of labor-based land conversion cost would not affect land use change results since the impacts on land use sectors were small. Thus, the difference between E3 and E4 in land use change results was mainly driven by the land productivity adjustment, but economic results and welfare decomposition were affected by the labor-based land conversion cost as well. To understand the impacts from different market-mediated responses on land use change, we decomposed the "gross" grain land area requirement in the US due to the 10% mandate increasing US grain consumption in the food sector based on the results from the scenario E4 (Fig. 3). The gross grain land area requirement is the land needed for producing the mandate at the initial crop yield. Due to the increase in crop prices, the requirement was compensated by the reduction in export and consumption. The impacts from the two yield margin responses were different in direction, and the intensive margin (price induced yield response) outweighed the extensive margin (land productivity adjustment). Since the CHF (0.92 for the US in base data) was assumed to be constant in the scenarios tested above (i.e., $\widehat{\varphi} = 0$) and the initial CHF for the US was smaller than 1, there would be negative cropland intensification response in which unused cropland might expand as well along with the expansion of cropland. The negative cropland intensification response was small because the cropland expansion was relatively small as most of the new grain was grown on areas originally producing other crops. The decomposition in the last column matched the results in Table 3.

The equivalent variation (EV) welfare change decompositions at the world level are presented in Table 4. The total world welfare decreased due to market distortion in the USA. Compared with the CET approach (E1), the ACET approach (E2) had $44 million welfare gain due to the physical land conversion and $15 million gain in allocative efficiency. The higher EV in E2 was because the lower land productivity due to, in this case, transforming low productivity land to higher productivity land and land conversion cost was not considered. After accounting for the physical land conversion gain through land productivity change implied by CET, E3 had the same total EV results as E1. The physical land transformation brought about a $47 million welfare increase, while the implicit land productivity decreases the welfare by $36 million. The remaining $11 million was land allocative efficiency loss due to the technical change. Moreover, in E4, the biophysical information implied that only $9 million welfare loss ($7 million technical change on land and $2 million associated allocative efficiency) was due to land productivity decrease, and the rest of physical conversion gain ($36 million) was ascribed to conversion costs including labor endowment shift ($26 million) and labor market allocative efficiency ($10 million). Note that comparing E4 with E2, not considering land heterogeneity and conversion cost (i.e., E2), results in a $55 million or 28% underestimation in the world welfare loss due to the grain mandate in the US. An additional scenario was tested based on E4, in which land productivity was not

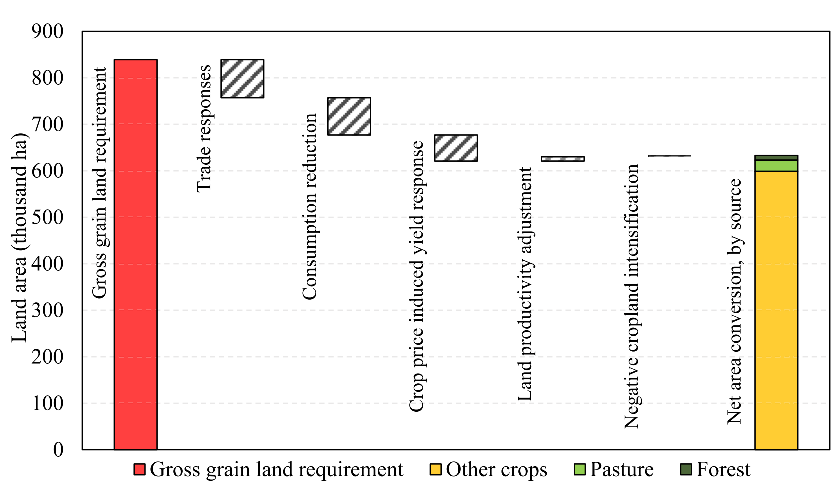

Fig. 3. Decomposition of gross grain land area requirement due to the 10% mandate increasing US grain consumption in the food sector for the scenario E4.

Table 4
Welfare change decomposition at the world level, in 2011 million dollars.

	E1. CET	E2. ACET	E3. IMTECH	E4. EXTECH & CC	E4.1. CC
Physical conversion gain	0	44	47	45	44
Endowment-labor (CC)	0	0	0	−26	−33
Allocative efficiency-land	0	0	−11	−2	0
Allocative efficiency-labor (CC)	0	0	0	−10	−11
Allocative efficiency-others	−200	−185	−200	−196	−196
Technology- land productivity	0	0	−36	−7	0
Total	−200	−141	−200	−196	−196

adjusted (i.e., $\eta_{i,j} = 1$), and the physical conversion gain was entirely ascribed to land conversion costs (see E4.1). The decomposition results are consistent with those in E4 except that land conversion costs bore all the physical conversion gain. Modelling land use physically provides more informative welfare decomposition results, and it indicates the importance of land productivity change and conversion cost in affecting welfare. This is a key difference between approaches.

6. Discussions

6.1. Land supply elasticity

As discussed in Appendix B, we calibrated ACET parameters to have similar cropland supply elasticity implied by the CET parameters to compare the two approaches on a similar basis. As expected, the land use change results (in Table 3) were not very different between CET and ACET experiments. In this section, we test a scenario of increasing the ACET transformation parameters to match the standard CET parameters. That is, $\omega_1 = \delta_1 = 0.0186$, $\omega_2 = \delta_2 = 0.0218$, and $\omega_3 = \delta_3 = 0.75$. The USA land use change results for E2 - E4 with the alternative parameters are presented in Table 5. The cropland increase from these experiments are much higher than the results from standard CET or "ad hoc" adjustment showed previously. It appears that the transformation parameters play important roles in affecting land use change results. It also confirms that, when comparing different land use modelling approaches, land supply elasticity other than the transformation parameters should be reconciled for a consistent comparison. Furthermore, these tests also indicate that the impact from land productivity heterogeneity adjustment becomes larger when cropland supply elasticity increases (e.g., deforestation increased by 5 thousand hectares or 13% from E2 to E4 while it was hardly changed in Table 3). Because land mobility increased due to the increase in the cropland supply elasticity, overall more pasture and forest (with low productivity) were converted (about 17% of the new grain area).

6.2. Land conversion cost

Land conversion cost is usually overlooked in economic modelling literature. Land conversion cost affects land use modelling from two aspects. (1) It influences the land owner's decision on land conversion or, more specifically, land mobility and (2) it generates value flows since land conversion is a service produced with other factors. In this study, the land transformation parameters governed the first impact of the land conversion cost. For the second impact, labor was used to supply land conversion service in the above experiments. An additional test, presented in Section S3 in SOM, was conducted of using capital to explain the land conversion cost based on E4. EXTECH & CC.

Table 5
Land use change results for the USA with alternative ACET land transformation parameters, in thousand hectares.

Land use change		E2. ACET	E3. IMTECH	E4. EXTECH & CC
Harvested area	Grain	633	667	649
	Other crops	−536	−563	−546
	Total	97	105	103
Land cover	Cropland	106	114	112
	Pasture	−66	−66	−69
	Forest	−39	−48	−44

6.3. Cropland intensification response

To this point, cropland intensification responses (i.e., multi-cropping practices and use of unused cropland) have not been discussed, and the CHF was assumed to be constant in the scenario tested above (i.e., $\widehat{\varphi} = 0$). The cropland intensification responses were rarely modeled explicitly in the literature due to the challenges from non-traceable land supply, data availability, and theoretical linkages in the model. We conducted additional tests based on E4, to examine how results would be affected with intensification responses (see S3 in SOM for details). The results indicate that in the current modelling framework, the cropland intensification responses do not only affect land supply, but also interact with other market-mediated responses. In practice, if the information is available, the specific crop intensity index (SCII) can also be introduced in the area preserving condition in the ACET derivation to distinguish crops by their abilities for multiple cropping or use of unused cropland.

6.4. Implications for policy evaluation and future development

This paper speaks to the global economic and integrated assessment modelling literature that examines land use and related impacts of agriculture, biofuels, or climate change policy. For example, biofuels induced land use change (ILUC) emissions have been widely studied using global economic and integrated assessment models (Calvin et al., 2014; Laborde and Valin, 2012; Taheripour et al., 2017b; Zhao, 2018). Policy bodies such as California Air Resources Board (CARB) and US Environmental Protection Agency (EPA) have considered ILUC emissions in calculating biofuels life-cycle emissions for the policy-making process (EPA, 2010; Gohin, 2016; Leland et al., 2018). Our results imply that incorporating biophysical information implied land heterogeneity on the extensive margin would provide more accurate land use results, and ignoring cropland intensification would overestimate land use change and related emissions. Furthermore, Giesecke et al. (2013) evaluated the impacts of removing the land designation policy for paddy rice in Vietnam with a physical land transformation approach that ignores land heterogeneity. However, as implied by our method, rice yield would increase when acreage decreased if considering a land heterogeneity pattern implying that relatively lower quality land would be converted to other uses first when removing the designation policy. Incorporating land heterogeneity will clearly lead to different results for land use change and by extension welfare impacts. Similarly, land heterogeneity and conversion cost may have important implications for evaluating other land-related policies such as potential land fallow policies in China (Wang et al., 2018) or land taxes in Australia (Nassios et al., 2019).

Land use and trade impacts from climate change have been evaluated in the literature (Costinot et al., 2016; Gouel and Laborde, 2018; Verburg et al., 2009). Considering a land conversion cost would provide a more comprehensive understanding of the welfare impacts of climate change and trade liberalization. Schmitz et al. (2014) compared ten well-established economic models for estimating land use change trajectories to 2050 under the Shared Socioeconomic Pathways (SSPs) and climate change scenarios. The results showed fairly large differences in future land use projection across the models, and disparities in land use modelling methods appeared to be the key drivers. The generalized framework proposed in this study provides a necessary structure for reconciling and comparing empirical studies and identifying causes of divergence.

In addition, the intuition of using land quality heterogeneity and conversion cost to interpret the gap between value and volume in land transformation may provide important implications for other related issues, such as aggregating homogeneous goods (e.g., Armington structure for trade in Siddig and Grethe (2014) and Sebestyén (2017)) and studying labor mobility (e.g., Marouani and Nilsson (2016)) (i.e., the employment rate could be similar to crop harvest frequency in affecting supply), when physical results other than "effective" results are needed.

In this study, we have demonstrated theory and application with a scaled-down illustrative model and experiment for pedagogical objectives. It is not difficult to scale and leverage the proposed land use modelling framework for empirical applications when more data are available for land productivity and land conversion cost. For instance, as mentioned earlier, the elasticity of effective cropland with respect to cropland expansion parameter developed in Taheripour et al. (2012a) based on the (NPP) data at the AEZ level can be employed for estimating land productivity changes. Also, another recent development in Zhao et al. (2019) incorporated the ACET and the Ricardian approaches so that it allows considering land heterogeneity implied comparative advantage using land productivity distributions provided by high-resolution agronomic models. Furthermore, instead of using only labor, more sophisticated cost shares may be employed for the land conversion service. This is particularly manageable in dynamic models in which the land conversion cost may be built into the database. It is also important to note that by using the new approach, the parameters in ACET need to be re-calibrated to match land supply elasticity implied by the literature. Finally, on the basis of the proposed land use modelling framework in this study, future development should focus on (1) developing a more refined linkage between biophysical information and land productivity on the extensive margin, (2) providing a more sophisticated estimation and definition of land conversion cost based on empirical data in a dynamic framework, and (3) incorporating cropland intensification responses in parameter estimation and model calibration.

7. Conclusion

In this article, we extended the existing literature to develop a consistent and communicable approach to modelling land use in a global economic model. In particular, the approach employed a physical land transformation functional form, the additive form of the constant elasticity of transformation (ACET), for land transformation. It incorporated biophysical information for adjusting land productivity changes due to land heterogeneity from the land demand side, and also explicitly accounted for the conversion cost for maintaining welfare traceability. The simulation tests demonstrated that the new approach had important advantages compared with the conventional approach. These advantages include: (1) it provides traceable physical land use change results so that land use policies targeting physical land area can be implemented directly; (2) it links biophysical information to the economic framework to flexibly handle land productivity differences; (3) it offers detailed welfare decomposition in light of land productivity adjustment and land conversion cost, and (4) it permits incorporating cropland intensification responses through multi-cropping practices and use of unused cropland consistently into land supply derivation. In other words, the problems that have plagued the estimation of the impacts of land use change in the past can be solved with this new approach. The new land use modelling framework was tested with an experiment of mandating a 10 percent increase in grain consumption in the US food sector in a computable general equilibrium (CGE) model. The results indicated that the conventional constant elasticity of transformation (CET) approach had a physical land imbalance of 257 thousand hectares. Also, ignoring land productivity difference and conversion cost would result in a 28 percent underestimation of the world welfare loss due to the US agricultural policy. That is, failing to properly account for land heterogeneity and conversion cost can lead to biased policy analysis. The framework developed here can be implemented to improve land use change modelling and analysis.

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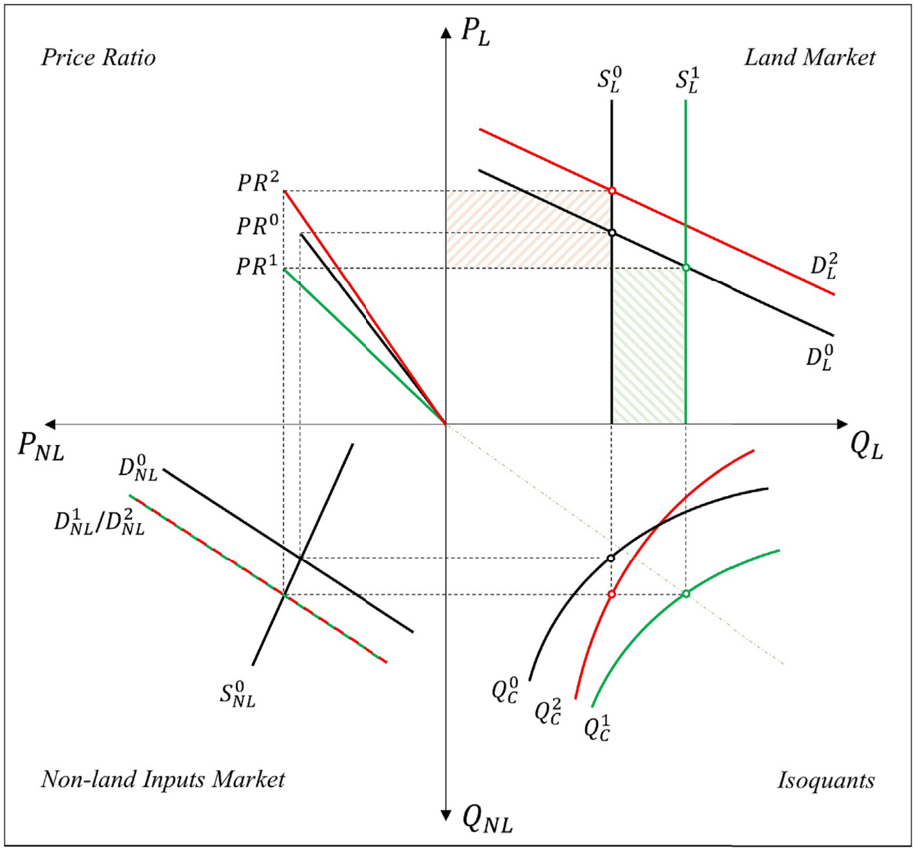
Appendix A. Factor productivity change: effective factor supply shift vs. technical shock on factor demand

In economic equilibrium models, a factor productivity change is usually imposed from shifting the "effective factor" supply (particularly common in a general equilibrium framework), in which "effective factor" takes into account both the quantity and the efficiency of a factor (Burfisher, 2011). Alternatively, a factor productivity change can also be implemented from the factor demand side as a factor biased technical shock. Even though the former approach might be more practical in implementation, it is important to note that by shifting effective supply, the factor market equilibrium would represent the effective factor market rather than the physical factor market, while identical equilibria would be reached for any other markets between the two approaches. Fig. A1 illustrates the two approaches of implementing a land productivity change using a partial equilibrium example of producing an aggregated crop (the only land-use sector) using land and non-land inputs, assuming a perfectly elastic crop demand. The notations are presented in the figure note. The aggregate land supply is inelastic because the total endowment is fixed. Equilibrium 0 ($b = 0$, black lines) represents the initial equilibrium. In the traditional approach, when land productivity increases, the initial land supply (S_L^0) is shifted to the "effective land" supply (S_L^1), and the new equilibrium is represented by equilibrium 1 ($b = 1$, green lines). It encourages a lower "effective land" price and increases in crop production and non-land inputs demand. As a result, the price ratio between "effective land" and non-land inputs becomes smaller (PR^0 to PR^1) so that the "effective yield" decreases due to factor substitutions. In the alternative approach (equilibrium 2 in Fig. 1, $b = 2$, red lines), striking a land productivity growth with a land biased technical shifter in crop production makes the isoquant of crop production steeper, implying that less land is needed in producing the same amount of crop. In this case, land demand in per unit production decreases while the land demand curve may shift up or down depending on non-land input supply elasticity and crop production technology. Fig. A1 demonstrates a case of shifting up D_L^2 and the case of shifting down D_L^2 is presented in Fig. A2. If the shifter on "effective land" supply in the first approach and the land biased technical shifter in the second approach are commensurate, the two approaches of implementing a land productivity change would result in identical equilibria in the non-land inputs market (D_{NL}^1 and D_{NL}^2 overlaps) and the crop market ($Q_C^1 = Q_C^2$). The only difference is that the first approach provides the "effective land" market equilibrium while the second approach provides the physical land market equilibrium. The two shaded areas in Fig. A1 or Fig. A2 are the same in size since the total land rental revenue should be the same between the two approaches.

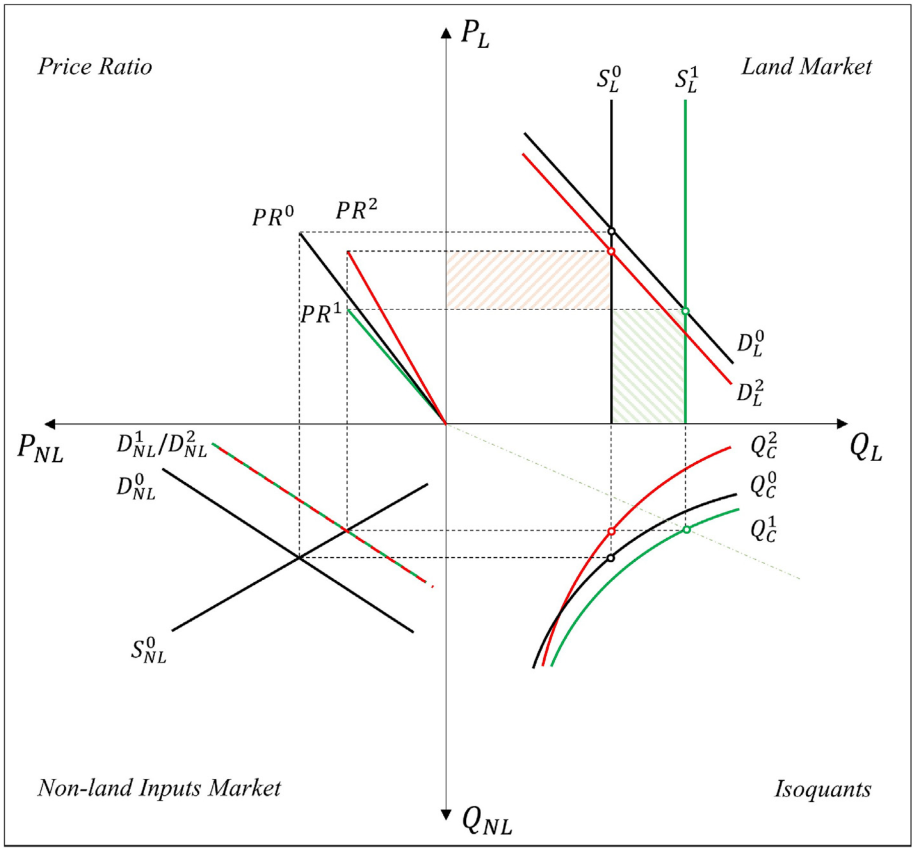


Note: the notations in the figure can be represented by X_a^b, whereas

$$X = \begin{cases} D: \ demand \\ S: supply \\ Q: \ quantity \\ P: price \\ PR: \ price\ ratio\ between\ land\ and\ nonland\ inputs \end{cases}$$

$$a = \begin{cases} L: land \\ NL: nonland \\ C: crop \end{cases} \quad b = \begin{cases} 0: \ initial\ equilibrium \\ 1: \ equilibrium\ with\ effective\ land\ supply\ shifter \\ 2: \ equilibrium\ with\ land\ biased\ technical\ shifter \end{cases}$$

Fig. A1. Two approaches to implementing a land productivity change.



Note: the notations in the figure can be represented by X_a^b, whereas

$$X = \begin{cases} D:\ demand \\ S: supply \\ Q:\ quantity \\ P: price \\ PR:\ price\ ratio\ between\ land\ and\ nonland\ inputs \end{cases}$$

$$a = \begin{cases} L: land \\ NL: nonland \\ C: crop \end{cases} \quad b = \begin{cases} 0:\ initial\ equilibrium \\ 1:\ equilibrium\ with\ effective\ land\ supply\ shifter \\ 2:\ equilibrium\ with\ land\ biased\ technical\ shifter \end{cases}$$

Fig. A2. Two approaches to implementing a land productivity change (the case of decreasing physical land demand).

Appendix B. Model and parameter

For this study, we develop a small-scale model with three regions and seven industries. The model is general equilibrium and follows the standard GTAP framework and assumptions (Hertel and Tsigas, 1996). Private households maximize a constant difference of elasticity (CDE) utility function subject to a budget constraint. Producers minimize cost with nested CES production function earning zero pure profit. The Armington structure is used for international trade. Commonly used parameters for CDE derived household demand functions, elasticity for Armington assumptions, and elasticity of factor substitution are suggested along with the GTAP data base (Aguiar et al., 2016). The detailed illustrations of the standard GTAP modelling framework are presented in Corong et al. (2017). Furthermore, following Keeney and Hertel (2009), the elasticity of crop yield with respect to crop price (intensive margin) is endogenously calibrated to 0.25 via factor substitution. That is, the post-simulation yield elasticity would be around 0.25 with no yield responses on the extensive margin.

Table B.1 presents CET and ACET parameters used in this study. These parameters are used uniformly across regions. The CET parameters are the same as the parameters calibrated in Taheripour and Tyner (2013) for the US. It is important to note that the supply responses implied by the two approaches may be different since the land supply elasticity implied by CET are in "effective land" while the elasticity in ACET reflects physical land mobility. To make the results comparable across scenarios, we calibrate ACET parameters to have similar cropland supply elasticity implied by the CET parameters. Based on the elasticity of land transformation and land rental shares, the initial cross-price elasticities of land supply are derived via Allen-Uzawa elasticity of substitution (AUES) for the CET approach. The derivation of the land supply matrix for the nested ACET approach is more complicated. Both land rental shares and land area shares are required, and the chain rule is used based on the totally differentiated supply functions.

We choose a set of ACET parameters (presented in Table B.1) to reconcile the own price elasticity of cropland supply with the CET approach. The own- and cross-price elasticity of land supply for CET and ACET are presented in TableS B.2 and B.3, respectively. The CET and ACET function forms are not flexible enough to have similar values for the entire matrix. Making use of the CRETH and ACRETH may provide a better comparison between effective land transformation and physical land transformation approaches. The sector mapping used for aggregating the 57 GTAP sectors to the 7 sectors used in this study is presented in Table B.4. Note that grain ethanol was an independent sector in the standard GTAP database and it was likely that grain ethanol was aggregated in the food and the livestock sectors. We did not make any modifications in the data base so that results from this study can be easily replicated.

Table B1
CET and ACET parameters.

Parameter description	CET parameter	ACET parameter
Elasticity of land transformation across forestry and pasture & cropland	−0.0186	−0.0040
Elasticity of land transformation across cropland and pasture	−0.0218	−0.0067
Elasticity of land transformation across crop harvested areas within cropland	−0.75	−0.75

Table B2
The own- and cross-price elasticity of land supply for land m (column) to the price of land n (row) for standard CET.

$\rho_{m,n}$	Grain area	Other crops area	Cropland	Pasture	Forest
Grain area	0.5221	−0.5178	0.0043	−0.0023	−0.0020
Other crops area	−0.2279	0.2322	0.0043	−0.0023	−0.0020
Cropland	0.0013	0.0030	0.0043	−0.0023	−0.0020
Pasture	−0.0054	−0.0122	−0.0175	0.0195	−0.0020
Forest	−0.0045	−0.0102	−0.0147	−0.0019	0.0166

Table B3
The own- and cross-price elasticity of land supply for land m (column) to the price of land n (row) for ACET.

$\rho_{m,n}$	Grain area	Other crops area	Cropland	Pasture	Forest
Grain area	0.5544	−0.5501	0.0043	−0.0029	−0.0014
Other crops area	−0.1956	0.1999	0.0043	−0.0029	−0.0014
Cropland	0.0015	0.0028	0.0043	−0.0029	−0.0014
Pasture	−0.0008	−0.0016	−0.0024	0.0038	−0.0014
Forest	−0.0001	−0.0002	−0.0003	−0.0023	0.0026

Table B4
Mapping between GTAP database to the database in this study.

No.	GTAP data base	Sectors in this study	No.	GTAP data base	Sectors in this study
1	pdr	Other crops	30	lum	Manufacture
2	wht	Other crops	31	ppp	Manufacture
3	gro	Grain	32	p_c	Manufacture
4	v_f	Other crops	33	crp	Manufacture
5	osd	Other crops	34	nmm	Manufacture
6	c_b	Other crops	35	i_s	Manufacture
7	pfb	Other crops	36	nfm	Manufacture
8	ocr	Other crops	37	fmp	Manufacture
9	ctl	Livestock	38	mvh	Manufacture
10	oap	Food	39	otn	Manufacture
11	rmk	Livestock	40	ele	Manufacture
12	wol	Livestock	41	ome	Manufacture
13	frs	Forestry	42	omf	Manufacture
14	fsh	Food	43	ely	Manufacture
15	coa	Manufacture	44	gdt	Manufacture
16	oil	Manufacture	45	wtr	Service
17	gas	Manufacture	46	cns	Service
18	omn	Manufacture	47	trd	Service
19	cmt	Food	48	otp	Service
20	omt	Food	49	wtp	Service
21	vol	Food	50	atp	Service
22	mil	Food	51	cmn	Service
23	pcr	Food	52	ofi	Service
24	sgr	Food	53	isr	Service
25	ofd	Food	54	obs	Service
26	b_t	Food	55	ros	Service
27	tex	Manufacture	56	osg	Service
28	wap	Manufacture	57	dwe	Service
29	lea	Manufacture			

Note: See GTAP data base documentation from Aguiar et al. (2016) for detailed descriptions.

Appendix C. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.econmod.2019.03.003.

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