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THE CRITICAL ROLE OF CONVERSION COST AND COMPARATIVE ADVANTAGE IN MODELING AGRICULTURAL LAND USE CHANGE

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The difference in land use modeling approaches is an important uncertain factor in evaluating future climate scenarios in global economic models. We compare five widely used land use modeling approaches: constrained optimization, constant elasticity of transformation (CET), the additive form of constant elasticity of transformation (ACET), logit, and Ricardian. We demonstrate that the approaches differ not only by the extent of parameter uses but also by the definition of conversion cost and the consideration of comparative advantage implied by land heterogeneity. We develop a generalized hybrid approach that incorporates ACET/logit and Ricardian to account for both conversion cost and comparative advantage. We use this hybrid approach to estimate future climate impacts on agriculture. We find a welfare loss of about 0.38–0.46% of the global GDP. We demonstrate that ignoring land heterogeneity or land conversion costs underestimates climate impacts on agricultural production and welfare.

Keywords: Land use modeling; land heterogeneity; conversion cost; Ricardian model; climate impact; welfare.

1. Introduction

Despite being one of the most important factors in agricultural production, land has long been overlooked in the literature of global economics (Hertel *et al.*, 2009). This has changed in the past decade. To evaluate the role of agriculture, forestry, and other land use in greenhouse gas emission reduction, land has been explicitly introduced into global economic models (Lee, 2005; Havlík *et al.*, 2011; Wise *et al.*, 2014; Calvin *et al.*, 2018). The modeling of land was also facilitated by the recent development of data for global land use, rental rates, productivity, and emissions (Lee *et al.*, 2005;

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Fischer *et al.*, 2012; Gibbs *et al.*, 2014; Baldos, 2017) and the advancement of theories representing landowner's behavior (Sands and Leimbach, 2003; Schneider *et al.*, 2007; Hertel *et al.*, 2009; Costinot and Donaldson, 2012; Golub and Hertel, 2012; Wise *et al.*, 2014). Recent applications of the land-focused global economic models include, for example, estimating biofuels induced land use change emissions (Valin *et al.*, 2015; Wise *et al.*, 2015; Taheripour *et al.*, 2017; Zhao, 2018), developing and evaluating Shared Socioeconomic Pathways (SSPs) to understand dual challenges of reducing greenhouse gas emissions and adapting to future climate change (Calvin *et al.*, 2017; Popp *et al.*, 2017; Riahi *et al.*, 2017), and studying the climate impacts on agriculture, trade, and land use (Schmitz *et al.*, 2014; Costinot *et al.*, 2016; Gouel and Laborde, 2018).

Robust economic modeling of land use is crucial to improving analysis of the agricultural system and its linkages to other systems (e.g., energy and water). The theoretical framework, along with the parameters of land use, define the landowners' behavior for distributing land among a variety of different uses given the rental profit. However, modeling land use change based on the relationships of land value, physical quantity, and productivity has been challenging (van Tongeren *et al.*, 2017). Depending on the method used, concerns arise with respect to (1) maintaining the physical balance of land, (2) accounting for the comparative advantage implied by land heterogeneity, and (3) including land conversion cost (Zhao *et al.*, 2020). Widely used land use modeling methods include constrained optimization, constant elasticity of transformation (CET), the additive form of constant elasticity of transformation (ACET), logit, and Ricardian (Table 1). Yet, none of the existing approaches addresses all of these concerns simultaneously and consistently. The motivation of this study is to theoretically compare commonly used land use modeling approaches, aiming to explore and understand the differences and connections among these approaches.

A standard assumption in economic models is the fixed total physical land endowment, reflecting a resource constraint. This is true in all of the approaches except CET (Golub and Hertel, 2012). CET may account for land heterogeneity and conversion cost in a way that sacrifices physical land accounting (see Sec. 2 for explanations). Models using CET may have additional adjustments to translate CET results into physical units. Given the physical nature of land, land use modeling with inherent physical land accounting is preferable for maintaining a resource constraint, studying land use policies, and calculating terrestrial carbon in climate-related studies. In the ACET and the logit approaches (Wise *et al.*, 2014; van der Mensbrugghe and Peters, 2016), physical land is preserved while the land conversion cost is considered in an implicit manner. The conversion cost in these approaches can be viewed as reflecting the preference of the landowner that accounts for factors beyond monetary conversion efforts but impedes land mobility, such as risk, management practices, technology accessibility, and unmeasured benefits from crop rotation (Golub *et al.*, 2010; Giesecke *et al.*, 2013). Furthermore, Ricardo's theory of comparative advantage predicts that, under perfect competition, economic specialization and geography are driven by relative productivity differences in factors of production (Deardorff, 1980). Comparative

Table 1. Summary of applications of different land use modeling methods.

Model	Type[1]	Land use model	Key study
FASOM	PE	Constrained optimization	Beach and McCarl (2010)
GLOBIOM	PE	Constrained optimization	Havlík *et al.* (2011)
MAgPIE	PE	Constrained optimization	Lotze-Campen *et al.* (2008)
MAGNET	GE	CET	Kavallari *et al.* (2014)
GTEM	GE	CET	Ahammad and Mi (2005)
ENVISAGE	GE	CET	van der Mensbrugghe (2010)
GTAP-BIO	GE	CET	Hertel *et al.* (2010)
MIRAGE	GE	CET	Al-Riffai *et al.* (2010)
LEITAP	GE	CET	Verburg *et al.* (2009)
ENVISAGE	GE	ACET	van der Mensbrugghe and Peters (2016)
PHAGE	GE	ACET	Mariano and Giesecke (2014)
MONASH-VN	GE	ACRETH[2]	Giesecke *et al.* (2013)
GCAM	PE	Logit	Wise *et al.* (2014)
AIM	GE	Logit	Fujimori *et al.* (2014)
Constructed GE	GE	Ricardian	Sotelo (2019)
Constructed GE	GE	Ricardian	Costinot *et al.* (2016)
AgLU	PE	Ricardian/original logit	Sands and Leimbach (2003)

Notes: [1]Models are categorized into general equilibrium (GE) or partial equilibrium (PE) models. [2]The additive form of the constant ratio of elasticity of transformation, homothetic (ACRETH) is a generalized function form of ACET.

advantage has been one of the most influential answers to "why do nations trade?" (Costinot *et al.*, 2015). Recent innovations of the Ricardian model used heterogeneity in land, implied by distributions of land productivity, as a driver for comparative advantage so that it also answered "how land is used?" (Costinot *et al.*, 2016; Sotelo, 2019). However, the effect of the land conversion cost on the optimal land use dis-tribution implied by comparative advantage has been ignored, given the static nature of the Ricardian model.

In this paper, we review the theoretical development of several land use modeling approaches and then mathematically dissect the land allocation approaches to explore their connections to a simple constrained optimization model. We demonstrate that the land use modeling approaches differ not only by the extent of parameter uses, but also, more importantly, by the consideration of land heterogeneity and conversion cost, and the definition and the treatment of land conversion cost. We show that, when a type of land expands, CET, ACET, and logit describe an increasing marginal cost of land conversion, while the Ricardian method stipulates a marginally decreasing land productivity. Also, the land conversion cost in the CET approach is charged to physical land (i.e., physical land grows or contracts to reflect conversion costs), whereas the conversion cost in ACET and logit is linked to changes in landowner's preference or changes in conversion service or maintenance cost generated in other markets that are not modeled or explicitly accounted for. The connection between these models and a simple constrained optimization model is also illustrated. In particular, the constrained optimization model would reconcile with ACET or logit if incorporating the conversion cost constraint decomposed from ACET or logit, and it would reconcile with Ricardian if incorporating the land productivity change constraint decomposed from Ricardian. Building on the comparison of different approaches, we develop a hybrid approach by incorporating both the ACET/logit and the Ricardian approaches. This method features both conversion cost and land heterogeneity as it has a parameter governing the curvature of the land conversion cost and a land productivity distribution parameter reflecting the degree of land heterogeneity.

To test and compare different methods, we built a one-region (world) partial equilibrium model following the framework of the Agriculture and Land Use (AgLU) module in the Global Change Assessment Model (GCAM). We first employed a simple comparative static experiment of a 5% subsidy on global corn production to study the land use and economic impacts from different modeling approaches. These tests demonstrated the sensitivity of land use change results to parameter specification and land allocation methods.

We then applied our model to estimate future climate impacts on agricultural land use change and welfare. We used high-resolution maps of future potential yield under climate scenarios estimated in the Global Agro-Ecological Zones (GAEZ) model (Fischer *et al.*, 2012). The GAEZ model projects potential yield based on future global weather data projected by General Circulation Models (GCM) and other high-resolution agronomic data such as soil quality, topography, sunshine fraction, and wind speed. We used potential yields in the 2080s estimated in GAEZ based on HadCM3, a coupled atmosphere-ocean GCM developed at the UK Hadley Centre, and the A1FI scenario, one of the high-emission scenario in the Special Report on Emissions Scenarios (SRES) from the UN's Intergovernmental Panel on Climate Change (IPCC) (Nakicenovic *et al.*, 2000). The same climate scenario was used in Costinot *et al.* (2016) and Gouel and Laborde (2018) for studying the role of international trade in reducing the consequences of climate impacts on agricultural market with the Ricardian approach. Following the previous studies, we assume future climate impacts would shift the distribution of potential yield for all crops. The heterogeneous shifts in potential yield alter the comparative advantage pattern of growing different crops, which results in changes in crop production and land use. We estimate, using our hybrid approach, the agricultural and welfare impact from the average yield shifts while considering land conversion cost.

Echoing Schmitz *et al.* (2014) and Alexander *et al.* (2017), our results demonstrate that different land use modeling approaches are an important source of uncertainty for evaluating the implications of future climate scenarios on land use and crop production. Also, note that the Ricardian model of land heterogeneity and the Ricardian analysis developed in Mendelsohn *et al.* (1994) share a similar theoretical foundation that farmers would change uses of land to maximize rental profit and it would help farmers adapt to the changing climate. Results from our model also demonstrate that land use change (or crop switching) is important for reducing the welfare losses due to climate impacts on agriculture. However, the higher land conversion costs implied by either change in conversion and maintenance service costs or land owner's preference would dampen the adaptation potential.

The rest of this paper is structured as follows. In Sec. 2, we review the theoretical development of commonly used approaches for land allocation in the literature. Based on the understanding of the state of the literature, Sec. 3 provides the theoretical details of different land use modeling approaches as well as the newly developed hybrid approach that incorporates responses from both conversion cost and land heterogeneity. In Sec. 4, we develop a simple model and design experiments to compare different land use modeling approaches. In Sec. 5, we studied the impacts of changes in future climate on agricultural land use change and welfare to utilize and test the hybrid approach we developed and to further compare land use modeling approaches. While our study makes important contributions to understanding the role of land heterogeneity and conversion cost in land use modeling and for reconciling different approaches, there are also important areas that require further exploration. The implications and limitations of the study are discussed in Sec. 6. Finally, Sec. 7 concludes the study.

2. Review of the Theoretical Background

Dating back to Adams *et al.* (1993), a constrained optimization model, Agricultural Sector Model (ASM) was developed to examine the social costs of forest carbon sequestration on US agricultural land. The ASM laid the theoretical foundation for the development of widely used models including the Forest and Agricultural Sector Optimization Model (FASOM) (Beach and McCarl, 2010) and the Global Biomass Optimization Model (GLOBIOM) (Havlík *et al.*, 2011; Valin *et al.*, 2015). Constrained optimization models are usually partial equilibrium with an objective function of maximizing welfare (the sum of consumer surplus and producer surplus, e.g., GLOBIOM) or minimizing total cost (including land conversion cost, e.g., MAgPIE). The extent to which land productivity heterogeneity and conversion cost are considered mainly depends on the additional constraints implemented. For the example of GLOBIOM, a linear land use change cost function was assumed while no constraint was added for adjusting regional (within the simulation unit) land productivity[1] (Havlík *et al.*, 2011). Constrained optimization models may have different frameworks, while they have a common characteristic that land use or land use change are defined as variables and solved in the simulation. In contrast, only prices (either crop prices or land rental rates) are defined as variables in the equilibrium approaches (all non-constrained optimization methods in this study) and the only constraint is the market clearing condition. Most constrained optimization models for land use modeling do not

[1]Land heterogeneity could largely be accounted for if the simulation unit and land productivity are defined at fine-scale, and, though heavily rely on data and assumption, the land productivity for each use of the land at the fine-scale simulation describes the land productivity heterogeneity.

explain landowner's behavior or the initial land equilibrium. Rather, these models assume that the initial land use allocation is given and future land use equilibrium is calculated based on the initial land use with land use change being variables.[2] To facilitate the comparison with the equilibrium approaches, the constrained optimization approach in this study only includes the resource constraint (i.e., the sum of land supply across uses is limited by the total land available) and the relative rental rate (which implies a constraint of land conversion cost). That is, the initial economic equilibrium can be recovered with a vector of initial land uses and rental rates. This simple equilibrium-type constrained optimization model assumes homogeneous land and a linear conversion cost implied by the relative rental rate in the initial data. As illustrated in this study, a constrained optimization model with linear land conversion cost and limited consideration of within region land heterogeneity may provide more flexible (higher land supply elasticities) land transitions than approaches using marginally increasing conversion cost (e.g., ACET or logit) or approaches with continuous specification of land heterogeneity (e.g., Ricardian).

As the workhorse of land use modeling in the applied general equilibrium (AGE) literature, the CET approach assumes landowners maximize the total land rent revenue given a CET land transformation function (Hertel, 1996). It was introduced by Golub *et al.* (2009) and demonstrated by Zhao *et al.* (2020) that the CET effectively accounted for land heterogeneity from the supply side by assuming the land rental rate reflects land productivity so that CET results are productivity-weighted or per effective land unit. Also, as demonstrated in the present study, the CET approach can also be interpreted as implicitly applying an iceberg-type land conversion cost that is similar to the well-known iceberg transport cost[3] in the trade literature (Krugman, 1980). In other words, a fraction of land "melts or accumulates in transition" to compensate for the conversion cost or benefit. Due to either interpretation, CET does not directly provide physical land use results. In models using CET, ex-post adjustments were developed to translate CET results to physical land based on certain assumptions, e.g., Golub and Hertel (2012) documents the adjustment method used in GTAP-BIO.[4] It is important to note that different models may use different adjustments which may introduce additional uncertainty.[5] A discussion of the various methods used to translate CET results to physical land is outside the focus of this study.

[2]In these models, conversion cost coefficients are applied to land use change variables, and the total conversion cost is minimized in the objective function. The transition-based conversion cost coefficients are used as parameters governing land supply responses.

[3]The iceberg transport cost model relates transport costs with distance and pays these costs by reducing the arriving volume (Deardorff, 2014). The model provides a mathematically tractable way to incorporate trade cost without modeling the transportation sector (Hummels, 2010). The CET approach in land use modeling follows a similar intuition as it maintains the land value flows without modeling the land conversion sector explicitly. However, transport cost in the iceberg model is usually positive (when using the physical distance) while land conversion cost in this study could be negative (conversion benefit) depending on the definition (see Section 3.5).

[4]In GTAP-BIO, additional parameters mirroring biophysical information are introduced to account for land heterogeneity on the extensive margin in the additional adjustments of translating CET results to physical units.

[5]The *ex-post* adjustments are not all well-documented in the models using CET.

The concern of nontraceable physical land use change results from CET has received considerable recent attention (Giesecke *et al.*, 2013; Fujimori *et al.*, 2014; van der Mensbrugghe and Peters, 2016; Taheripour *et al.*, 2018; Zhao *et al.*, 2020). Indeed, any strictly quasi-convex transformation function (e.g., CET) will likely not preserve volume in a revenue maximization problem.[6] This pitfall can be avoided by assuming the landowner as utility maximizer with a utility function as a quasi-convex aggregation of revenue, subject to the resource constraint, as suggested by Giesecke *et al.* (2013) and van der Mensbrugghe and Peters (2016). The preference of the landowner would consider unobserved costs of conversion such as nonmarket costs from imperfect information, risk, geographical barrier, technology accessibility, etc.

Aiming to provide a remedy to the CET approach for maintaining the physical resource constraint, van der Mensbrugghe and Peters (2016) developed the additive form of the CET function, namely the ACET approach. ACET assumes landowners allocate land to different uses to maximize a CET aggregation of land rent revenue. Coincidentally, the land use sharing from the ACET approach has an inherent mapping to the logit approach used in Wise *et al.* (2014) and Fujimori *et al.* (2014). There was a long history of the development of the logit approach for modeling consumer choice under probabilistic conditions (McFadden, 1973, 2001). It is assumed that the utility-maximizing decision maker facing J choices has a random unknown part, ε_j, in the utility function of choosing alternative j. ε_j is independently, identically, distributed (*i.i.d.*), following a Gumbel, type I extreme value, distribution. The share of j over J equals to the probability that the decision maker chooses j, which can be derived using the property of extreme value distribution (Train, 2009). The approach was named a conditional logit model or multinomial logit model due to its connection with the logistic distribution that the difference between two Gumbel distributions is distributed logistic. A similar framework was employed in Clarke and Edmonds (1993) for modeling the cost minimizing decision maker's behavior of choosing different energy technologies, in which a Weibull (type III extreme value) instead of Gumbel was used for deriving cost distributions. Furthermore, building on Clarke and Edmonds (1993), Sands and Leimbach (2003) extended the logit framework for land use modeling in the Agriculture and Land Use (AgLU) model. It was assumed that crop yields would follow a Fréchet distribution (type II extreme value), which is a log-transformation of Gumbel distribution. Land use shares were derived from solving a problem of landowners choosing a crop to maximize the rental rate at each parcel. Both the energy technology sharing and the land use sharing derived from the logit framework were originally incorporated into GCAM. However, the conditional mean land rental rate derived using the original logit approach has to be equal across all choices, which is usually not supported by the observed data since land rental rate may vary

[6] This is because the resource constraint itself provides a linear transformation constraint that would usually discord with a quasi-convex transformation function. Similarly, any strictly quasi-concave production function (e.g., CES) will likely not preserve volume in a cost minimization problem. The same nontraceable issue exists when using CES to aggregate homogeneous products (e.g., electricity produced from different sources).

considerably across uses. That is, land heterogeneity in the original logit approach cannot adequately explain differences in rental rate across uses. As a result, the land use sharing in GCAM was updated to the logit approach presented in Wise *et al.* (2014) for empirical applications, in which (1) calibration parameters were introduced to account for variation in the rental rate across uses, (2) the yield was fixed within each region, and (3) the conversion cost, governed by the logit exponent, played an implicit role in controlling land transformation. Note that, if not otherwise specified, the logit approach for land use modeling in the analysis throughout this study refers to the approach used in Wise *et al.* (2014). Both logit and ACET do not consider land heterogeneity; as a result, new land would have the same productivity as the existing land within a region.

Zhao *et al.* (2020) demonstrated a reconciliation between the effective land transformation (e.g., CET) and the physical land transformation (e.g., ACET) approaches. In particular, by decomposing CET into ACET plus endogenous land productivity adjustments implemented from the land demand side, nonland market equilibrium would remain unchanged while land would preserve physical balance. Since no biophysical information was provided, the CET implied land productivity adjustment would completely compensate the ACET implied conversion cost,[7] which is too strong an assumption. Thus, Zhao *et al.* (2020) suggested to rely on physical land transformation approaches for land allocation and incorporate biophysical information for adjusting land productivity change due to transformation through technical shifters on the land demand side. And the value of conversion cost implied by the physical land transformation approach, either observed or preference implied, can be traced through welfare decomposition. Nevertheless, consistently incorporating biophysical information into the framework remained a challenge. The linkage to biophysical information in the Ricardian approach would provide important insights.

Recent studies from Costinot *et al.* (2016), Sotelo (2019), and Gouel and Laborde (2018) applied the Ricardian trade model from Eaton and Kortum (2002) to land use modeling for handling land heterogeneity. Eaton and Kortum (2012) and Costinot and Donaldson (2012) discussed the development of the Ricardian approach since the idea of comparative advantage from Ricardo (1891) in explaining economic specialization. The Ricardian approach for land use modeling is, in fact, analogous to the original logit approach developed in Sands and Leimbach (2003) that competitive farmers would choose use of land with the highest rental return on each parcel given Fréchet land productivity distributions for all candidate crops. It is important to note that the land productivity distribution used in the Ricardian approach is the unconditional distribution that is defined on all potential land, which is different than the observed values that are conditional on certain use of the land. Unlike Sands and Leimbach

[7] As discussed later in this study, the ACET implied conversion cost method postulates a relationship among rental rates. That is, conversion cost explains the difference in land rental rates across uses. Thus, in the CET decomposition, the demand side productivity adjustments hinge fully on relative land rental rates through ACET implied conversion cost.

Table 2. Comparison of land use modeling methods.

Method	Resource constraint	Conversion cost	Land heterogeneity	Landowner behavior
Constrained optimization	✓	*	*	Unspecified
CET		*	*	Revenue maximization
ACET	✓	✓		Utility maximization
Modified logit	✓	✓		Unspecified
Ricardian	✓		✓	Profit maximization
Hybrid	✓	✓	✓	Utility maximization

Note: *Depending on assumptions, conversion cost and land heterogeneity may be considered in a constrained optimization model with additional constraints. CET may be explained as effectively accounting for land heterogeneity and/or conversion cost in a way sacrificing resource constraint.

(2003) in which logit-sharing parameters that governed yield distributions (and land transitions) were not estimated due to the limitation of data, recent applications of the Ricardian approach estimated land productivity distributions based on the high-resolution yield data projected by the GAEZ model (Fischer *et al.*, 2012). The yield estimation in GAEZ considered a range of agronomic factors such as climate condition, soil suitability, topography, etc. Thus, future climate impacts on agriculture are perceived through their impacts on land productivity distributions. In this approach, comparative advantage, implied by the relative productivity differences across crops and plots, determines the pattern of land allocation. The theory closely connects the micro-level biophysical information from agronomic models and the economic model. However, partly because landowner is modeled as profit maximizer, conversion cost in any form was not accounted for, and the mean rental rate must be equal across land uses.

In the present study, we bridge the gap in the literature by connecting different streams of theories of land use modeling. We developed a generalized hybrid approach by incorporating ACET/logit and Ricardian to consider both conversion cost and land heterogeneity while preserving the resource constraint (Table 2).

3. Quantitative Implications of Land Allocation Models

3.1. *Crop production and land demand*

A representative agricultural producer of crop k seeks to maximize profit, π_k (Eq. (1)), by choosing a composite of nonland (L_k) and land (X_k) inputs, given the output price (p_k), nonland input price (w_k), land rental price (r_k), and the production technology, $Q_k = f(L_k, X_k)$. We assume a Leontief production technology[8] (Eq. (2)), whereas l_k and g_k are initial output yields regarding to nonland and land, respectively, and Q_k is

[8]A Leontief production technology implies inputs in production are used in fixed proportions regardless of changes in relative input price. Leontief production technologies are applied in GCAM.

the production output of k. T_k denotes the total factor productivity (TFP). Note that I_k and Λ_k are introduced as input augment technical shifters for non-land and land, respectively. Λ_k, I_k, and T_k equal to one in the base year observation calibration.

$$\text{Max } \pi_k = p_k \cdot Q_k - w_k \cdot L_k - r_k \cdot X_k \tag{1}$$

$$s.t.\ Q_k = T_k \cdot \text{Min}[l_k \cdot (I_k L_k), g_k \cdot (\Lambda_k X_k)]. \tag{2}$$

Solving the maximization problem, the input demand in production for land, $X_k = Q_k(T_k g_k \Lambda_k)^{-1}$, and for nonland, $L_k = Q_k(T_k l_k I_k)^{-1}$, can be derived. Given the constant return to scale (CRTS) production technology, the zero-profit condition should hold, shown in Eq. (3).

$$p_k \cdot Q_k - w_k \cdot L_k - r_k \cdot X_k = 0. \tag{3}$$

The land rental rate is derived in Eq. (4), where λ_k equals $(T_k p_k - \frac{w_k}{l_k I_k}) \cdot g_k$, which represents an index of land profitability. $\frac{w_k}{l_k}$ is nonland cost per unit output of k.

$$r_k = \left(T_k p_k - \frac{w_k}{l_k I_k}\right) \cdot g_k \Lambda_k = \lambda_k \Lambda_k. \tag{4}$$

The discussion so far has focused on the land demand in production. Following the partial equilibrium framework in GCAM, we assume the supply of non-land inputs is perfectly elastic. Next, we discuss different theories for modeling the behavior of landowner, from which land supply is defined.

3.2. *Constrained optimization*

As discussed earlier, the constrained optimization approach used in this study builds only on the resource constraint, $\sum_k X_k \leq Y$, that the summation of land supply across k should be constraint by the total land area (Y). However, the resource constraint alone does not provide any information on land rental rates. To close the model with a unique solution, the simplest assumption would be fixed relative rental rate ratio at initial values, $r_k/r_j = r_k^0/r_j^0$.[9] It implies a fixed relative cost of land conversion as the annualized marginal land conversion cost would be equal to the rental rate differences (Lubowski *et al.*, 2008; Rashford *et al.*, 2011). In this model, land is homogeneous so that yield does not change on the extensive margin. In solving the model, since the behavior of landowner is not explicitly modeled under constrained optimization, land supply, X_k, are variables. However, when landowner's behavior is explicitly modeled (see Secs. 3.3 and 3.4), land supply can be derived so that only prices are variables.

3.3. *ACET and logit*

In the ACET approach, it is assumed that the representative land owner maximizes the utility (U), which is a CET aggregation of land rent revenues ($r_k X_k$) across k (Eq. (5)),

[9]The constraint is also necessary for calibrating the model to the initial data.

subject to the area-preserving condition (Eq. (6)) (van der Mensbrugghe and Peters, 2016; Zhao *et al.*, 2020). γ_k are CET parameters calibrated based on the initial data. $\frac{\sigma}{\sigma-1}$ is the CET exponent and σ is the ACET parameter ($\sigma < 0$).

$$\max_{X_k} U = \left[\sum_k \gamma_k (r_k X_k)^{\frac{\sigma}{\sigma-1}}\right]^{\frac{\sigma-1}{\sigma}} \tag{5}$$

$$\text{s.t. } Y = \sum_k X_k. \tag{6}$$

Land supply can be derived through first-order conditions, as shown in Eq. (7).

$$X_k = \frac{\gamma_k^{1-\sigma} r_k^{-\sigma}}{\sum_j \gamma_j^{1-\sigma} r_j^{-\sigma}} \cdot Y. \tag{7}$$

Setting $\sigma = -\omega$ and $\gamma_k = \gamma_k'^{\frac{\omega}{1+\omega}}$, the ACET land supply matches logit land supply (Eq. (8)), where γ_k' are calibration parameters in the logit approach and ω is the logit parameter (Wise *et al.*, 2014). In the nested structure, the aggregate price index used in the logit approach is $r = [\sum_k (\gamma_k' r_k)^\omega]^{\frac{1}{\omega}}$, which equals the total land weighted utility in ACET (U/Y). In GE studies, the zero-profit condition, $r = \sum_k s_k r_k$, where s_k are land area shares, has been used as the aggregate price index (van der Mensbrugghe and Peters, 2016; Zhao *et al.*, 2020). The difference between the two hinges on the definition and the treatment of land conversion cost, as discussed in Sec. 3.5. The aggregate price index does not matter when only one nest is used, as in the tests in this study.

$$X_k = \frac{\gamma_k'^{\omega} r_k^{\omega}}{\sum_j \gamma_j'^{\omega} r_j^{\omega}} \cdot Y. \tag{8}$$

Based on the derived land supply, the relationship between the relative rental rate and the relative land share ($s_k = X_k/Y$) is derived in Eq. (9). It indicates that, as the share of a land type increases, the relative conversion cost implied by the relative rental rate will also increase. That is, ACET or logit implicitly imposes a marginally increasing relative land conversion cost when a land use expands. A higher value of ω implies a lower magnitude of the increase in the relative land conversion cost or higher flexibility in land transformation.

$$\frac{r_k}{r_j} = \left(\frac{s_k}{s_j}\right)^{\frac{1}{\omega}} \left(\frac{\gamma_k'}{\gamma_j'}\right)^{-1}. \tag{9}$$

Note that if the constraint of a fixed relative rental rate in the optimization approach is replaced with the implicit conversion cost constraint implied by ACET or logit (Eq. (9)), the two approaches would be identical (see Sec. B.1 in Appendix B). In the case of nested ACET or logit, the rental rate ratio or the relative land conversion cost between lands in different nesting levels would be governed by additional parameters;

however, the reconciliation with the constrained optimization model would not be affected.

3.4. *Ricardian*

Following Sotelo (2019), the land owned by landowners consists of a continuum of plots. The set of plots is denoted by M and plots are indexed by μ so that the total land is $Y = \int_M d\mu$. Given that land is heterogeneous in quality, we assume that the vector of land qualities for producing k, $\Lambda_k(\mu)$, follows a Fréchet distribution with parameters $(\tilde{\gamma}A_k, \theta)$ and $\theta \in [1, \infty]$. The cumulative density distribution is

$$F_k(\Lambda) = e^{-\tilde{\gamma}^{\theta} A_k^{\theta} \Lambda^{-\theta}}, \tag{10}$$

where $\tilde{\gamma} = [\Gamma(1 - \frac{1}{\theta})]^{-1}$ and $\Gamma(\cdot)$ is the Gamma function. With the normalization of $\tilde{\gamma}$, A_k is the average land productivity[10] of the distribution, when all land is used for producing k. θ is an inverse measure of land heterogeneity. A_k and θ measure the relative land productivity difference across plots and crops (comparative advantage) which determines the land use patterns for rent-maximizing landowners. Note that A_k and θ are not directly observed. The comparative advantage setup provides a consistent connection on the extensive margin between land productivity and rental rate within a use of land (*within* effect). However, it is not adequate to explain the behavior of landowners when there are conversion costs for transitions across different land uses (*between* effect). As a result, the mean rental rate has to be equal across land uses in the Ricardian approach used in the literature (Costinot *et al.*, 2016; Gouel and Laborde, 2018; Sotelo, 2019). Here, we make modifications in the Ricardian approach to incorporate conversion costs. Note that the conversion cost can be either a real cost that increases the cost of crop production or a cost implied by the landowners' preference such as risk, cultural, knowledge, and market accessibility. In particular, instead of maximizing the rental profit, we assume that landowners are maximizing the utility, $\Upsilon(\mu)$ (Eq. (13)), which is a product of a variable, β_k, and the rental rate, $\lambda_k \Lambda_k(\mu)$, with a discrete choice problem of choosing k over μ. β_k is a measure of unobserved conversion cost of switching away from producing k, which could be calibrated using the base data. The introduction of β_k permits having different land rental rates across uses in the Ricardian approach with the Fréchet land productivity distribution. If setting β_k to one for all k, it becomes the original profit maximizing Ricardian problem, in which rental rates have to be equal for all land uses.

$$\Upsilon(\mu) = [\beta_k \cdot \lambda_k \cdot \Lambda_k(\mu)]. \tag{11}$$

Landowners choose a k at each μ to maximize utility which is a conversion cost adjusted the rental rate. Since there is a continuum of plots, the share of plots used for

[10] $\mathbb{E}[\Lambda_k(\mu)] = \tilde{\gamma} A_k \Gamma(1 - \frac{1}{\theta}) = A_k$.

k, s_k, can be calculated as the probability that k has the largest utility.

$$s_k = \Pr\left\{k = \arg\max_k \, [\beta_k \cdot \lambda_k \cdot \Lambda_k(\mu)]\right\}. \tag{12}$$

Given the assumed distribution of $\Lambda_k(\mu)$, $\beta_k\lambda_k\Lambda_k(\mu)$ would also follow a Fréchet distribution with parameters $(\tilde{\gamma}\beta_k\lambda_k A_k, \theta)$. Assuming $\Lambda_k(\mu)$ are independent distributions, the land shares can be calculated based on the property of Fréchet distribution.[11]

$$s_k = \frac{(\beta_k\lambda_k A_k)^\theta}{\Phi^\theta}, \tag{13}$$

where $\Phi = [\sum_k (\beta_k\lambda_k A_k)^\theta]^{\frac{1}{\theta}}$. The sum of s_k is equal to one. The equation indicates that higher conversion cost of switching away from k, higher profitability of producing k, or higher average land productivity of producing k would lead to higher land allocation to k.

Denote G_k as the conditional distribution of land productivity $(\Lambda_k(\mu)|\mu \in M_k)$ for k. $G_k(t)$ can be derived as following[12]:

$$G_k(t) = \mathbb{P}\left[\Lambda_k(\omega) \le t | \beta_k\lambda_k\Lambda_k(\mu) = \max_j \beta_j\lambda_j\Lambda_j(\mu)\right], \tag{14}$$

$$G_k(t) = \mathbf{exp}\left(-\tilde{\gamma}^\theta \left(\frac{\Phi}{\beta_k\lambda_k}\right)^\theta t^{-\theta}\right). \tag{15}$$

As a result, $G_k(t)$ also follows a Fréchet distribution with parameters $(\frac{\tilde{\gamma}\boldsymbol{\Phi}}{\beta_k\lambda_k}, \theta)$. Thus, the conditional mean land productivity $(\mathbb{E}[\Lambda_k(\mu)|\mu \in M_k])$, is $\frac{\Phi}{\beta_k\lambda_k}$, and the production of crop k in the region can be derived as $Q_k = \mathrm{T}_k g_k \Phi^{1-\theta}(\beta_k\lambda_k)^{\theta-1} A_k^\theta Y$. Also, the conditional mean rental rate is $\frac{\boldsymbol{\Phi}}{\beta_k}$ (Eq. (16)). Note that relative rental rate (r_k/r_j) will

[11] The probability is obtained by calculating $s_k = \Pr[\beta_k\lambda_k\Lambda_k \ge \max\{\beta_i\lambda_i\Lambda_i; i \ne k\}] = \int_\omega \Pi_{i\ne k} F_i(\Upsilon)\, dF_k(\Upsilon)$.

[12]

$$G_k(t) = \frac{\mathbb{P}\left[\frac{\beta_j\lambda_j}{\beta_k\lambda_k}\Lambda_j(\mu) \le \Lambda_k(\mu) \le t, \forall j\right]}{\mathbb{P}[\beta_k\lambda_k\Lambda_k(\mu) = \max_j \beta_j\lambda_j\Lambda_j(\mu)]} = \frac{1}{s_k}\mathbb{P}\left[\frac{\beta_j\lambda_j}{\beta_k\lambda_k}\Lambda_j(\omega) \le \Lambda_k(\mu) \le t, \forall j\right]$$

$$G_k(t) = \frac{1}{s_k}\int_0^t \prod_{j\ne k} \mathbb{P}\left[\frac{\beta_j\lambda_j}{\beta_k\lambda_k}\Lambda_j(\mu) \le v\right] f_k(v)dv$$

$$G_k(t) = \frac{1}{s_k}\int_0^t \prod_{j\ne k} \mathbf{exp}\left(-\left(\tilde{\gamma}^{-1}A_j^{-1}\frac{\beta_k\lambda_k}{\beta_j\lambda_j}v\right)^{-\theta}\right)\mathbf{exp}(-(\tilde{\gamma}^{-1}A_k^{-1}v)^{-\theta})\theta(\tilde{\gamma}A_k)^\theta v^{-\theta-1}dv$$

$$G_k(t) = \frac{1}{s_k}\int_0^t \mathbf{exp}\left(-(\tilde{\gamma}^{-1}\beta_k\lambda_k)^{-\theta}\sum_j (A_j\beta_j\lambda_j)^\theta v^{-\theta}\right)\theta(\tilde{\gamma}A_k)^\theta v^{-\theta-1}dv$$

$$G_k(t) = \int_0^t \mathbf{exp}(-(\tilde{\gamma}^{-1}\beta_k\lambda_k)^{-\theta}\Phi^\theta v^{-\theta})(\tilde{\gamma}^{-1}\beta_k\lambda_k)^{-\theta}\Phi^\theta\theta v^{-\theta-1}dv$$

$$G_k(t) = \mathbf{exp}\left(-\tilde{\gamma}^\theta\left(\frac{\Phi}{\beta_k\lambda_k}\right)^\theta t^{-\theta}\right).$$

be equal to β_j/β_k so that β_k can be calibrated based on the initial rental rates. The conditional mean utility, or the conversion cost adjusted rental rate, is equal across k (Eq. (17)).

$$\mathbb{E}[r_k(\mu)|\mu \in \mathrm{M}_k] = \lambda_k \mathbb{E}[\Lambda_k(\mu)|\mu \in M_k] = \frac{\Phi}{\beta_k}, \tag{16}$$

$$\mathbb{E}[\Upsilon_k(\mu)|\mu \in \mathrm{M}_k] = \beta_k \mathbb{E}[r_k(\mu)|\mu \in M_k] = \Phi. \tag{17}$$

Furthermore, the relationship between land productivity and land share can be derived (Eq. (18)). It indicates the average land productivity would decrease (increase) when s_k increases (decreases). In other words, when a land expands, new land would have a relatively lower productivity than the average of the existing land.

$$\mathbb{E}[\Lambda_k(\mu)|\mu \in M_k] = A_k s_k^{-\frac{1}{\theta}}. \tag{18}$$

It is important to note that if we simply add Eq. (18) as a constraint into the constrained optimization model, it would be reconciled with the Ricardian model (see Section B.2 in Appendix B).

3.5. *Conversion cost and CET*

In either ACET or Ricardian approaches discussed above, the utility of the landowner reflects a conversion cost adjusted rental revenue. The net conversion cost can be calculated as the difference between the rental revenue and conversion cost adjusted rental revenue. In other words, landowner's utility is interpreted as the difference between rental revenue and conversion cost, namely rental profit. The calculation would be the same with an integral of rental rate differences (marginal land conversion cost) over land use changes. The land conversion cost was calculated in a way maintaining value balance in land transitions (Lubowski *et al.*, 2008; Rashford *et al.*, 2011). However, the definition of conversion cost and its impact had hardly been elucidated in the related literature. In the context of this study, the conversion cost could be (1) an intermediate service employed to transform land from one to another (e.g., costs for land clearing or costs for accessing new technology), (2) a maintenance cost (or benefit) materialized in production (e.g., regional transportation costs, benefits from crop rotation, or a cost for maintaining land quality), or (3) a cost or benefit implied by landowner's preference (e.g., risk, culture, externality, or imperfect information). If explaining conversion cost as an intermediate land conversion service, there should be a sector in the economy producing the service with other factor or intermediate inputs, and the conversion cost would need to be capitalized into the cost of crop production. Similarly, if explaining conversion cost as a maintenance cost, it should be included in the operating cost of production. However, if explaining conversion as a change or a shift in landowner's preference, for example, the higher risk of switching to new crops or the acquirement of the knowledge of growing a more profitable crop, the conversion cost does not need to be explicitly considered since it is accounted for in rental rates to reflect landowner's utility change (e.g., as risk premium or rental benefit from new knowledge).

In approaches besides CET, land conversion cost was not explicitly accounted for so that they can be thought as assuming a preference-type conversion cost. Due to the limited data of land conversion cost, it had rarely been explicitly modeled in a traceable manner. In a version of the MIT Economic Projection and Policy Analysis (EPPA) Model, conversion cost was explicitly modeled as an intermediate service to explain rental rate differences (Gurgel *et al.*, 2016). Zhao *et al.* (2020) also tested describing conversion cost being produced with capital or labor and showed important impacts on welfare. These two studies ascribed conversion cost entirely to conversion service or maintenance costs. It is likely that conversion cost could be a combination of all the three types discussed above. The CET approach accounts conversion cost at the expense of physical land. In the CET approach, landowner maximizes the aggregate land rent revenue, $\pi = \sum_k r_k X_k$, subject to a CET function for land allocation. The land supply is derived in Eq. (19), where ρ is the elasticity of transformation and γ_k'' are CET coefficients.

$$X_k = Y\left(\frac{r_k}{\gamma_k''}\right)^{-\rho}\left[\sum_j \gamma_j''^{\rho} r_j^{1-\rho}\right]^{\frac{\rho}{1-\rho}}. \tag{19}$$

In ACET or logit, by charging the conversion cost to the physical land by making the physical land supply (Y) endogenous and driving conversion cost to zero, the CET approach emerges. This is demonstrated with the experiment in Sec. 4. That is, CET applies an iceberg-type conversion cost that a fraction of physical land "melts or accumulates in transition".

Given the discussion of conversion cost, in the nested ACET or logit, using the conversion cost adjusted aggregate rental rate as the aggregate price index to the upper nest would be more consistent given the landowner's preference. The nests would collapse into one nest when the same parameters are used in different nesting levels.

3.6. *A hybrid approach for land use modeling*

Based on the connections among the approaches investigated above, we develop a hybrid approach by incorporating ACET/logit and Ricardian to provide more flexible control of conversion cost and land heterogeneity. This model can be derived in three equivalent ways: (1) incorporating the Ricardian implied yield adjustment on extensive margin, Eq. (18), into the ACET or logit approach, (2) linking ACET/logit implied relative conversion cost condition (Eq. (9)) to the ratio of β_k in Ricardian, $\frac{r_k}{r_j} = \frac{\beta_j}{\beta_k}$, or (3) adding both ACET/logit implied conversion cost constraint (Eq. (9)) and Ricardian implied extensive margin yield adjustment constraint (Eq. (18)) into the constrained optimization model. The detailed derivations are shown in Section B.3 in Appendix B.

In this hybrid approach, both ACET/logit[13] (ω) and Ricardian (θ) parameters are important in affecting acreage responses. The hybrid approach (ω, θ) would collapse to Ricardian (θ) when ω is infinity, to ACET/logit (ω) when θ is infinity, and to the original constrained optimization model when both parameters are infinity.

4. A Model of Global Agriculture and Counterfactual Simulations

4.1. *Model structure and experiments*

To compare land use modeling approaches, we create a one-region (world) partial equilibrium model by simplifying the Agriculture and Land Use (AgLU) module in the Global Change Assessment Model (GCAM). The model includes 12 GCAM crops and employs data extracted and aggregated from the GCAM data system. The mapping of the 12 GCAM crops to FAO (Food and Agriculture Organization of the United Nations) crops are presented in Appendix Table A.1. The base data represent the equilibrium of the crop markets and the land market in 2010. The data showed that the total land area for crop production was 1.36 billion hectares and the total crop revenue was 833 billion dollars (in 1975$). As discussed in the theoretical model in Sec. 3, a Leontief production function is used for crop production and nonland input in production is assumed to be perfectly elastic. It does not allow any sort of intensification responses and instead focuses on the acreage responses.[14] Land allocation methods also follow the theoretical models discussed in Sec. 3. The land heterogeneity parameter (θ) estimated in previous studies was 2.46 in Costinot *et al.* (2016) and 1.66 in Sotelo (2019). The CET parameter (ρ) used in several GTAP models for cropland allocation was -0.75 (Golub and Hertel, 2012; Zhao *et al.*, 2020) while the logit parameter (ω) used in GCAM was 1.75 (Calvin *et al.*, 2018). The use of these parameters may be contingent on base data, modeling boundary, and region. Thus, instead of setting the reference values, we provide results with a range of parameters. The linkage of these parameters to acreage elasticities is discussed in Sec. 6. The total cropland area is assumed to be fixed and no nesting structure is used for land supply. To close the model, we assume crops are consumed by a representative consumer with a constant elasticity of substitution (CES) utility function. A substitution elasticity of 0.25 is used for calibrating the demand elasticities of the crops (-0.13 to -0.25). We purposefully keep the model simple to provide traceable and communicable illustrations.

We employ two comparative static experiments to compare economic and land use results from different land use modeling methods. The first experiment imposes a 5% subsidy on global corn production. This experiment would have land use responses analogous to studies estimating biofuel policies induced land use change.

[13] For simplicity, we use ω to represent the parameter of both ACET and logit in later tests and analysis given that the two approaches are practically identical.

[14] Note that the current version of GCAM does include intensification through shifts among different Leontief technologies. This is not included in the simplified version of the model developed here.

The theoretical models in Sec. 3 are tested, and the model reconciliations are demonstrated. The second experiment, as detailed in Sec. 5, we explore the effect of future climate impacts on agriculture and welfare using our hybrid method.

4.2. *Results from the corn subsidy experiment*

A comparison of land use change results, crop price change, and corn yield change across different land use modeling methods with different parameters is presented in Figure 1. As expected, with a subsidy on corn, the corn producer price increases and corn area expands at the expense of other cropland, mainly oil crop, wheat, rice, and other grain, for all results. Land use change results vary considerably across both parameter and approach. The CET land use change results are similar to the ACET with corresponding parameters, though there is a land imbalance of over 0.1 million ha (Mha) in the CET approach. Since we did not apply any additional adjustments to translate CET results to physical units to avoid introducing complexity and uncertainties, the land imbalance represents the discrepancy between the CET results and physical hectares. The CET discrepancy could grow in experiments with larger shocks. The land resource constraint was preserved in all other approaches. Compared with constrained optimization, ACET/logit resulted in a smaller corn area increase due to the conversion cost while Ricardian had larger corn area increase because of the lower corn yield on the new land. However, the corn producer price was higher in both Ricardian and ACET/logit results compared with constrained optimization. The difference among land use modeling approaches is more than parameter-wise.

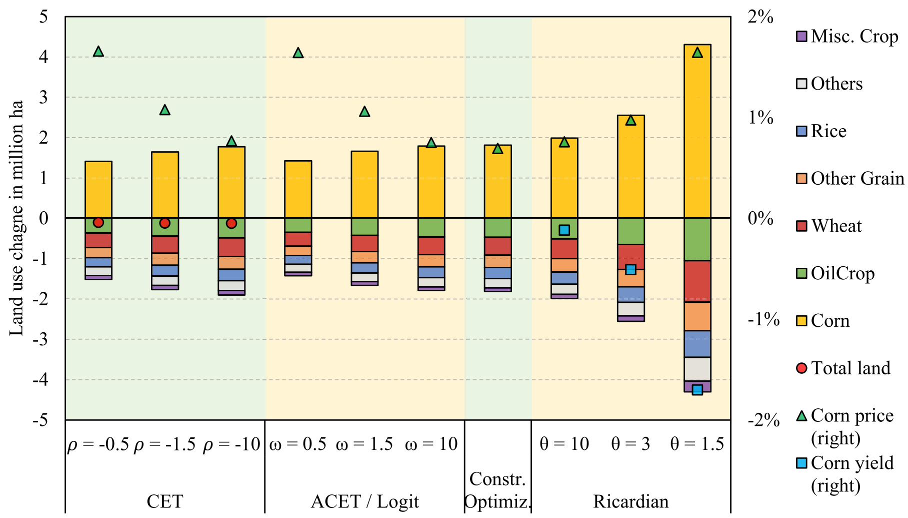

Figure 1. Comparison of land use change decomposition results, crop producer price change, and corn yield change across different land use modeling methods. GCAM crops not shown are aggregated into others. Note that the CET results have land imbalances as we have not applied any additional adjustments.

Table 3. Heatmap of corn area change across Ricardian (θ) and ACET/logit (ω) parameters.

Corn area change (%)		ω									
		∞	100	50	10	5	3	1.5	0.75	0.5	0.2
θ	∞	1.1	1.1	1.1	1.1	1.1	1.1	1.0	0.9	0.9	0.7
	100	1.1	1.1	1.1	1.1	1.1	1.1	1.0	0.9	0.9	0.7
	50	1.1	1.1	1.1	1.1	1.1	1.1	1.0	0.9	0.9	0.7
	10	1.2	1.2	1.2	1.2	1.2	1.1	1.1	1.0	0.9	0.7
	5	1.3	1.3	1.3	1.3	1.3	1.3	1.2	1.1	1.0	0.7
	3	1.5	1.5	1.5	1.5	1.5	1.5	1.4	1.2	1.1	0.8
	1.5	2.6	2.6	2.6	2.5	2.4	2.4	2.1	1.8	1.6	1.0
	1.2	4.0	4.0	3.9	3.8	3.6	3.4	3.0	2.4	2.0	1.1
	1.1	5.2	5.2	5.1	4.9	4.6	4.3	3.6	2.8	2.3	1.2

For this experiment, conversion costs and land heterogeneity would both lead to the higher production cost of corn, but they encouraged different acreage responses. Note that in the Ricardian results, the average corn yield decreased while the average yield of all other crops increased. Furthermore, as θ approaches infinity, Ricardian would converge to constrained optimization, since land would become more homogeneous. Also, as ω approaches infinity, ACET/logit would converge to constrained optimization, since the relative conversion cost becomes more linear.

From the perspective of the hybrid approach, ACET/logit has a land distribution parameter (θ) of infinity and Ricardian has a conversion cost parameter (ω) of infinity. With the hybrid approach, we create a heatmap of changes in corn area and crop producer price across θ and ω parameters, as presented in Tables 3 and 4, respectively. The slope of the isoline is negative in the corn area heatmap and positive in the corn price heatmap. With the combination of conversion cost and land heterogeneity in the hybrid approach, corn price becomes higher than either approaches while corn area expansion lay in between the two original approaches. Compared with the original approaches, the hybrid approach has a higher degree of freedom so that it is able to

Table 4. Heatmap of corn producer price change across Ricardian (θ) and ACET/logit (ω) parameters.

Corn price change (%)		ω									
		∞	100	50	10	5	3	1.5	0.75	0.5	0.2
θ	∞	0.7	0.7	0.7	0.8	0.8	0.9	1.1	1.4	1.6	2.5
	100	0.7	0.7	0.7	0.8	0.8	0.9	1.1	1.4	1.7	2.5
	50	0.7	0.7	0.7	0.8	0.8	0.9	1.1	1.4	1.7	2.5
	10	0.8	0.8	0.8	0.8	0.9	1.0	1.2	1.5	1.8	2.6
	5	0.8	0.8	0.9	0.9	1.0	1.1	1.3	1.6	1.9	2.8
	3	1.0	1.0	1.0	1.1	1.1	1.2	1.4	1.8	2.1	3.0
	1.5	1.6	1.7	1.7	1.8	1.9	2.0	2.3	2.7	3.0	3.8
	1.2	2.5	2.5	2.5	2.6	2.7	2.9	3.2	3.6	3.8	4.4
	1.1	3.3	3.3	3.3	3.4	3.5	3.6	3.9	4.2	4.4	4.8

Table 5. Heatmap of the corn yield change across Ricardian (θ) and ACET/logit (ω) parameters.

Corn yield change (%)		ω									
		∞	100	50	10	5	3	1.5	0.75	0.5	0.2
θ	∞	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	100	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	50	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	10	−0.1	−0.1	−0.1	−0.1	−0.1	−0.1	−0.1	−0.1	−0.1	−0.1
	5	−0.3	−0.3	−0.3	−0.3	−0.3	−0.3	−0.2	−0.2	−0.2	−0.1
	3	−0.5	−0.5	−0.5	−0.5	−0.5	−0.5	−0.5	−0.4	−0.4	−0.3
	1.5	−1.7	−1.7	−1.7	−1.6	−1.6	−1.5	−1.4	−1.2	−1.0	−0.7
	1.2	−3.2	−3.2	−3.2	−3.0	−2.9	−2.8	−2.4	−2.0	−1.6	−0.9
	1.1	−4.5	−4.5	−4.5	−4.2	−4.0	−3.7	−3.2	−2.5	−2.0	−1.1

provide a broader range of results. Thus, with the hybrid approaches, it would be more flexible to calibrating the model to reflect the observed data. Also, for both parameters, the results would be more responsive when they are small and more insensitive when they become larger. When ω is large enough (e.g., $\omega = 100$), the hybrid approach would be effectively turned to the Ricardian approach ($\omega = \infty$) and, similarly, when θ is large enough (e.g., $\theta = 1$), the hybrid approach would be effectively turned to the ACET/logit ($\theta = \infty$) approach. Table 5 presents a heatmap of the yield change in the corn subsidy experiment. Since there was no endogenous intensification responses or exogenous yield shocks in this experiment, the yield change was entirely on the extensive margin. That is, corn expanded on the new area had relatively lower yield so that the average corn yield decreased. The degree of the extensive margin yield change depended on the distribution parameter and its interaction with the conversion cost parameter. When land was assumed to be heterogeneous, as implied by comparative advantage, land parcels that were relatively more suitable for corn but less suitable for other crops would be more likely used for corn first. Thus, when corn area expended due to the subsidy, the average corn yield decreased. Also, the extensive margin yield response for corn would be larger if land was more heterogeneous for corn initially (smaller θ), or if corn area expanded more due to the lower land conversion cost (larger ω).

The heatmap of the conversion cost is presented in Table 6. The conversion cost from this experiment is relatively small compared with the rental revenue ($220 billion), which explains the small difference between CET and ACET results. With the ACET/logit approach, when ω was 0.75, the total land conversion cost was $43 million. When switching to the CET approach with a corresponding parameter (ρ) of -0.75, the total land supply decreases since physical land was sacrificed to compensate conversion cost. As a result, corn area would not increase as much as before, and other crop areas decreased more. The total physical area loss in CET was over 0.11 Mha with a worth of $18 million. Thus, not all $43 million was charged to physical land because land conversion cost decreased by $25 million as a consequence of shifting the physical land supply.

Table 6. Heatmap of the conversion cost across Ricardian (θ) and ACET/logit (ω) parameters.

Conversion cost (million 1975$)		ω									
		∞	100	50	10	5	3	1.5	0.75	0.5	0.2
θ	∞	21	21	21	22	24	27	32	43	52	84
	100	21	21	21	23	24	27	33	43	53	85
	50	21	21	21	23	25	27	33	43	53	85
	10	22	23	23	24	26	29	35	46	56	90
	5	25	25	25	27	29	32	38	50	61	95
	3	28	29	29	31	33	36	44	57	68	104
	1.5	45	46	46	49	53	57	67	85	99	138
	1.2	65	65	66	70	74	80	93	114	129	168
	1.1	81	81	82	87	93	100	115	137	153	188

5. Climate Impacts on Agriculture

5.1. *Climate impacts on potential yield*

We apply our model to estimate future climate impacts on agriculture and welfare. In particular, we use one of the illustrative scenarios, the A1FI (Fossil Intensive) scenario, in Special Report on Emissions Scenarios (SRES) (Nakicenovic *et al.*, 2000). As one of the high-emission scenarios, A1FI has an emphasis on fossil fuels based on the A1 storyline that depicts a future world of rapid economic growth and introduction of new and efficient technologies, while global population peaks in mid-century. The weather impacts from the emission scenarios created in SRES were later estimated by different General Circulation Models (GCMs) (Parry *et al.*, 2007). The GAEZ model then estimates future potential yield based on global weather data projected by GCMs and other high-resolution agronomic data such as soil quality, topography, sunshine fraction, and wind speed (Fischer *et al.*, 2012). GAEZ reported future yield potential maps at 5-arc-minute for 49 crops for 11 GCM-SRES pairs. We use potential yields estimated based on HadCM3 and the A1FI scenario. GAEZ allows choosing water supply and input level. We use rainfed and intermediate input. The projection allows for carbon fertilization. Note that scenarios in SRES have been superseded by the Representative Concentration Pathway (RCP) scenarios in the fifth Assessment Report (AR5) of IPCC (IPCC, 2014; Pachauri *et al.*, 2014). In our study, we use the original scenarios from SRES to take advantage of the high-resolution estimations from the GAEZ model. GAEZ has a baseline of the 1970s (i.e., the 30-year average of 1961–1990) and it projects potential yield to the 2080s (i.e., the 30-year average of 2070–2100) in each grid cell for each of the GAEZ crops. Ramankutty *et al.* (2008) provided the cropland map in 2000 at 5-arc-minute, which detailed the cropland share in each grid cell. Since our study includes only cropland, we calculate cropland area weighted mean yield for each GCAM crop for the baseline and the projection. Thus, the shift in the mean potential due to climate can be calculated (presented in Figure A.1). The yield changes estimated by GAEZ crops are then aggregated to

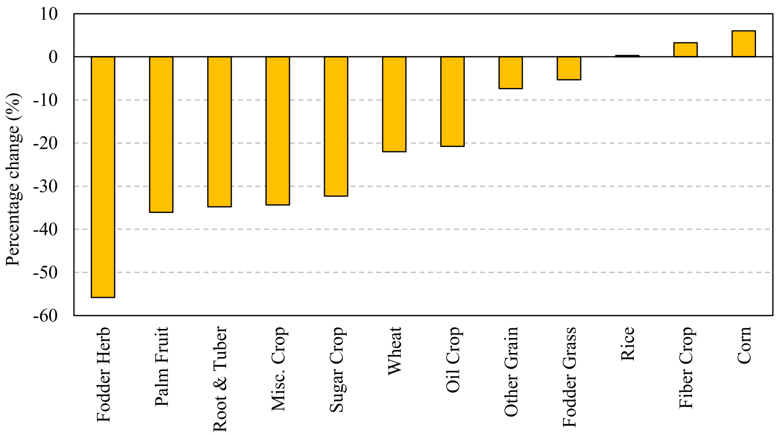

Figure 2. Climate impacts on mean yield of GCAM crops in the HadCM3-A1FI scenario.

GCAM crops (see Appendix Table 1 for mapping). Note that miscanthus, switchgrass, reed canary grass, jatropha, and pasture legume in GAEZ crops were removed as they did not map to FAO crops. Also, cocoa was removed since GAEZ did not provide a projection for it. Thus, 43 GAEZ crops (Fig. A.1) were mapped to 12 GCAM crops to calculate the average future change in mean crop yield (Fig. 2). It is also important to note that the shifts in mean yield are calculated based on unconditional yield distributions that defined on all the areas in the study (cropland). They are used to shock A_k in the model. It avoids the yield data aggregation problems discussed in Sec. 6. However, there could be discrepancies for the aggregated yield estimation caused by inconsistency in the time of the input data used given that the base year of GCAM data is 2010. These discrepancies are likely to be unimportant given the long-term projection and also given that the main purpose of this experiment is to further compare different land allocation approaches and to test the hybrid approach developed in this study. Also, the A1FI scenario is comparable to RCP 8.5 that emissions would exceed 100 Gigatonnes CO_2 equivalent by 2100 (Riahi *et al.*, 2011; van Vuuren *et al.*, 2011). Recent estimates of potential yield change for maize, wheat, rice, and soy under the RCP 8.5 scenario showed a fairly large range (Rosenzweig *et al.*, 2014). And our estimates based on A1FI fall in that range for the four major crops estimated for RCP 8.5.

5.2. *Agriculture consequences from climate impacts induced yield shocks*

A comparison of changes in land use, corn price, and corn yield due to climate shocks across different parameter scenarios from the hybrid approach is presented in Fig. 3. These scenarios focused on a smaller range of parameters that are closer to literature values (i.e., $\theta \in [1.5, 3]$ and $\omega \in [0.75, 3]$). The concentrated parameter range implied by literature values likely provides more plausible estimates. The analysis in this section focused on these scenarios. The calibration of the parameters is discussed in Sec. 6 in more detail. The full heatmap results of changes in land use, price, and yield

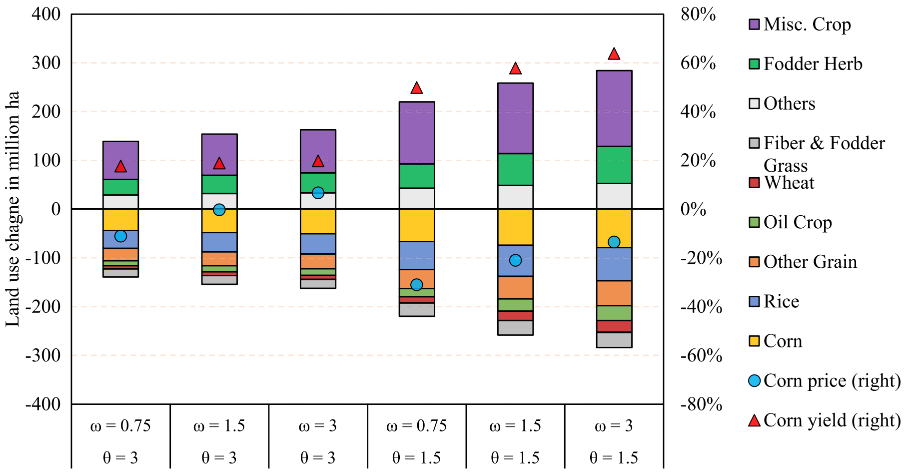

Figure 3. Change in land use, corn price, and corn yield due to climate shocks (GCAM crops not shown are aggregated into others).

for corn and wheat from the climate impacts induced yield shocks are presented in Tables 11–16. In most of the results, the cultivated area for wheat, oil crop, other grain, and fodder grass decreased despite the climate induced reduction in the future mean yield (e.g., over 20% for wheat and oil crop). This was because of the much stronger land demand from the crops with larger yield reductions. With the shifts in land productivity distributions of all crops, cultivated area increased for crops with a relatively larger reduction in mean yield (i.e., misc. crop, fodder herb, and others including palm fruit, sugar crop, and root & tuber). Given a positive corn yield shift, the hybrid approach would have smaller corn price increase than either ACET/logit or Ricardian alone, while the land use change results from the hybrid approach are in-between the two original approaches with corresponding parameters. The results sensitivity across parameters and land allocation methods followed the same patterns discussed in Sec. 4.

Across the hybrid scenario results presented in Fig. 3, the land use change (i.e., total cultivated area change) due to climate impacts was estimated to be 139–284 Mha, or 10–21% of the total cropland. For the example of corn which was the least vulnerable to climate impacts in the scenario, the area decreased by 44–79 Mha, or 27–48% compared with the base data (165 Mha in 2010) while the mean yield increased by 18–64%, much higher than the 6% positive climate-induced shift in the unconditional mean corn yield. Corn area with relatively lower quality was converted to other crops, so the mean yield increased. As a result, corn production decreased by 92–144 million tonnes (Mt) or 11–17%. For wheat, area decreased by 6–24 Mha, or 3–11%, compared with the base data (211 Mha). The mean yield dropped by 16–21%, which is smaller than the 22% decrease in the climate-induced unconditional mean wheat yield. Thus, the production of wheat decreased by 160–170 Mt, or 23–25%. The production change for the hybrid scenarios for major crops is summarized in

Table 7. Changes in crop production due to the climate shock (%).

Parameters		Corn	Wheat	Rice	Oil Crop	Misc. Crop	Fodder Herb & Grass	Others
$\theta = 3$	$\omega = 0.75$	−14	−23	−15	−23	−20	−26	−24
$\theta = 3$	$\omega = 1.5$	−16	−24	−17	−24	−19	−24	−23
$\theta = 3$	$\omega = 3$	−17	−24	−18	−24	−18	−23	−23
$\theta = 1.5$	$\omega = 0.75$	−11	−24	−13	−23	−24	−30	−26
$\theta = 1.5$	$\omega = 1.5$	−13	−24	−15	−24	−23	−29	−26
$\theta = 1.5$	$\omega = 3$	−15	−25	−17	−25	−22	−28	−26

Note: GCAM crops not shown are aggregated into others.

Table 7. Compared with corn and other crops, the variation in wheat production was relatively smaller. This was because the land productivity distribution for wheat calibrated to the base data implied relatively smaller variation so that wheat was relatively insensitive to the extensive margin yield adjustments. Furthermore, fodder crops had the largest production reduction (23–30%) across all crops in these scenarios. This was driven by the large decrease in the mean yield (64–79%), of which about 56% was directly owing to the climate shocks, and the rest was because of the adjustments on the extensive margin. In our simple model, regions are aggregated so that regional specifications of land productivity distributions and geographic barriers were ignored. Thus, it implied more optimistic adaptations for crops that were more vulnerable to the changing climate. In other words, if tropical crops (e.g., banana, coffee, tea) prone to climate impacts were disaggregated in the model and geographic specifications were considered, it would show larger impacts on the production of these crops.

We employ equivalent variation (EV) to evaluate the welfare impacts of climate shocks. EV calculates the change in wealth at current prices that would have the equivalent utility with post-climate change utility. That is, EV provides a monetary measure of consumers' willingness to pay to avoid climate impacts. The heatmap of EV from the climate shocks across Ricardian (θ) and ACET/logit (ω) parameters is presented in Table 8. Assuming farmers were not allowed to adapt to climate change

Table 8. Equivalent variation due to the climate shocks.

EV (billion 1975$)		ω									
		∞	100	50	10	5	3	1.5	0.75	0.5	0.2
θ	∞	−155	−156	−156	−156	−157	−157	−160	−164	−169	−187
	100	−156	−156	−156	−156	−157	−158	−160	−164	−169	−187
	50	−156	−156	−156	−156	−157	−158	−160	−165	−169	−187
	10	−158	−158	−158	−158	−159	−160	−162	−167	−172	−190
	5	−160	−160	−160	−161	−162	−163	−165	−170	−176	−195
	3	−165	−165	−165	−166	−166	−168	−170	−176	−182	−201
	1.5	−188	−199	−199	−198	−197	−197	−198	−202	−208	−223
	1.2	−216	−216	−216	−217	−217	−218	−221	−226	−231	−242
	1.1	−238	−238	−238	−238	−238	−239	−240	−244	−246	−253

through changing the use of the land, representing an infinitely high conversion cost, crop production would change by just as much as the yield shifts presented in Fig. 2. In this nonadaptation case, EV would be $-$\$272 billion (1975\$), or about 33% of the total expenses (\$833 billion) on crops in 2010. On the other extreme, EV evaluated with the constrained optimization model would have the smallest welfare loss, $-$\$155 billion, or 19% of expenses on crops. That is, considering higher conversion cost (smaller ω) and stronger land heterogeneity (smaller θ) could lead to a decrease of \$117 billion, or about 0.27% of GDP, considering that crop outputs accounted for about 1.9% of the global GDP in 2010. Mendelsohn *et al.* (1994) demonstrated that the conventional production function approach (nonadaptation case) would overestimate the climate impacts on agriculture since it ignored farmer's adaptation through changing the use of land. Besides, our study also demonstrated that assuming perfect adaptation and homogeneous land, represented by constrained optimization results, would understate climate impacts on agriculture. It also suggested that the original approaches, either ACET/logit or Ricardian alone, would likely underestimate the welfare impacts from climate change.

The six hybrid scenarios resulted in an EV range of $-$\$202 to $-$\$168 billion. However, the range of conversion cost for the six hybrid scenarios was fairly large, from \$9 to \$144 billion (Table A.8). As discussed in Sec. 3, conversion cost in ACET/logit or the hybrid approaches was not defined as an intermediate service or a maintenance cost, so it was not explicitly accounted for. For example, in the hybrid scenario of $\theta = 3$ and $\omega = 0.75$, the conversion cost was \$38 billion. If not providing feedbacks into the model to trace conversion cost, it would be explained as a preference-type conversion cost and it implied that the land conversions encouraged a worth of \$38 billon gain in rental revenue. If explaining a portion of the gain as intermediate service or maintenance cost, it would imply an increase in the operating cost (e.g., a shift in I_k to increase the nonland cost in our model) in crop production. However, if imposing a conversion cost by shifting the nonland input supply to crop production, the results from our model would not be affected because nonland input was not constrained. In other words, in our partial equilibrium model with perfect elastic nonland input supply, the welfare change would not be affected by the type of conversion cost. In contrast, the conversion cost would be affected if charging to a constrained input. In the hybrid scenario of $\theta = 3$ and $\omega = 0.75$, we tested charging the entire conversion cost to land (following the CET approach), EV would further decrease by \$31 billion to \$207 billion. The test suggests that explicitly accounting for intermediate service or maintenance cost types of conversion would likely lead to a welfare loss. The bottom line is lower conversion costs of any types would promote farmers to better adapt to climate change and encourage a smaller welfare loss.

6. Discussions and Implications

6.1. *Parameterization and acreage elasticity*

Because the simple model we developed had one aggregated region and it only included cropland, we did not provide estimations or calibrations of the parameters used in land use modeling methods. Instead, we compare land use modeling approaches across a range of parameters. However, both the conversion cost parameter in ACET/logit and the land heterogeneity parameter in Ricardian played important roles in determining acreage responses. In this section, we demonstrate the linkage between these parameters to acreage elasticities and calculate these elasticities for the hybrid approach using parameters from previous studies. Note that since our model did not include endogenous cropland intensification responses, the yield response was entirely on the extensive margin. The relationship between land supply and crop prices is derived in Eq. (20), based on the log-differentiation of Eqs. (4), (8), and (18). Note that hat (^) denotes proportional change (e.g., $\hat{X} = \Delta X/X$). The own- and cross-price acreage elasticities (i.e., $\frac{\hat{X}_k}{\hat{p}_k}$ and $\frac{\hat{X}_k}{\hat{p}_j}$) can be derived from Eq. (20).

$$\hat{X}_k = \hat{Y} + \omega\left[\frac{p_k}{p_k - \frac{w_k}{l_k}} \cdot \hat{p}_k + \hat{A}_k - \frac{1}{\theta}(\hat{X}_k - \hat{Y})\right] - \omega \sum_j \left[s_j\left(\frac{p_j}{p_j - \frac{w_j}{l_j}} \cdot \hat{p}_j + \hat{A}_j - \frac{1}{\theta}(\hat{X}_j - \hat{Y})\right)\right]. \tag{20}$$

The parameterization in previous studies followed different strategies. For Ricardian models, Costinot *et al.* (2016) estimated a land heterogeneity parameter (θ) of 2.46 using the global data from GAEZ land productivity maps. Sotelo (2019) used the same data and estimated a θ of 1.66 for Peru. In the Ricardian model in Gouel and Laborde (2018), instead of estimating based on land productivity data, θ was calibrated in order to match acreage elasticities for maize and soybean in the U.S to literature estimations. The calibrated θ of 1.1 was relatively small, likely because the conversion cost was not considered in Ricardian. The conversion cost parameters used in the literature studies, either ACET/logit or CET, were mostly calibrated to land supply elasticities or tuned based on model validation. Commonly used conversion cost parameter (ω) for crop switching ranges from 0.75 to 1.75 (Taheripour and Tyner, 2013; Wise *et al.*, 2014; Calvin *et al.*, 2018; Zhao *et al.*, 2020). Thus, we pick parameter ranges of $\theta \in [1.5, 3]$ and $\omega \in [0.75, 3]$ to compute acreage elasticities. Note that $\theta = 1.1$ suggested in Gouel and Laborde (2018) would lead to extreme yield adjustments in some scenarios in our study so that it was not considered. These ranges were also highlighted in results from climate shocks in Sec. 5. Table 9 presents the own- and cross-price acreage elasticity for major crops when $\theta = 3$ and $\omega = 0.75$. The own- and cross-price acreage elasticity matrices calculated for several other parameter combinations are provided in Tables A.9–A.12. In general, these acreage elasticities are mostly higher than the literature estimations. Note that previous econometric estimations focused on a particular region. For example, Hendricks *et al.* (2014) estimated long-run own- and cross-price acreage elasticity to be 0.29 and −0.22 for corn and 0.26 and −0.33 for soybeans, using data from three US corn belt states (Iowa, Illinois, and Indiana). The own-price acreage elasticity for corn and soybeans estimated in Miao *et al.* (2015) for

Table 9. Own- and cross-price acreage elasticity for major crops, $\theta = 3$ and $\omega = 0.75$ ($\hat{X}_k$ in column and $\hat{p}_j$ in row).

	Corn	Wheat	Oil crop	Rice	Fodder grass	Fodder herb	Misc. crop
Corn	0.99	−0.17	−0.14	−0.15	−0.06	−0.09	−1.28
Wheat	−0.14	0.88	−0.14	−0.15	−0.06	−0.10	−1.29
Oil crop	−0.14	−0.17	0.78	−0.15	−0.06	−0.10	−1.29
Rice	−0.14	−0.17	−0.14	1.11	−0.06	−0.09	−1.28
Fodder grass	−0.13	−0.17	−0.14	−0.15	1.63	−0.09	−1.26
Fodder herb	−0.13	−0.17	−0.14	−0.15	−0.05	3.35	−1.26
Misc. crop	−0.14	−0.17	−0.14	−0.15	−0.06	−0.10	6.43

the U.S. was 0.45 for corn and 0.63 for soybeans. A recent study from Iqbal and Babcock (2018) estimated the global long-run own-price acreage elasticity to be 0.274, 0.793, 0.279, and 0.05 for corn, soybeans, wheat, and rice, respectively. The elasticity database from Food and Agricultural Policy Research Institute (FAPRI, 2019) summarized acreage elasticities for several other crops, and the own-price elasticities are mostly smaller than 0.5 for these crops for a country. Since our model described an aggregated world, the acreage responses are expected to be higher because regional specification and geographic barriers are ignored. Also, note that the own-price elasticities for fodder herb and misc. crops were relatively large, driven by the relatively small share of land cost ($\frac{w_k}{l_k}/p_k$) in production. This explained the higher acreage responses for these crops in results from climate shocks. Two other responses not included are an extensive margin response of total cropland expansion and an intensive margin response of cropland intensification. Allowing total cropland to expand would increase the own-price acreage elasticity of crops through increasing the supply of $\hat{Y}$. Note that cropland expansion responses can be incorporated when non-cropland covers (e.g., forest and pasture) are included in the hybrid approach.[15] Allowing cropland intensification would decrease the own-price acreage elasticity as yield would increase when crop price increases. In a multi-region model, acreage elasticity along with other model responses can be better calibrated through tuning θ and ω. Applying nesting structures would also provide more flexibility in parameter calibration.

6.2. *Connecting data to the model*

6.2.1. *Potential yield from agronomic models*

Future climate impacts on crop yields are estimated by agronomic models (e.g., GAEZ) based on future climate and agronomic conditions. Unlike changes in TFP, climate impacts on yields are spatially heterogeneous. Agronomic models simulate the

[15] Including noncropland covers requires additional data such as the unconditional land productivity distribution, rental profit, and physical area of the land covers.

potential yield of crops for all land parcels regardless of the current use of the land parcel. Nevertheless, it leads to a question of how to connect yield estimated from agronomic models to relatively more aggregated economic models, bearing in mind that the observed yield used in the economic model is the yield conditional on the crop being cultivated. This was particularly an issue for models with relatively coarse spatial resolution (e.g., country, AEZ, or water basins). The simplest assumption was to filter the future yield map of a crop based on the base year harvested area map of the crop by assuming time-fixed harvested area. Other methods could allow some extent of time-varying changes in future harvested area to estimate conditional yield changes to be implemented in economic models (Kyle *et al.*, 2014; Fujimori *et al.*, 2018). Previous studies have shown that the yield aggregation method could be an important uncertain factor for estimating climate impacts (Porwollik *et al.*, 2017; Fujimori *et al.*, 2018). Technically speaking, the reason for the discrepancy was that limited land heterogeneity was considered so as the unconditional distributions were not included in the economic boundary. However, this was not an issue in the Ricardian model or its derived hybrid approach. The Ricardian approach uses unconditional distributions of land quality so that shifts in unconditional distributions driven by climate change can be directly implemented in the model. That is, our model presents a consistent connection with the potential yields estimated by agronomic models. Nevertheless, it is important to note that future climate change would likely also affect the shape of land productivity distributions and the correlations among them besides shifting the mean. This should be addressed in future studies with more refined models. Models with higher resolution and smaller simulation unit can make better use of the high-resolution yield data provided by Agronomic models. The land heterogeneity within the simulation unit of high-resolution models (e.g., $0.5^\circ \times 0.5^\circ$ grid in MAgPIE and GLOBIOM) can also be considered with the Ricardian approach which provides a continuous specification of land heterogeneity.

6.2.2. *Land productivity distributions*

Taking one step back, there are also important limitations in calibrating the land productivity distributions used in the simple model we developed. First, since the model has one aggregated region, the regional specification for land productivity distributions was ignored. That is, the shape of land productivity distributions could be different across regions. Also, the Fréchet distributions for land productivity are defined on a positive range so that zero yields were not allowed. Figure A.2 presents an illustration of the maximum Fréchet distribution of conversion cost adjusted rental rate. In a model with multiple regions or higher resolution, the list of candidate crops for farmers to choose could be shortened since crops with no yield would not compete for land. Ignoring regional specification for land productivity distributions would likely understate climate impacts since it allowed more flexible adaptations. This was also an important reason for the large acreage elasticities used in our model. Second, since we did not have a high-resolution land productivity map corresponding to GCAM base data, the distribution parameters (A_k) were calibrated contingent on θ, to recover the initial land use allocations. It is also important to note that, following previous studies, land productivity distributions, $\Lambda_k(\mu)$, were assumed to be independent. However, land productivity data from agronomic models may imply correlations among crops so that they may need to be considered if estimating distribution parameter based on yield data. However, as discussed in footnote 14 in Eaton and Kortum (2002) and in Appendix in Sands and Leimbach (2003), a correlation coefficient can be incorporated into θ so that higher correlation would imply higher θ or more homogeneous land. Sands and Leimbach (2003) also discussed nesting structures of a Ricardian model, which would permit more flexible yield adjustments on the extensive margin.

6.2.3. *Conversion cost*

As discussed in Sec. 3 and demonstrated in Sec. 5, the definition of conversion cost matters in maintaining the value balance of the model. In our study, we did not explain the conversion cost as an intermediate service cost or a maintenance cost since we did not have information of to what extent of the total conversion cost was in these types. Particularly for crop switching, these two types of conversion cost are likely small. From another perspective, the conversion cost calculated in our model also to some extent reflects the trade cost (either international or domestic) that would be accounted if the geographic barrier was considered. Furthermore, the nesting structure of ACET/logit would provide more flexible control of land conversion cost in affecting land transitions. Nesting structures of both Ricardian and ACET/logit could be extremely helpful when including other land covers (e.g., grass and forest) into modeling boundary. When the data for conversion service and maintenance types of land conversion cost are available, future research should investigate in more depth how land conversion cost would affect landowner's behavior and ways to reduce conversion cost for facilitating adaption.

6.3. *Climate impacts on agriculture*

In our study, we estimated the welfare loss from a high-emission scenario (A1FI) to be \$202 to \$168 billion (1975\$). The welfare loss amounts to a 20–24% of agricultural crop output value or approximately 0.38–0.46% of GDP (considering that crop outputs account for about 1.9% global GDP). In contrast, Costinot *et al.* (2016) estimated a reduction of 0.26% in global GDP or one-sixth of total crop value from the same climate scenario. Costinot *et al.* (2016)[16] Another recent study from Stevanović *et al.* (2016) estimated the welfare impact from another high-emission scenario in SRES, A2, which provided comparable end of century emissions with A1FI. The future potential yield was estimated using 19 GCM and LPJmL (Lund-Potsdam-Jena with

[16]Costinot *et al.* (2016) included 50 major countries and 10 major crops (71% of total crop value).

managed Land). The study showed that with the liberalized trade scenario, climate shocks would lead to an average welfare loss of 0.3% of global GDP at the end of the century.

Notably, the welfare impact from a high-end future climate change scenario induced yield changes estimated in our study are comparable to but larger than the estimates reported in previous studies, even given that regional specification and geographic barriers (i.e., trade cost) were not considered, and no intermediate service or maintenance types of conversion cost was explicitly accounted. One potential reason is that our hybrid approach included both acreage responses from conversion cost and land heterogeneity, which was demonstrated to have synergy on welfare loss. Furthermore, our results also indicate that efforts on reducing yield responses on the extensive margin (lower land heterogeneity) or reducing land conversion cost would help farmers better adapt to climate change and alleviate its impacts on farm revenue and welfare.

7. Conclusion

In this paper, we compared land use modeling approaches that are widely used in global economic models, including constrained optimization, CET, the ACET, logit, and Ricardian. These approaches were decomposed to explore their differences and connections. We demonstrated that the approaches differ not only by the extent of parameter uses, but also by the consideration of land heterogeneity and the definition of conversion cost. In particular, when a type of land expends, CET, ACET, and logit described an increasing marginal cost of land conversion while the Ricardian method, building on comparative advantage implied by heterogeneity in land productivity, stipulated a marginally decreasing land productivity. The connection between these models and a simple constrained optimization model implying homogeneous land and linear conversion cost was also illustrated. Also, the CET approach implied an iceberg-type conversion cost as it was charged to physical land while conversion cost in other approaches was deemed as changes in landowner's preference or changes in conversion service or maintenance cost generated in other unaccounted markets.

Based on the understanding of the different approaches, we developed a generalized hybrid approach by combining the ACET/logit and the Ricardian approaches. The hybrid approach permitted a simultaneous control of both the curvature of land conversion cost and the degree of land heterogeneity. To test and compare different methods, we build a one-region partial equilibrium model following the framework of the Agriculture and Land Use (AgLU) module in the Global Change Assessment Model (GCAM). With simple tests, the connections among land use modeling approaches including the hybrid approach were illustrated. Furthermore, we applied our simple model with the hybrid approach to estimating the impacts on agriculture and welfare from a high-emission climate scenario. The results indicated a welfare loss of 20–24% of agricultural crop value output, which implied stronger damage compared with similar estimates in previous studies. The hybrid approach indicated larger climate impacts on agriculture compared with using ACET/logit or Ricardian alone. That is, ignoring land heterogeneity or land conversion cost would underestimate climate impacts on agriculture. Also, the results also implied that farmers of at least 10–21% of cropland would change the use of their land to alleviate climate impacts on their revenue. It was also indicated that reducing yield responses on the extensive margin (lower land heterogeneity) or reducing land conversion cost would help farmers better adapt to climate change.

The major contribution of this study is threefold. First, the study reviewed, compared, and reconciled widely used land use modeling approaches, based on which a generalized hybrid approach was proposed. Second, the study illustrated the role and the definition of land conversion cost and land heterogeneity implied comparative advantage in land use modeling, and highlighted the future research needs for better quantifying land conversion cost and utilizing land productivity data. Third, this study demonstrated the hybrid approach, with the consideration of both conversion cost and land heterogeneity, would provide important new insights in empirical applications.

Appendix A

Table A.1. Crop mappings used in this study.

GCAM	GAEZ	FAO
Rice	Dryland rice, Wetland rice	Rice, paddy
Corn	Maize	Maize, Maize (green), Popcorn
Wheat	Wheat	Wheat
OtherGrain	Barley, Buck wheat, Foxtail millet, Oat, Pearl millet, Rye, Sorghum	Barley, Buckwheat, Canary seed, Cereals, nes, Fonio, Millet, Mixed grain, Oats, Quinoa, Rye, Sorghum, Triticale
SugarCrop	Sugarbeet, Sugarcane	Sugar beet, Sugar cane, Sugar crops, nes
OilCrop	Groundnut, Olive, Rapeseed, Soybean, Sunflower	Castor oil seed, Groundnuts, with shell, Hempseed, Jojoba Seeds, Kapok Fruit, Karite Nuts (Sheanuts), Linseed, Melonseed, Mustard seed, Oilseeds, Nes, Olives, Poppy seed, Rapeseed, Safflower seed, Sesame seed, Soybeans, Sunflower seed, Tung Nuts
PalmFruit	Coconut, Oilpalm	Coconuts, Oil palm fruit
Root_Tuber	Cassava, Sweat potato, White potato, Yam Cocoyam	Cassava, Potatoes, Roots and Tubers, nes, Sweet potatoes, Taro (cocoyam), Yams, Yautia (cocoyam)
FiberCrop	Cotton, Flax	Agave Fibers Nes, Coir, Fiber Crops Nes, Flax fiber and tow, Hemp Tow Waste, Jute, Manila Fibee (Abaca), Other Bastfibres, Ramie, Seed cotton, Sisal

Table A.1. (*Continued*)

GCAM	GAEZ	FAO
FodderHerb	Alfalfa	Alfalfa for forage and silage, Beets for Fodder, Cabbage for Fodder, Carrots for Fodder, Clover for forage and silage, Green Oilseeds for Silage, Leguminous for Silage, Maize for forage and silage, Sorghum for forage and silage, Swedes for Fodder, Turnips for Fodder, Vegetables Roots Fodder
FodderGrass	Grass	Forage Products, Grasses Nes for forage;Sil, Grasses Nes for forage;Sil, Rye grass for forage & silage
MiscCrop	Banana, Cabbage, Carrot, Chickpea, Citrus, Coffee, Cowpea, Dry pea, Gram, Onion, Phaseolus bean, Pigeonpea, Tea, Tobacco, Tomato	Almonds, with shell, Anise, badian, fennel, corian., Apples, Apricots, Arecanuts, Artichokes, Asparagus, Avocados, Bambara beans, Bananas, Beans, dry, Beans, green, Berries Nes, Blueberries, Brazil nuts, with shell, Broad beans, horse beans, dry, Cabbages and other brassicas, Carobs, Carrots and turnips, Cashew nuts, with shell, Cashewapple, Cauliflowers and broccoli, Cherries, Chestnuts, Chick peas, Chicory roots, Chillies and peppers, dry, Chillies and peppers, green, Cinnamon (canella), Citrus fruit, nes, Cloves, Cocoa beans, Coffee, green, Cow peas, dry, Cranberries, Cucumbers and gherkins, Currants, Dates, Eggplants (aubergines), Figs, Fruit Fresh Nes, Fruit, tropical fresh nes, Garlic, Ginger, Gooseberries, Grapefruit (inc. pomelos), Grapes, Hazelnuts, with shell, Hops, Kiwi fruit, Kolanuts, Leeks, other alliaceous veg, Leguminous vegetables, nes, Lemons and limes, Lentils, Lettuce and chicory, Lupins, Mangoes, mangosteens, guavas, Mate, Mushrooms and truffles, Nutmeg, mace and cardamoms, Nuts, nes, Okra, Onions (inc. shallots), green, Onions, dry, Oranges, Other melons (inc. cantaloupes), Papayas, Peaches and nectarines, Pears, Peas, dry, Peas, green, Pepper (Piper spp.), Peppermint, Persimmons, Pigeon peas, Pineapples, Pistachios, Plantains, Plums and sloes, Pome fruit, nes, Pulses, nes, Pumpkins, squash and gourds, Pyrethrum, Dried, Quinces, Raspberries, Sour cherries, Spices, nes, Spinach, Stone fruit, nes, Strawberries, String beans, Tallowtree Seeds, Tangerines, mandarins, clem., Tea, Tea Nes, Tobacco, unmanufactured, Tomatoes, Vanilla, Vegetables fresh nes, Walnuts, with shell, Watermelons

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