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Exploring the impacts of biofuel expansion on land use change and food security based on a land explicit CGE model: A case study of China

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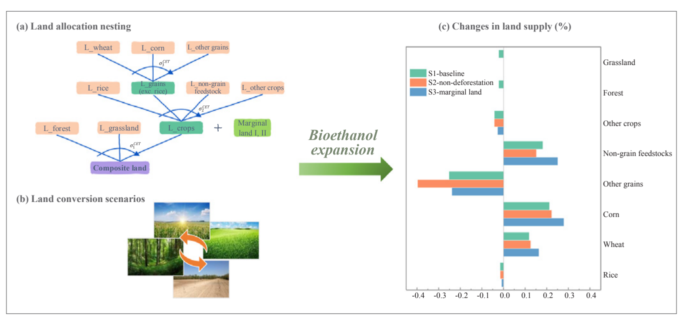
HIGHLIGHTS

- Built a general equilibrium model incorporating an explicit land use module.
- Different patterns of land use management were considered.
- Quantified land use changes among alternatives induced by bioethanol expansion.
- Planting energy crops on marginal land could alleviate cropland occupation.

GRAPHICAL ABSTRACT

Based on a computable general equilibrium (CGE) model augmented with an explicit land allocation module (a), land use changes induced by China's bioethanol expansion are quantified. The simulation results of different land conversion scenarios (b) indicate that planting non-grain feedstocks on newly reclaimed marginal land could increase non-grain feedstocks by 10% and save 0.217% of croplands with no deforestation by 2020 (c).



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ABSTRACT

Biofuel plays an important role in the transition to low-carbon energy systems. However, the large-scale expansion of biofuels may cause drastic land use change (LUC) due to feedstock cultivation and further result in other sustainability impacts (e.g., food supply), which are the key concerns for policy makers when designing bioenergy policies. However, biophysical models omit the indirect LUC from interactions of economic agents, whereas economic models lack the depiction of heterogeneous land use types. Thus, through either technique, it has formidable challenges to simulate land conversions among alternative uses driven by socioeconomic activities, especially policy mandates. To bridge the gap between these models by simultaneously considering land heterogeneity and market mechanisms and to gain better insights into specific national/regional cases to supplement previous global biofuel and LUC analyses, in this study, we develop a national computable general equilibrium (CGE) model augmented with an explicit land allocation module and design a scenario approach to simulate different patterns of land use management. Food grains and dedicated energy crops are considered feedstock sources and marginal land is incorporated as a potential land supply. Using this model, the case study of China quantifies the direct and indirect LUC driven by the bioethanol (one of the main biofuels) expansion of the new nationwide E10 mandate (gasoline containing 10% ethanol) in 2020, as well as the further impacts on

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food security. The results show that a slight land reallocation occurs with decreases in the land supply for rice (−0.016%), other non-feedstock grains and crops, as well as forest and grassland (−0.023%). The land competition among existing croplands would be intense in the non-deforestation scenario. If marginal land is reclaimed for feedstock cultivation, the cropland competition could be softened. The results of sensitivity analysis indicate that the total LUC scale would be 4.0–5.9% with no corn stockpile serving as feedstock. Additionally, the bioethanol expansion would trigger higher food prices (around +0.1%). To alleviate the negative impacts on land resources and food security, planting energy crops on marginal land could increase non-grain feedstocks by 10% and save 0.217% of croplands; therefore, it may be one of the promising pathways for sustainable biofuel development in China. This study can lay a common foundation for further integrated impact assessments of biofuel expansion.

1. Introduction

In an energy shortage and carbon constrained world, biofuel is widely considered to be a prospective option to address these two problems. However, recent doubts about the sustainability impacts on food security [1], water resources [2], soil carbon [3], biodiversity [4], etc. have hindered the rapid development of biofuels in reality and have raised hot debates on the large-scale deployment of bioenergy, especially for bioenergy with carbon capture and storage (BECCS), in global deep decarbonization pathways [5–7]. To date, there has been no consistent understanding of the mitigation potential and the sustainability of biofuels; one of the reasons is that many of the previous studies analyzed the above-mentioned impacts in a separated and incomparable manner, lacking an integrated systematic analysis. In fact, as proposed in studies [8–11], most of the impacts of biofuel production are related to land use change (LUC) due to feedstock planting. Therefore, to lay a common foundation for integrated impact assessments and provide concrete directions for policy making, it is imperative to explore the explicit LUC impact of biofuel expansion.

LUC caused by biofuel production can be direct or indirect. Direct LUC (DLUC) occurs when feedstocks for biofuel (e.g., corn for bioethanol) displace prior land use (e.g., forest), while indirect LUC (ILUC) refers to the changes outside of the areas of feedstock planting when the DLUC pressure on agriculture induces LUC in other land use types through economic interactions [12]. Previous research has demonstrated that ILUC is significantly greater than DLUC [13,14]; therefore, it cannot be neglected. Spatially explicit biophysical models are commonly used to simulate LUC [15]. Because these models lack terms for interactions or feedbacks from economic activities, they do not capture the ILUC driven by socioeconomic systems. In contrast, market equilibrium models exhibit strengths for estimating the total LUC (including DLUC and ILUC) due to changes in biofuel demand from human society. In previous studies, two types of market equilibrium models have been applied to estimate LUC induced by biofuel production, i.e., partial equilibrium (PE) models and computable general equilibrium (CGE) models. Most PE models are agricultural and energy sector models, such as GLOBIOM [16,17], GCAM [18], and other sector optimization models [19], thus the linkages with other economic sectors are not captured. On the other hand, CGE models depict the entire macroeconomic system and the interactions among different sectors and can accommodate land use and land valuation by treating land as a primary factor of production. Therefore, a CGE model is a better tool for capturing all sources of ILUC than biophysical or PE models.

However, several limitations have been found in previous CGE analyses focusing on biofuel development and the induced LUC. First, the representation of land heterogeneity is an important but challenging issue in CGE modeling. Other than certain advanced global models such as MAGNET [20], EPPA [21], FARM [22,23], and AIM/CGE [24,25], many CGE models do not consider the land supply constraint caused by the heterogeneity of various land use types; therefore, they cannot simulate land conversion among alternative uses and the land supply response to price variation would be exaggerated. Second, the LUC resulting from biofuel development represents the combined effects of the biofuel production target, climate mitigation target, and land use management (e.g., strict land conversion policies). Most previous studies have only explored the LUC intensity under various biofuel production or climate mitigation targets [26,27], whereas they neglected the impacts from different land use policies, hence reducing the practicality of the research results. Third, although advanced global CGE models have advantages for determining the biofuel impacts at the macro level, they usually have weaknesses in terms of capturing local characteristics (such as complex land mobility and diversity of local feedstocks). Therefore, region or country-specific studies represent important supplements to global studies and provide more solid support for local policy design. Existing national/regional studies mostly focused on the US [28], Brazil [29], and the EU [27,30], whereas little attention was paid to other countries.

In this context, this study aims to address the aforementioned research gaps by introducing land heterogeneity into a national CGE model augmented with detailed depictions of eight sub-accounts of the land type, the potential marginal land supply, and dedicated energy crop sectors. Furthermore, the explicit LUC and food security impacts under different land conversion scenarios can be quantified, aiming to suggest a suitable land use management pattern that maximizes the synergies of biofuel expansion while alleviating negative impacts. This analytical framework is then applied to the case study of China to quantify the total LUC (including DLUC and ILUC) and food supply impacts driven by China's bioethanol (one of the main biofuels) expansion in 2020. Although the case study is focusing on China, the transparent model structure and scenario approach can serve as common ground for assessing the LUC impacts of biofuel expansion, making feedstock choice, and designing land use policies in other countries or regions.

The remainder of this paper is organized as follows. Section 2 and Section 3 describes the methodology and scenario design. Section 4 represents the model results of different land conversion scenarios and detailed interpretations. In Section 5, we provide discussions on the DLUC and ILUC, LUC sensitivity, marginal land availability, and limitations. Finally, Section 6 provides the main conclusions and policy recommendations.

2. Modeling approach

2.1. Research area

In this study, China is chosen as a case study because biofuel and land use are extremely significant topics in the largest developing country. China began to produce bioethanol in 2002 and has become the third largest bioethanol producing country in the world [31]. A new nationwide E10 mandate (gasoline containing 10% ethanol) announced in September 2017 will require about 12 million tons of ethanol in 2020 [32,33], which triples the early proposed goal in the 13th Five Year Plan [34]. Although the corn stockpile can be an important feedstock source in the short term, it would be depleted by the end of the 2019/2020 crop year [35]. Therefore, attaining this mandate will require additional plantings of feedstock and corresponding land resources and will inevitably trigger land competition [36]. Most of the existing studies on China's bioethanol development have focused on estimating the production potential [37–40], as well as assessing its economic impacts on agricultural output and energy consumption [41,42] or climate impacts on carbon emissions [43]; however, no studies have been conducted to date on the quantification of the LUC impact of bioethanol expansion. A global CGE analysis on biofuel-related LUC [26] included China as a specific region, but only grains and sugar crops were considered feedstocks and the potential marginal land supply was not modeled. In this study, we use a national CGE model to conduct a comparative static analysis of the LUC and food security impacts caused by exogenous bioethanol expansion in China.

2.2. Data and model overview

The Social Accounting Matrix (SAM) is obtained from the 2012 Input-Output (IO) table from the National Bureau of Statistics of China [44]. Moreover, we perform aggregation and separation of the original sectors and primary factors based on the relevant data selected from the Costs and Benefits Compilation of the National Agricultural Products from the National Development and Reform Commission (NDRC) [45], the Statistical Yearbook of China from the National Bureau of Statistics (NBS) [46], China's Annual Report of Biofuels from the United States Department of Agriculture (USDA) Foreign Agricultural Service [33,47], the Database of the Food and Agriculture Organization of the United Nations (FAO) [48], etc. Specifically, the original "agricultural products" sector is divided into rice, wheat, corn, non-grain feedstocks, and other agricultural products. It should be noted that due to the cultivation scale and data availability, the non-grain feedstocks only refer to two energy crops - sweet sorghum and cassava in this study. The "wine and alcohol" sector is split to generate the bioethanol production sector [49,50]. The other sectors are highly aggregated into "other industrial sectors" and "service sectors" because they are not directly related to our research objectives. Consequently, there are eight identified economic sectors. In addition, we separate the land factor from the "capital" account of the agricultural sectors, and then land is divided into eight sub-accounts (land for rice, wheat, corn, other grains, non-grain feedstocks, other cropland, forest, grassland). Based on the SAM, a calibration process is conducted to obtain the scale parameters and share parameters in the CGE model.

The CGE model used in this study is a national multi-sector model augmented with an explicit land allocation module. Two features of the model require clarification. First, it is a static model. This study aims to reveal the complex interactions among bioethanol expansion, LUC, and food supply and to identify the response direction and potential scale of the impacts, rather than making predictions; therefore, the comparative static analysis is a suitable method that excludes the effects of other unrelated dynamic factors in the economic system [51]. In this case, except for the bioethanol expansion shock, all the exogenous variables remain unchanged at the base-year level in our model. Second, the model is built based on the closed economy assumption for two reasons. For one thing, excluding the consideration of international trade helps to obtain extreme estimates of domestic LUC and to assess the potential risks. The increased import supply of bioethanol or feedstocks may relieve the pressure on domestic LUC in an open economy [52] but its effect is quite uncertain due to the large fluctuations in recent trade tariffs. For another, relying on imports to achieve the bioethanol mandate is not the intention of the Chinese government; meanwhile, the domestic production of bioethanol and its feedstocks is strongly encouraged and is being deployed [32]. Additionally, in an open economy CGE model, it is difficult to distinguish whether the imported food products are consumed by households or utilized for bioethanol production, thus the closed economy assumption is adopted.

The general model structure and main substitution elasticity parameters are consistent with those of the static version of the China Hybrid Energy and Economic Research (CHEER) model [53]. According to the research focus of this study, we explain in detail the newly extended land allocation module and the adjusted production structure of the agricultural sectors in the following sections.

2.3. Land allocation module

2.3.1. Nesting structure of land allocation

The different land rents of various land use types imply that land factor does not move freely between alternative uses. There are many possible reasons for this, such as conversion costs, inertia, and unmeasured benefits from crop rotation [54]. Considering the land heterogeneity and land conversion constraints, here we employ the constant elasticity of transformation (CET) function by which an aggregate land endowment (i.e., composite land) can be transformed across alternative uses and a three-level nested structure governs the land supply responses to the changes in the relative price. The nested structure is similar to that used in [26]. On the first level of the nested CET representation, the total available land is allocated to forest, grassland, and cropland. On the second level, the crops are partitioned into rice, aggregated grains (except rice), non-grain feedstocks (sweet sorghum and cassava), and aggregated other crops. Finally, the grains are further divided into wheat, corn, and other grains in the third level. Fig. 1 shows the nesting structure. This nested land allocation structure is reasonable because not all crops are in direct competition. For

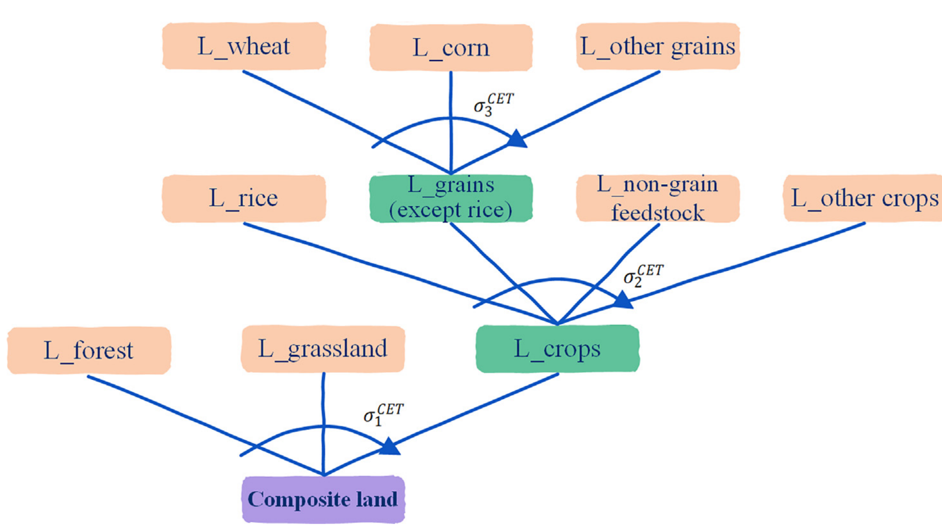

Fig. 1. Nesting structure of land allocation.

example, rice typically does not compete directly with other crops for available land.

Eq. (1) is the CET function. It illustrates how the composite land conducts allocation in terms of the land profit generated by each land use type:

$$Q_{TL} = A\left[\sum_{i\in I}\delta_i Q_i^{\rho_i}\right]^{\frac{1}{\rho_i}} \tag{1}$$

where $i \in I$ is a set of land use types, Q_{TL} is the total land endowment (i.e., the monetized value of the composite land), Q_i is the monetized value of land use type i, and ρ_i is an exponent determined by the land elasticity ($\sigma = \frac{1}{1-\rho}$ is the elasticity of transformation). The calibration parameters A and δ_i represent the scale coefficient and the share coefficient of land i, respectively. The symbol Σ (sigma) represents a summation.

When the total land profit is maximized, the land allocation among different land uses obeys the following equation:

$$\frac{P_i Q_i}{P_{TL} Q_{TL}} = \frac{\delta_i Q_i^{\rho_i}}{\sum_{j\in I}\delta_j Q_j^{\rho_i}} \quad \forall\, i \in I \tag{2}$$

where P_{TL} is the aggregated land profit and P_i is the profit of land use type i. $j \in I$ represents the set of land use types.

The transformation elasticities of the CET functions which represent the possibilities of land conversion are defined as in previous studies [55,56], as shown in Table 1.

2.3.2. Incorporating marginal land

The utilization of marginal land (also called wasteland or degraded land) and the appropriate cultivation of high-yield dedicated energy crops has been proposed as one of the vital directions for future bioenergy development in China [57,58], though the actual effects of the commercial adoption are not clear so far. To capture this potential land supply, we identify and incorporate marginal land into the CGE model for a comparison of the LUC with or without marginal land reclamation for the same bioethanol demand. The physical available area and land productivity are two core attributes that need to be characterized when incorporating marginal land into the land allocation module.

Based on the nationwide investigation of marginal land resources conducted by the Ministry of Agriculture, Ref. [59] analyzed the quantity and quality of marginal land in China, as well as the biofuel production potential. Table 2 presents the statistical results of that study. Considering the natural suitability, economic costs, and water constraints of reclaiming marginal land, it is impossible to utilize marginal land at level III before 2025 [57]. In this case, only marginal land at level I and II is incorporated into the land allocation module and the reclaimable area shown in Table 2 is used as the physical available area.

Land rent has been recognized as a productivity indicator of the heterogeneity of land [60,61]. It is well known that marginal land is less productive than general cropland; therefore, based on the estimated productivity of general cropland and marginal land in [59,62], here we adopt the land rent to represent the marginal land productivity at different quality levels. Specifically, the land rent of marginal land I is assumed to be 70% of the general cropland, indicating that this marginal land is 30% less productive than cropland. The productivity of marginal land II is 85% (3.00/3.50 as shown in Table 2) of marginal land I, so its land rent is 60% of the land rent of general cropland.

To incorporate the marginal land at level I and II into the land allocation module, two new types of cropland are created in the second nesting level of the land allocation structure, which means the amount of cropland is increased due to the newly entered marginal land (see Fig. 2). Additionally, it is significant to note that, although the value of the composite land is increased by the addition of the marginal land, we retain the economic value of the total composite land-capital endowment by adjusting the capital endowment of the households.

2.3.3. Features of the land allocation module

The land allocation module has three distinct features for modeling LUC (conversion and expansion) and the land market.

- The land nesting is a multi-level structure based on the CET functions, as shown in Fig. 1. The different transformation elasticities of each level represent the various possibilities of land conversion among alternative uses at the same level; this captures the heterogeneity of the different land types and compensates for the limitations of a single CET nest as mentioned in a previous study [63]. In the nesting structure, the conversions among heterogeneous land types are endogenously determined by the land demand of each agricultural sector and the relative land rent of each land type.
- In addition to cropland, forest and grassland are also incorporated into the land allocation structure, as well as the reclaimable marginal land which is usually neglected in traditional land market modeling. This broad incorporation of various land use types provides a mechanism that allows for cropland expansion into other land uses, especially under the pressure that the demand for and price of cropland have increased dramatically due to the response of the crop supply to the scarcity.
- Diverse land conversion and expansion rules can be conducted based on this flexible land allocation module which are significant for the allocation behavior and the associated LUC results [26]. For instance, in Fig. 1, if the share of land types at the first level is fixed, forest and grassland would be protected and cannot be diminished by cropland expansion. The specific scenario settings of this case study are explained in detail in Section 3.

2.4. Agricultural production structure

In our CGE model, all sectors are assumed to operate under constant returns to scale and cost optimization. Producers pursue profit maximization subject to technological and resource constraints. The production in each sector is modeled by nested constant elasticity of substitution (CES) production functions and Leontief functions (a special case of CES function when the substitution elasticity equals zero), which represent the different substitution and complementarity relationships across the various inputs in each sector.

The major improvement is the refinement of the agricultural production functions, as the nesting structure illustrated in Fig. 3. The top level is a Leontief combination of intermediate inputs from other economic sectors and a composite value added, indicating that there are no substitutive relationships among them. At the second level, the value added consists of the composite capital-land factor and the labor factor using a CES function. At the third level, a CES production function represents the possibility of substitution between the composite land factor i and the capital factor. To date, no consistent standard approach has been developed in terms of the nesting structure of the primary factors of land, labor, and capital and the nesting structure is treated differently in the existing literature and is based on different assumptions. We follow previous studies [41,64,65] and combine capital and land first and subsequently, the composite capital-land and labor are aggregated to generate composite value added. The elasticities of the substitution are consistent with [41] ($\sigma_{AD}^{CES} = 0.8$, $\sigma_{Land,K}^{CES} = 0.3$).

Table 1
Elasticities of transformation in the nesting structure of land allocation.

Nodes	Elasticity of CET	Possibility of conversion
Composite land	1.00	Low
Land for crops	1.50	Middle
Land for grains (except rice)	1.75	High

Table 2
Marginal land area and biofuel production potential of land with different quality levels.

Level of marginal land	Land area (10,000 ha)	Reclaimable area (10,000 ha)	Production potential for biofuel	
			Productivity t/ha	Total production (10,000 t)
Level I	433.33	260.00	3.50	910.00
Level II	873.33	524.00	3.00	1572.00
Level III	1373.33	824.00	2.50	2060.00
Total	2679.99	1608.00	/	4542.00

Source: [59].

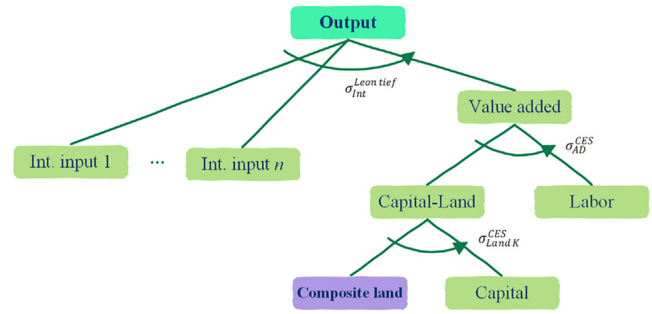

Fig. 3. Nesting production structure of the agricultural sectors.

Together with the land allocation module and the agricultural production structure, the mechanism of interactions between the agricultural product market and the land market have been explicitly captured. As shown in Fig. 3, land is one of the primary factors for agricultural production, which means that the infinite expansion of agricultural production will be constrained by the limited supply of land resources. Under the condition of bioethanol expansion, the market demand for feedstock crops will increase. When crops are in short supply, their price will rise and the production will expand. The production expansion increases the demand for land resources, which, in turn, triggers higher land prices, as well as the conversion and expansion of cropland among different sectors and alternative uses. In the end, the economic system will reach a new equilibrium.

3. Scenario description

A previous study [66] demonstrated that suitable land use policies can alleviate negative land use changes caused by biofuel expansion, such as deforestation. Inspired by this, to compare the different land use impacts of various patterns of land use management, we make a distinction between the land conversion assumptions in the following three scenarios. Table 3 displays the treatment of land mobility across various uses under each scenario.

- Baseline scenario (S1): Land conversion occurs between the existing cropland, forest and grassland; forest and grassland can be transformed into feedstock land; the composite land endowment remains constant.
- Non-deforestation scenario (S2): Land conversion occurs between the existing cropland; forest and grassland are protected to remain constant over time; the land endowment remains the same as in the base year.
- Marginal land scenario (S3): Land conversion occurs between the existing cropland and the newly reclaimed marginal land; the cropland endowment is increased due to the reclamation of the marginal land; forest and grassland are protected from other uses.

In addition, the exogenous bioethanol expansion shock is modeled based on the latest nationwide E10 mandate, which will require about 12 million tons of ethanol by 2020. Here according to the corn stock estimates provided in [35], we assume that 2/3 of the ethanol demand (8 million tons) are provided by corn stocks and other sources with no LUC and food supply impacts, while the rest 1/3 (4 million tons) is provided by newly planted domestic feedstocks. It is worth noting that the ratios of ethanol production based on corn stocks and on newly planted domestic feedstocks in 2020 are quite uncertain due to the significant variations of bioethanol policies and the uncertain development of the bioethanol industry. Given this situation, this paper aims to reveal the impact mechanism between bioethanol expansion and LUC and to identify the response direction and the potential scale rather than making predictions.

Under the assumption that 1/3 of the bioethanol demand is provided by newly cultivated domestic feedstocks, each of the above-mentioned scenarios represents one of the potential land use management patterns which can influence the simulation results of the LUC and food security. Complementally, the discussion in Section 5.2 provides insights into the LUC sensitivity to more ambitious bioethanol expansion because it is assumed that the feedstock demand will increase with the depletion of corn stocks.

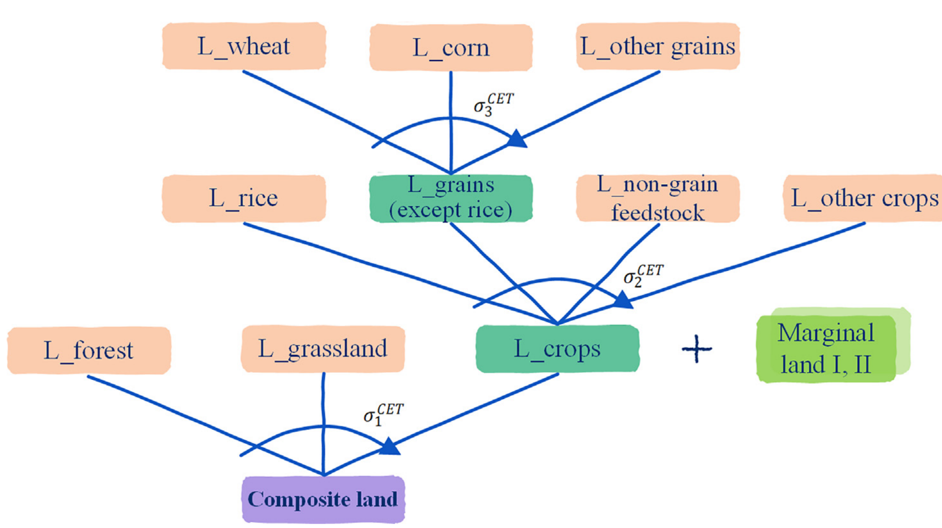

Fig. 2. Incorporating marginal land into the land allocation nest.

Table 3
Land conversion scenarios.

Scenario name	Land supply sources for bioethanol feedstock cultivation	
Baseline scenario (S1)	Existing cropland, forest, and grassland	  
Non-deforestation scenario (S2)	Existing cropland	  
Marginal land scenario (S3)	Existing cropland and newly reclaimed marginal land	   

4. Simulation results

4.1. Land use change

To achieve China's bioethanol demand in 2020, the changes in the aggregate land allocation among different land uses are summarized in Fig. 4.

In the baseline scenario (S1), the land supply for planting wheat, corn, and non-grain feedstocks increases by 0.119%, 0.213%, and 0.182%, respectively because these three crops can be used for bioethanol production whereas the land supply for other uses declines to some extent. For instance, the land for rice planting decreases by 0.015%, which may have further negative impacts on food security. Furthermore, the sacrifice of forests (−0.023%) and grasslands (−0.023%) may affect soil carbon sequestration. According to the land use emission data of the FAO database [48], we calculate the changes in greenhouse gas (GHG) emissions and removals from cropland, forest land, and grassland induced by the LUC; the results indicate that the net emissions from the total land use would increase by 71,000 tons/year in this scenario.

In the non-deforestation scenario (S2), the land supply for planting wheat, corn, and non-grain feedstocks increases by 0.126%, 0.223%, and 0.152%, respectively. The increased land demand for bioethanol feedstocks is totally realized by occupying cropland that was originally used for cultivating rice, other grains, and other crops and their decrease rates are 0.016%, 0.398%, and 0.043%. Since forest and grassland are protected from converting to cropland in this scenario, the competition among the existing cropland uses becomes more intense than in S1.

In the marginal land scenario (S3), due to the increment of potential cropland supply from the newly reclaimed marginal land which can be used for bioethanol feedstock cultivation, the land competition is eased to some extent. For example, the decline rate of rice land is 0.009% in this scenario and is lower than in S1 and S2. By accumulating the total LUC in croplands, we find that 0.217% of croplands can be saved in S3 compared to S1. Nevertheless, as shown in Fig. 4, the land supply for planting rice, other grains, and other crops still shows slightly decreasing trends to satisfy the land demand for bioethanol expansion. This can be explained by the relatively low productivity of the marginal land, which makes it less competitive; therefore, large-scale

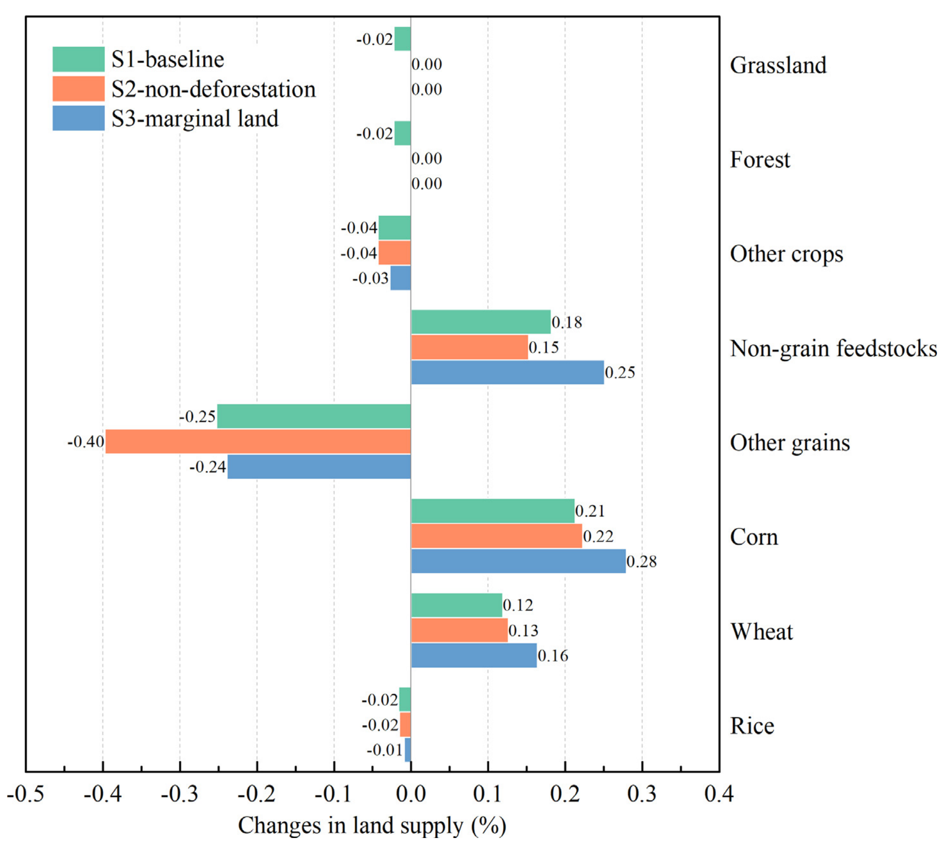

Fig. 4. Land use changes (%) after bioethanol expansion.

reclamation and application of marginal land may not be cost-effective. This finding is consistent with the research findings of [61].

4.2. Structure of feedstock supply

As mentioned in Section 1, the feedstocks for bioethanol production in China are mainly food crops and their cumulative proportion was more than 80% at the end of the 12th Five Year Plan [31]. Here we gain an insight into the feedstock supply structure in the three land conversion scenarios after the policy shock of the bioethanol expansion in 2020, as shown in Fig. 5.

In the baseline scenario (S1) and the non-deforestation scenario (S2), the feedstock structures are almost the same. The proportion of non-grain feedstocks (sweet sorghum and cassava) is small while the corn and wheat take up about 83%, so the main feedstocks are still food grains. In these two scenarios, bioethanol expansion is likely to affect the adequate food supply for final consumption; this is discussed in detail in Section 4.3. In contrast, non-grain feedstocks account for 26.97% of China's bioethanol production capacity in the marginal land scenario (S3); this proportion is larger than that in S1 and S2. Meanwhile, corn feedstock and wheat feedstock decrease to 58.37% and 14.66%, respectively. The following is the reason behind this phenomenon. The newly reclaimed marginal land increases the cropland endowment and it is suitable for planting non-grain feedstocks. Besides, according to previous studies [10,57,62,67], the bioethanol yields per unit area (tons/ha) from cassava and sweet sorghum are higher than those from wheat and corn (as shown in Table 5 in Section 5.1), which means that dedicated energy crops are more land-saving than traditional grain feedstocks. In this case, more sweet sorghum and cassava would be cultivated for bioethanol production, which would decrease the demand for traditional grain feedstocks. Therefore, utilizing marginal land could diversify the feedstock sources to meet the announced bioethanol mandate and may simultaneously benefit other sustainability goals, such as no deforestation and an adequate food supply.

4.3. Food security impacts

Rice, wheat, and corn are the principal food grains in China and their adequate supply is essential for people's nutrition. In this section, we investigate the impacts of China's 2020 bioethanol expansion on the food price, food production, and final consumption.

As indicated in Table 4, expanding bioethanol production leads to an increase in food prices in all three scenarios, except for the rice price in the marginal land scenario (S3). Under the driving force of achieving increasing bioethanol demand, the partial primary factors (land, capital, and labor) move from the other crop sectors to the feedstock sectors. For instance, land that was used to cultivate rice is converted to bioethanol feedstock planting; this reduces the rice supply and further triggers a higher market price. The demand for grain feedstocks such as wheat and corn increases to meet the bioethanol target, hence, their prices would also rise due to the market mechanism. Compared with the baseline scenario (S1), forest and grassland cannot be converted to other uses in the non-deforestation scenario (S2), so the available land for bioethanol feedstock planting is less in S2 than in S1. Therefore, the food price in S2 is much higher. Owing to the potential land supply from reclaimed marginal land, the land competition among different uses is released, resulting in a slight increase in food prices in the marginal land scenario (S3), whereas the rice price even presents a small decreasing trend (−0.0122%).

Figs. 6 and 7 show the amount of production and final consumption of the three food grains. The rice production in the baseline scenario (S1) and the non-deforestation scenario (S2) both have slight decreasing trends (−0.016% and −0.017%), while the production increases by 0.008% when the cropland endowment is increased in the marginal land scenario (S3). In contrast to rice, the production of wheat and corn increases in all three scenarios. The increasing rate in S3 is the highest, i.e., 0.184% for wheat and 0.260% for corn. Nevertheless, the changes in final consumption are not consistent with the increased production. As shown in Fig. 7, the final consumption of the three food grains would decline under the bioethanol expansion, except for a slight increase in the rice consumption in S3. The rice production and consumption both decline in S1 and S2 due to the factor reallocation, especially the land factor conversion to the feedstock sectors. For wheat and corn, their added production in Fig. 6 and part of the initial production are used as bioethanol feedstocks; therefore, in a closed economy without compensation from import supply, the total supply of wheat and corn for households declines so the final consumption decreases, as shown in Fig. 7. Specifically, the changes in wheat consumption in S1, S2, and S3 are −0.065%, −0.090%, and −0.023% and the corn consumption decreases by −0.086%, −0.118%, and −0.028%, respectively. To satisfy the households' nutritional demand, the declined consumptions would be compensated for by other food products aggregated in the "other agricultural products" sector through the substitution mechanism in the CGE model; these products include soybeans, tomatoes, and other food products.

These results illustrate that bioethanol expansion would have negative impacts on the food price and food supply, which are important indicators of food security; however, these impacts would be softened when marginal land could be reclaimed as a new land supply. In other words, the simulation results imply that food security may be at risk due to bioethanol production expansion and the potential marginal land may mitigate this but rather than solve it.

5. Discussion

5.1. Direct LUC and total LUC

Direct land use change (DLUC) occurs when planting biofuel feedstock displaces the prior land use, while indirect land use change (ILUC) describes the changes that occur outside of the feedstock planting areas when the DLUC pressure on agriculture induces LUC in other land uses through economic interactions. As mentioned in the introduction, the CGE model has the strength in estimating the total LUC caused by biofuel expansion, including the DLUC and ILUC. To examine this argument, we calculate the DLUC caused by feedstock planting and compare it with the total LUC simulated by the CGE model (as described in Section 4.1).

Table 5 shows the bioethanol yields from different feedstocks (tons/ha). Based on this, in order to achieve the bioethanol production of 4 million tons, the land demand for feedstock planting (i.e., the DLUC) would be 820–2200 thousand ha, occupying 0.135–0.362% of the

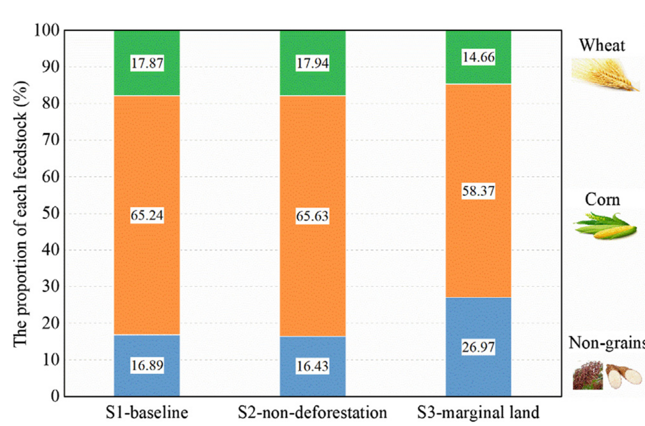

Fig. 5. Feedstock structure of the bioethanol production capacity (component ratio %). Notes: The bioethanol production capacity here only refers to the 1/3 of the total bioethanol demand (4 million tons) made from the newly cultivated feedstocks. Ethanol produced by corn stocks is not considered here, so feedstocks in this figure do not include the corn stockpile.

Table 4
Changes in food price (%) for different scenarios.

Food type	S1-baseline	S2-non-deforestation	S3-marginal land
Rice	0.0594	0.0602	−0.0122
Wheat	0.0849	0.1266	0.0423
Corn	0.0861	0.1318	0.0439

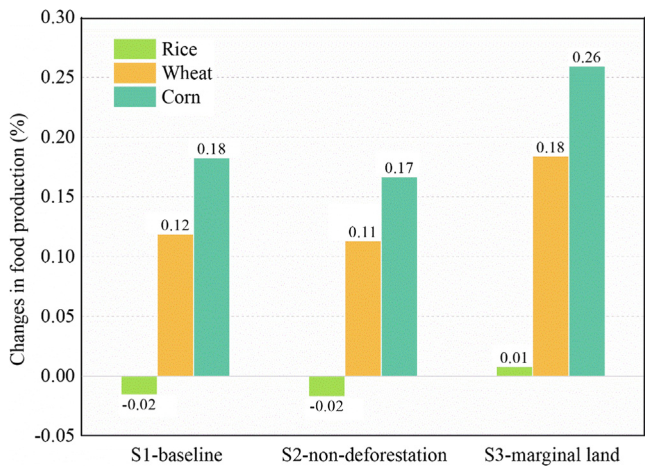

Fig. 6. Changes in food production (%) for different scenarios.

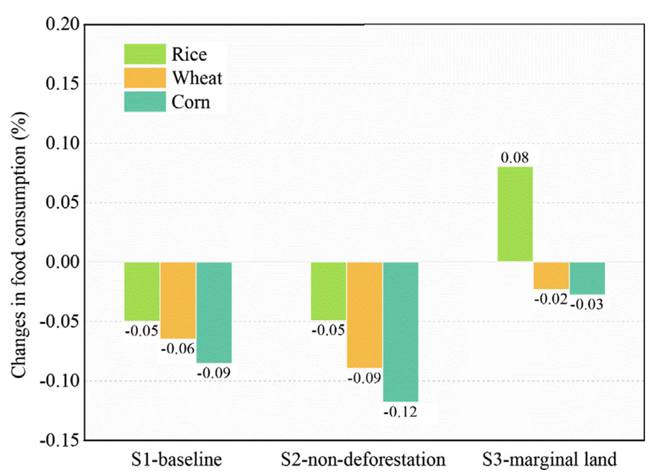

Fig. 7. Changes in food consumption (%) for different scenarios.

Table 5
The bioethanol yields from different feedstocks.

Feedstock type	Wheat	Corn	Cassava	Sweet sorghum
Bioethanol yield (t/ha)	2.0–2.4	1.8–2.4	3.9–4.9	3.9–4.2

Source: [10,57,62,67].

existing agricultural land (the sum of cropland, forest, and grassland) in 2015. The uncertainty range is due to the different choices of bioethanol feedstocks.

Based on the LUC results of the alternative land use types as simulated by the CGE model (Fig. 4), Eq. (3) is used to measure the total LUC:

$$LUC_T = \sum_{i \in I} |(Q_i^{'} - Q_i^0)/Q_i^0| \tag{3}$$

where $i \in I$ is the set of land use types, Q_i^0 is the initial monetized value of the land use type i, $Q_i^{'}$ is the value of the land use type i after the shock of bioethanol expansion. LUC_T is the accumulated absolute value of the differences between Q_i^0 and $Q_i^{'}$, representing the total LUC intensity in each scenario. The symbol Σ (sigma) represents summation.

Comparing the total LUC with the DLUC (Table 6), it is obvious that when the ILUC is considered, the scale of total LUC is about 2 to 6 times larger than that of the DLUC; this is consistent with the emphasis on the ILUC induced by biofuel expansion, which has been demonstrated in previous studies [13,14].

Table 6
The DLUC and the total LUC (%).

DLUC (%)	Total LUC (%)		
	S1-baseline	S2-non-deforestation	S3-marginal land
0.135–0.362	0.870	0.957	0.971

Notes: The range of DLUC is derived from different choices of feedstocks because the bioethanol yields from different feedstocks per unit area vary greatly. While for the total LUC, there is only one value in each scenario because the feedstock structure (as shown in Fig. 5) is automatically selected under the market mechanism in the CGE model.

5.2. LUC sensitivity to higher feedstock demand

The foremost result of this study is the LUC induced by China's bioethanol expansion (Fig. 4). However, the actual bioethanol feedstock demand in 2020 and beyond is likely to be greater, especially when there will be no feedstock supply from corn stocks. In this context, we test the sensitivity of the LUC to higher feedstock demand.

Specifically, we simulate the potential LUC impacts under the E10 mandate with less corn stockpile supporting, which means a higher demand for newly cultivated feedstocks. Compared with the original bioethanol expansion shock of 4 million tons, here more ambitious shocks are set in the enhanced target (ET) scenarios from 150% ET to 300% ET, i.e., 6 million tons to 12 million tons; 300% ET is equivalent to the total ethanol demand of E10 mandate without the corn stock feedstock. Subsequently, Eq. (3) is applied to calculate the total LUC.

Table 7 shows the total LUC results under the enhanced scenarios. It is evident that the scale of LUC becomes larger with increasing bioethanol feedstock demand. In the baseline scenario (S1), the total LUC is 1.673% for the 150% ET and exceeds 4% for the 300% ET. Additionally, more drastic LUC would occur in the non-deforestation scenario (S2) and the marginal land scenario (S3). For instance, for the 300% ET scenario, the total LUC in S2 and S3 will be 5.745% and 5.899%, respectively. It should be noted that the LUC in S3 incorporates the LUC from the marginal land entering, so the LUC of the original land use types will not be such large.

In addition, the impact of long-term bioethanol expansion is a vital issue for China's mid-century strategy for climate mitigation. Since the static CGE model used in this study has a weakness in long-term

Table 7
The total LUC (%) for a higher demand of bioethanol feedstock.

Enhanced scenario	S1-baseline	S2-non-deforestation	S3-marginal land
100% ET (1/3 E10)	0.870	0.957	0.971
150% ET	1.673	2.154	2.203
200% ET	2.476	3.351	3.435
250% ET	3.279	4.548	4.667
300% ET (total E10)	4.082	5.745	5.899

Notes: The "100% ET" scenario represents the original shock of 4 million tons per year based on the assumption that 1/3 of the ethanol demand of the E10 mandate needs to be achieved by the additional feedstock cultivation, while the reminder can be directly produced by the corn stock with no LUC impacts. The "300% ET" scenario means three times the original bioethanol expansion shock, i.e., 12 million tons per year, which is equivalent to the total ethanol demand for the E10 blend goal.

dynamic simulation, a rough estimate is made based on additional data from the literature. The mid-century bioethanol demand is derived from a recent report of the Natural Resources Defense Council (NRDC), which indicates that the bioethanol consumption would reach 85.1 million tons in 2050 in the 1.5 °C scenario [68]. Then, according to the land footprints of various bioethanol feedstocks [62], we found that the total feedstock land for bioethanol consumption in 2050 would occupy 15.9–37.8% of the existing cropland (the range represents the uncertainties of various feedstock selection). If we reclaim all the marginal land of level I, II, and III, this proportion would be lowered to 3.9–25.9% but it still represents a large proportion.

In general, there is no doubt that bioethanol expansion would lead to LUC because of land competition between feedstock cultivation and other land uses. The LUC sensitivity analysis demonstrates that a higher bioethanol demand would trigger more drastic LUC, especially in the deep decarbonization scenarios. In this case, policy makers need to be very cautious about the bioethanol mandate setting and land use planning to avoid uncontrollable large-scale LUC and other sustainability impacts.

5.3. More insights into marginal land availability

The simulation results of the three land conversion scenarios in this study illustrate that marginal land can be a prospective land supply for energy crops and would increase the non-grain bioethanol feedstocks by 10% and save 0.217% of croplands with no deforestation by 2020. However, it is crucial to gain better insights into other issues, such as the technical and economic viability, as well as environmental, social and, political constraints [69].

The sparse distribution of marginal land is likely to limit the actual reclaimable area. Fig. 8 shows the marginal land distribution in seven main regions in China and the potential for bioethanol production. The Tibetan Plateau has the most abundant marginal land resources, especially land at level I, followed by the southwest and the Loess Plateau (Fig. 8a). However, in these regions, the cost for biomass collection and infrastructure may not be economical because of the remote and mountainous locations, as well as the shortage of water resource [41,58]. Correspondingly, the differences between the actual production in 2017 and the total production potentials show large gaps in these three regions (Fig. 8b). Most of the existing ethanol facilities locate in the northeast, Middle-Lower Yangtze River, North China, and South China [47].

Furthermore, biomass transportation consumes fuels and increases the bioethanol production costs and GHG emissions [70]. Biodiversity loss and ecosystem degradation are also potential risks of excessive marginal land reclamation [31]. In this case, considering the economic and other external costs, the available area of marginal land estimated in previous studies at 8 to 137 million ha [39,59,71,72] may be overestimated. For example, through a hierarchical assessment of the physical, biological, environmental, and economic constraints, a recent study [73] concluded that the largest estimate of marginal land in China is only 5.48 million ha, reminding us that the exploitable area of marginal land is not very large. For future researches on marginal land, it is essential to provide integrated assessments of its availability and sustainability, which can help to seek a concrete bioenergy deployment pathway (e.g., facility siting) supplemented by improved land use planning and management.

5.4. Limitations and future work

In this study, a CGE model was used to capture the economy-wide effects of bioethanol expansion, including inter-sectoral linkages and constraints on labor, capital, and heterogeneous land factors, as well as to determine all prices in the equilibrium market. Unlike non-market biophysical land use simulation models and PE models, general equilibrium models incorporate all drivers of LUC resulting from complex socioeconomic activities and announced policy mandates, clearly revealing the interactions between the biofuel sectors and agricultural sectors.

However, there are several limitations of the CGE model adopted in

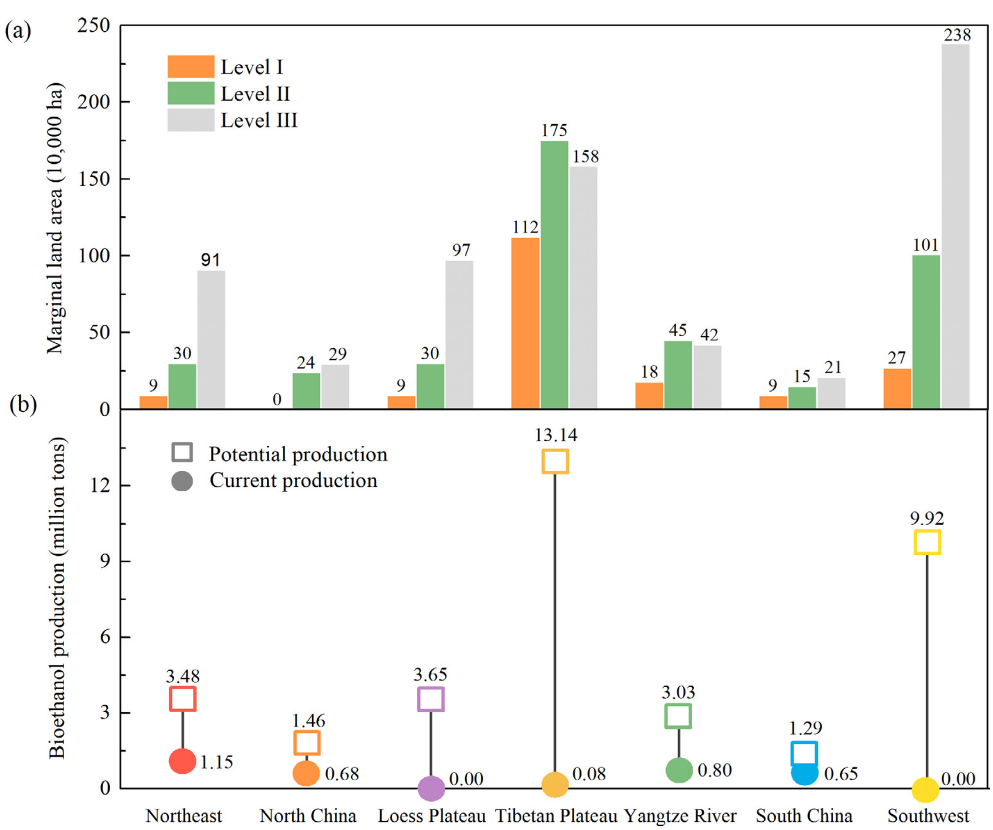

Fig. 8. Distribution of marginal land and production potential of bioethanol. (a) The marginal land areas in seven main regions in China. They are the arable areas estimated by [57,59] and are divided into three levels based on land quality; level I has the highest productivity and level III has the lowest productivity. (b) Bioethanol production potentials of marginal land in seven main regions in China. A comparison of the potential production and current production in 2017 is shown. The potential production is based on the physical marginal land area and productivity in [59] and the current production data is obtained from [47]. Note that "Yangtze River" in this figure refers to the Middle-Lower Yangtze River.

this study. First, as a national macroeconomic model, it lacks spatial information; therefore, the exact locations of projected LUC are uncertain and the adaptability of crops to different climatic conditions or other local constraints (traffic accessibility, water availability, etc.) throughout China is not considered. Second, the CGE model requires numerous parameters (e.g., elasticities) from empirical evidence which is poorly supported [8,74]. A common method to determine these exogenous parameters is to use data from existing studies, as we did in this study. But there exist inconsistencies in the regional and temporal scope. Finally, the CGE model is unable to depict technical details. For example, many biofuel conversion technologies such as combustion, fermentation, and transesterification cannot be described in detail in the highly aggregated production functions, but the costs and efficiencies of these technologies usually play important roles in energy production.

In recent years, land use has become one of the key elements in general equilibrium models for food security and agricultural assessments, as well as the biofuel boom. Nevertheless, the wide application of CGE models in LUC studies still has formidable challenges and requires further improvement. The integration of spatially explicit biophysical models, the parameter calibration with more reliable econometric estimates, and the incorporation of detailed technical information would be plausible directions for future model development.

6. Conclusions

To explore the sustainability impacts of biofuel expansion on land use change (LUC) in a specific country, we develop a national land explicit computable general equilibrium (CGE) model and design a scenario approach representing different patterns of land use management. The case study of China quantifies the domestic direct and indirect LUC induced by bioethanol expansion based on the E10 mandate (gasoline containing 10% ethanol) in 2020, as well as the potential impact on food security. The following implications can be drawn from this study.

First, LUC occurs when existing land use types are converted to other uses to satisfy the new land demand induced by bioethanol expansion. In the baseline scenario (S1), the land supply for planting wheat, corn, and non-grain feedstocks (sweet sorghum and cassava) would increase whereas the land supply for other uses would decrease (−0.015% for rice land, −0.023% for both forest and grassland). In the non-deforestation scenario (S2), land competition among existing croplands would become more intense because forest and grassland are protected from conversion to cropland. The land supply for planting rice, other grains, and other crops would decline by 0.016%, 0.398%, and 0.043%, respectively. When marginal land can be reclaimed as a potential land supply in the marginal land scenario (S3), the land competition is alleviated slightly, e.g., the rice land decreases by 0.009%, which is lower than the proportions in S1 and S2. However, the cropland supply for non-feedstock grains and crops still presents slight decreasing trends. The sensitivity analysis demonstrates that the more ambitious the production expansion (more feedstock demand), the greater the LUC would be. For instance, under the 300% ET scenario, i.e., 12 million tons per year consistent with the total ethanol requirement of the E10 mandate relying on no corn stocks, the total LUC would be 4.0–5.9%.

Second, regarding the feedstock structure, more non-grain feedstocks would be cultivated in the marginal land scenario (S3); the proportion is 26.97% whereas it is 16.89% and 16.43% in S1 and S2, respectively. Thereby, utilizing marginal land could diversify the feedstock sources to expand bioethanol production; this is not only limited to sweet sorghum and cassava but also includes other potential energy crops not considered in this study. Bioethanol expansion would also endanger food security due to the discrepancy between the land availability and the increasing market demand for feedstock crops. Because some rice land will be converted to plant feedstocks, the reduced rice supply will trigger higher prices (+0.059% in S1, +0.060% in S2). For wheat and corn, which can be used as feedstocks, the increasing demand raises their market price and supply but the final consumption of households still decreases. In the marginal land scenario (S3), the food price declines slightly because the bioethanol production depends on more non-grain feedstocks (dedicated energy crops) cultivated on reclaimed marginal land, which softens the land competition.

Finally, we provide some suggestions for policy decisions according to the above findings. Non-grain energy crops grown on marginal land could contribute to bioethanol feedstock resources, thereby promoting the sustainable development of bioethanol without compromising food security and forest protection. This approach may become an effective alternative or complementary pathway to expand biofuel production in China. In this context, the government is suggested to improve the traditional pattern of land use management and to encourage cultivating diverse non-grain feedstocks on marginal land to achieve the announced bioethanol mandate, thereby implementing a sustainable low-carbon transition in the fuel energy sectors. However, excessive marginal land reclamation needs to be avoided.

In this study, we quantify the total LUC driven by China's bioethanol expansion in 2020 and suggest sustainable approaches for land use management and feedstock selection to avoid potential negative impacts on land resources and food security, which may also inspire other countries and regions. The proposed methodology for incorporating heterogeneous land use types into the production function of the CGE model and the scenario approach for representing various patterns of land use management can lay a common foundation for estimating the LUC impact of bioenergy development in other national/regional cases and assessing the broader potential impacts on sustainability. In future work, we intend to investigate long-term LUC using a multi-region dynamic CGE model with more detailed bioenergy sectors and higher spatial resolution. Moreover, deep discussions on the economic costs and other sustainability impacts such as the ecological vulnerability of reclaiming marginal land are required.

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