

Article

Agricultural Land, Sustainable Food and Crop Productivity: An Empirical Analysis on Environmental Sustainability as a Moderator from the Economy of China

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Abstract: The availability of agricultural land is central to stimulating reserves in sustainable food and crop production amidst accelerating economic sustainability and growth. Therefore, this article aims to investigate the influence of agricultural land (AGL) on food production (FP) and crop production (CP) with the linkage of environmental sustainability (ES) as a moderator from 1990 to 2021 for the economy of China with the autoregressive distributed lag (ARDL) bounds testing estimation model. Our findings showed that the ARDL model estimates the long-term and short-term joint matching relationships between agricultural land and the independent variables in the model, which is a statistically significant outcome. Therefore, in the long term, the food and crop production adjustment for speed to steadiness was huge as it was projected at 1.337%, 53.6%, 133.5%, and 37.4%, respectively, in all the models, which shows that the adjustment for speed of models is a good post-shock association process. We found evidence for a significant and positive relationship between agricultural land and food and crop production in ordinary least square (OLS) estimation, which also ensured the outcomes of the primary model. Furthermore, Toda–Yamamoto Granger causality test estimation found reverse causality between food production (FP) and crop production (CP) and showed evidence of the conservation hypothesis. We found bidirectional causality between food production and agricultural land and between crop production and agricultural land, which shows evidence of the feedback hypothesis. Additionally, the empirical findings of a robustness check with fully modified ordinary least square (FMOLS) and dynamic ordinary least square (DOLS) techniques showed consistency with the investigations of ARDL estimation in the long run, ensuring the validity and strength of the primary outcomes. Overall, the present paper brings fresh knowledge about agricultural land use, and food and crop production to promote environmental sustainability.



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Keywords: agricultural land; food production; crop production; environmental sustainability; China

1. Introduction

Agricultural land delivers a prime segment of dietary sources and confirms the essential quantity of environmental facilities (e.g., provision of nutrition, energy, and fiber) [1–4]. Research in agricultural economics has been dedicated to the international question of the growing problem of food safety from the perspective of farming land structures (i.e., artificial methods of livestock farming and agricultural land production) [5–7]. The works carried out are very diverse [8], unlike methodological schemes (for instance, the paradigm of geography, the study of ecology, the study of soil science, agronomy study, and the study of the economy) [9]. Moreover, agriculture as an economic action dramatically depends on the environment/climate to harvest the food, fiber, and materials required to endure social lives [10]. Even though declining crop yield gaps have projected a path to reduce stress on food production structures [11,12], the main advantage of the given approaches lies in their environmental benefits, as they are no longer constrained by resource limitations, particularly water availability. Since the late 1980s and early 1990s, as a consequence of the adaptation of globalization, two models of agriculture have appeared: (a) an industrial model [13], and (b) a sustainable agriculture and quality food production model [14]. The industrial model promotes the utilization of superior input/output concentrated land farming to achieve higher productivity [13]. The “sustainable agriculture and quality food production model”—including biological agriculture, reformative agriculture, environmentally smart agriculture, CO₂ capture agriculture, and nature-grounded resolutions—emphasizes mainly refining environmental sustainability over agriculture-level practices [15]. However, in modern times across the globe, the agriculture sector is facing discouraging encounters; hence, in the second half of the 20th century, the shift from long fallow to short fallow was more prominent in farmers, who moved to multiple harvesting cycles per year concerning annual cropping [16].

Diversified agricultural measures (such as grasslands, ecosystems, and biodiversity facilities) are an operative means of stabilizing the green effects of food production, crop production, and ecosystems. Advanced harvesting methods, which attain improved soil safety and environmental resilience, need optimal soil security and field diversity [17]. In the future, agricultural research and invention should emphasize reserve competence, production stability, reducing environmental effects, safeguarding extreme trials, and adjusting to the natural environment. Agricultural production is the sector most susceptible to changes in rainfall and fluctuations in average external temperature [18,19]. As a result, agricultural production has weakened radically. Therefore, the influence of environmental changes has weakened the world’s dietary well-being, as sustainable living in low-income nations is highly dependent on the agricultural sector [20,21]. Climate changes are the maximum dynamic base of hazards that directly or indirectly interrupt crop production. Growing temperatures and environmental variation arrangements have a direct influence on the timing of crop harvesting [21]. The rise in temperature changes the agricultural arrangements, which is unsuitable for agricultural production timings and accounts for the long-term negative influence on crop yield. Moreover, variations in weather shift the timings of rainfall, which is a central problem that harms crops in the short term. Mean temperature and its variations have a significantly negative relation to cereal production [21].

The present literature on agricultural economics shows significantly sound research figures on exploring the relationships between agricultural land and food production, and between agricultural land and crop production [22,23]. However, these studies mainly show the relations among agricultural land, food, and crop production to drive domestic economic growth [24]. Few studies have investigated the influence of agricultural land on food and crop production from the dietary pattern perspective of population and urbanization [25,26]. Among these studies, a small number have also focused on the

nexus of food production and agricultural land [27], crop production, and agricultural land [28] for developing economies, but to the best of our knowledge, this nexus is scant from the perspective of the Chinese economy. Specifically, environmental sustainability as a moderator has not been explored in the context of the Chinese economy on broader grounds. We endeavor to bridge this gap in the present study.

In the present paper, we attempt to examine the relationships among agricultural land, food, and crop production with the linkage of environmental sustainability as a moderator using a large sample of data from 1990 to 2021 for the economy of China. We undertook the present study for the agricultural economy because of the unique economic settings of China, which may have some policy limitations for farming and cultivating crops and food productivity. As an incredibly crowded and mainly agricultural state, China uses merely 9% of the Earth's territory, backs 25% of the biosphere's nutrition, feeds one fifth of the world's people, and provides significant support to world nutrition security [23]. Facts and figures show that land resources for agriculture in China have been under an excessive load over an extended period, and the land possessions per capita cover less than the Earth's half-sphere [29]. In 1986, the Chinese government carried forward the basic nationwide rule for cultivated land protection, reflecting the severest agricultural land defense structure in the domain. It expressed China's rule of managing basic dietary needs based on national properties. Moreover, the No. 1 Central Document emphasized land safety for more than 10 subsequent years [30]. Regardless, the constraints of developed land bottom lines and eminent red lines certainly do not cease. Since 2010, among the world's major cities located at higher altitudes, China's land resources have reduced considerably [4]. Irrational agricultural procedures have led to a decline in the output and excellence of cultivated terrestrial properties, creating agricultural product supply and demand in China as a controlled balance [31].

Following the present literature [32–41], we examined the relationships between agricultural land and the food production nexus, and between land for agriculture and the crop production nexus, with the linkage of environmental sustainability as a moderator using Chinese annual data from 1990 to 2021. The findings are robust and significant, especially since the study found that land for agriculture has a substantial positive impact on food and crop productivity for the economy of China. Secondly, the empirical findings revealed that environmental sustainability as a moderator in terms of low degradation of the environment, low CO₂, and greenhouse gas emissions positively influences agricultural output. Therefore, to fulfill dietary needs, it is projected that over one third of the Earth's sphere should be utilized for farmland or grasslands [42]. Growth in administration, for instance, superior inheritances, increased fertilizer claim charges [42], and healthier cattle feed [43], also had a positive impact. It is evident from the empirical findings of the present literature that agriculture is highly dependent on many factors, e.g., land, water, and additional inherent resources that mark it as open to the degradation of the atmosphere [44,45]. Thus, our paper is also linked to research that investigated the effect of environmental sustainability as a moderator on agricultural land, food production, and crop production relationships. For instance, [46] examined the influence of CO₂ emissions and the environment on the harvesting and land use for key crops in Pakistan. Third, the bounds test for ARDL estimation ensures the relationship between the short term and long term. Fourth, this study applies the Toda–Yamamoto approach to Granger causality testing among the variables, which also confirms the presence of causality among the nexus of primary constructs. Furthermore, the unrestricted error correction model (ECM) also shows worthy extrapolative enactment through the investigation period of the study and can be applied for the resolution of economic policy purposes. Additionally, the outcomes of robustness checks (CUSUM and CUSUMSQ) of the ARDL model are depicted, and show

that parameter steadiness and model consistency are attained once the stages of CUSUM and CUSUMSQ persist in the 5% critical series visible lines in red dashed form, which makes this study more robust and reliable. Moreover, the empirical findings of the robustness check with both fully modified ordinary least square (FMOLS) and dynamic ordinary least square (DOLS) techniques showed consistency with investigations of ARDL estimation in the long term, ensuring the validity and robustness of the main findings. Finally, this research study will seal the breach in the collected works on agriculture management, sustainable food, and crop productivity with environmental sustainability as a moderator in the context of the economy of China.

The remainder of the paper is systematized in the following ways. The subsequent segment is the theoretical framework and development of the hypotheses, and discusses the theory and the hypotheses. The section on the construction of the model and sources of data shows the model structure, methods, and sources. The Results segment presents details of the experiential investigation, and the Discussion section discusses the findings of outcomes. The final segments are Implications and Conclusions.

2. Theoretical Framework and Development of Hypotheses

Our paper aims to investigate the influence of agricultural land on food production and crop production with the linkage of environmental sustainability as a moderator for the economy of China. This segment discusses the theoretical framework in the first phase and then presents the development of the hypotheses.

The Unified Theory of Technology Acceptance and Use (UTAUT) is a valued theoretical context for discovering technology implementation in business and managing organizations in their search for efficacy and excellence in gigantic balance processes [47,48]. In the context of the growing farming industry in China, the UTAUT model is a key background for understanding the multilayered dynamic forces of expertise implementation and operative proficiency. The model is united by larger goals, such as countryside growth and farming innovation [49]. The UTAUT model applies to different business structures—including large specialized farms, family farms, and specialized farmer cooperatives—providing a comprehensive approach [50–52]. It supports the approval of user-responsive, instinctive skills that align with specialized agriculturalists' aid, promoting mass adoption and market competitiveness [53–55]. Smart agricultural farming employs advanced technology to improve every aspect of the business. These areas comprise environmental observation, food and nursing supervision, virus inhibition, and full-chain chase [56–58]. These technologies can help improve productivity, reduce costs, and promote eco-balance [59,60]. It is difficult to reveal how the adjustment of agricultural land and environmental sustainability affect food production and crop production because the studies in China are more basic from a national or regional perspective. Farmland and ecological sustainability are ignored in food production and crop production. In current environmental sustainability settings, China's food and crop production has not been predominantly achieved from a sustainability and growth perspective. Since it is gradually becoming interconnected with other parts of the world's economy, agricultural land and environmental sustainability are a part of it. In that case, the impact of agricultural land is the primary influence, and environmental sustainability is the prime moderator in present studies for sustainable food and crop production models, which have an impact only from a general or local standpoint in China. The influence of agricultural land as a key driver and environmental sustainability as a prime moderator on the change of China's sustainable food and crop production models and maintainable growth might be undervalued in the long run.

Agriculture plays a vital role in endorsing socio-economic growth. The theoretical background for the agricultural economy is rooted in [61], who first offered the theory of

population growth, and warned that in a little while, the population of the Earth would reach its limits. Primarily, Malthus's theory is grounded in the hypothesis of a paradigm of a closed economy. Yet, in the latest available data, it was [62] who suggested that food security may be solved by equipping the agrarian sector with modern farming technology. As a result, from 1950 to 1960, a green revolution took place worldwide. Specifically, it touched South Asia. Additionally, it was [63] who first put forth the currently accepted belief. It proposed that social inferences were the actual cause after rigorous agricultural practices and the quick growth in agrarian technology, which ultimately enhanced the pressure on agricultural communities worldwide. However, the farming sector is also connected to the theoretical paradigm of environmental problems, which needs to be controlled to ensure environmentally sustainable agriculture production. Agriculture is the mainstay of nearly every state [64,65]. Agricultural activities are probably affected by environmental variation. These procedures typically need certain nutrients, temperature, rainfall, and other conditions [29]. Therefore, in that regard, linked to environmental sustainability, the theoretical framework of CO₂ is the prime GHG that adds significantly to global warming, and it is considered to be the main element triggering the change in global climate [66,67]. As a result, all economies should prioritize de-carbonization, as surging CO₂ emissions are expected to have disastrous influences [68,69]. Subsequently, prior research related to the environmental impact has generally carried out sustainability and value with the level of CO₂ emissions [14].

In conclusion, prior research has focused mainly on agricultural land and environmental sustainability and established equal negative and positive impacts on food production and crop production [70–77]. Though not looking at the problem from a theoretic investigation or experiential point of view, research analysis needs additional tests and improvements regarding the influence of agricultural land on environmental sustainability, food production, and crop production. For instance, a study by [78] with data from 30 Chinese provinces used the estimator of the generalized method of moments (GMM). It showed that high CO₂ emission is due to enhanced farming productivity. Moreover, the results also showed that agrarian productivity harms the ecology only through key grain-generating provinces of China where grain production is low. Additionally, econometric evidence and theoretical underpinnings in prior literature suggest that many studies used the ARDL technique for the estimation of the long- and short-term dynamics (such as using quarterly data for 29 countries from 2000 to 2011 [79] in the pooled mean group (PMG) method for analysis of regression, [80] to find causality amid financial growth and populace evolution for Malaysia [81], and to assess the impact of CO₂ emission on agrarian output using data from six nominated Sub-Saharan African states to examine the relationships among ecological pollution, economic growth, use of energy, and foreign direct investment. In conclusion, it can be said that most research has utilized the econometric methodology of ARDL to find the long- and short-term dynamics of heterogeneous data. Thus, following the prior econometric paradigm, to achieve intuition in long and short-term dynamics for agricultural land, environment sustainability, sustainable food production, and sustainable crop production, the present study uses the Ordinary Least Square (OLS) estimation technique, the ARDL model, the ECM model, bounds testing, the cointegration test method, and the Toda–Yamamoto causality analysis technique, and proposes resultant hypotheses and policy recommendations on this basis. Figure 1 displays the conceptual model of the present study.

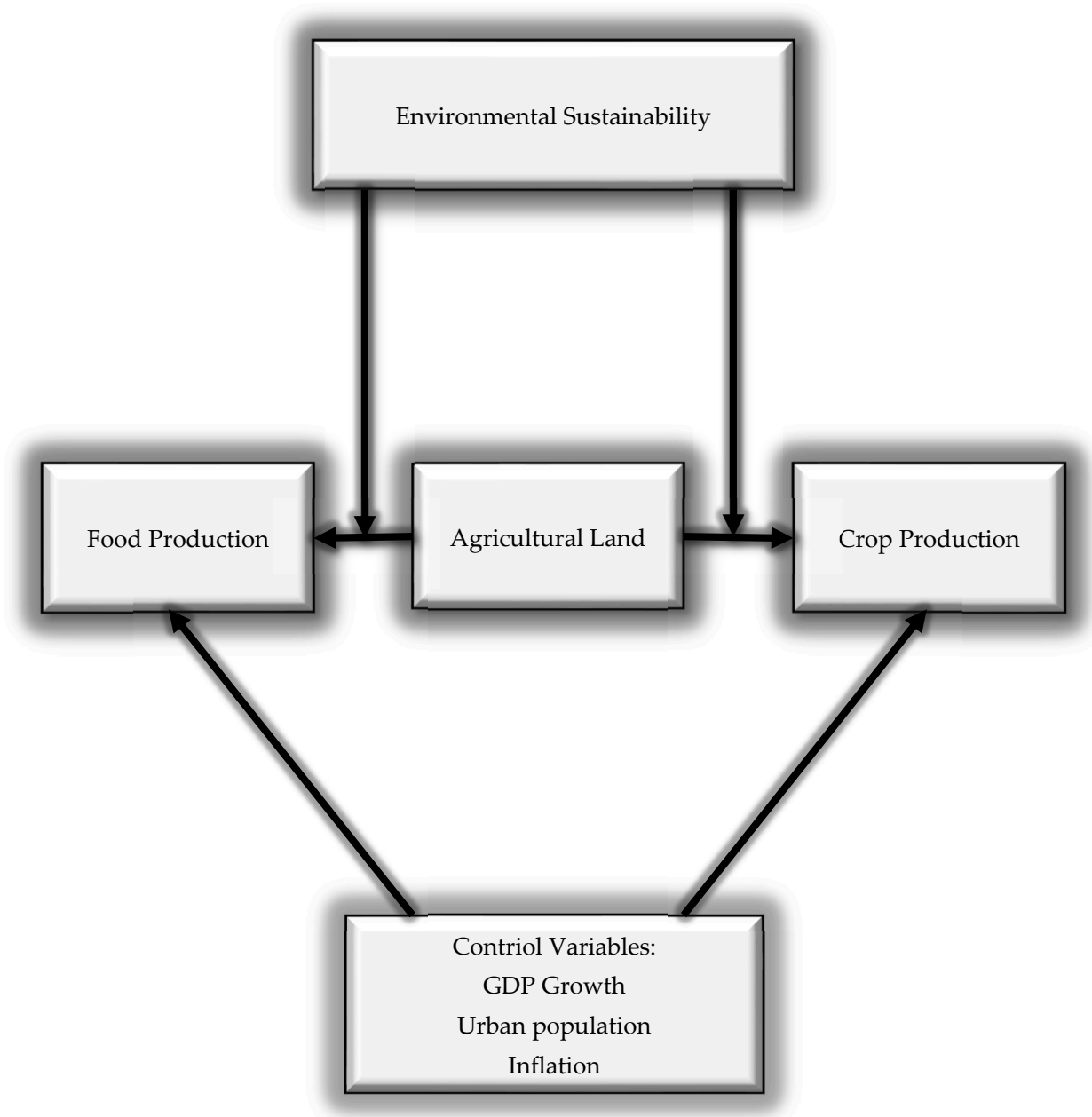


Figure 1. Conceptual framework of the study.

2.1. Development of Hypotheses

2.1.1. Agricultural Land and Food Production

Land systems signify the terrestrial constituent of the global structure and cover the entire procedure and actions linked to the social practice of the land [82]. Amid the worldwide terrestrial arrangement, farming land structures offer the key bio-geophysical foundation for sustainable food productivity [6]. Firstly, all available agricultural land must be expanded to increase food productivity. In the past, increased food productivity was attained through farmland expansion, obtained at the cost of reducing natural habitat and ecology by clearing the land to grow food products [83]. Due to cropland expansion, world grain production has increased by about 12% [84]. Due to the surge in demand for feed and food products [85], it has been necessary to restructure the use of global land and land covers not merely in Europe but also in China and other developing economies. So, terrestrial land used for farming is termed the key influencer on changes in land use [13]. Numerous results of previous research show that to meet the food needs of the increasing

population by 2050, agrarian output has to rise by 70–110% [86]. Several studies, for instance, [87,88], have specified that most of the best agricultural land on Earth is now being used for manufacturing. Soil produces (directly or indirectly) over 95% of the world's food output.

The projected worldwide rise of the global populace from 6.8 billion in 2009 to 9.2 billion in 2050 [89] will lead to a substantial rise in the demand for food. Worldwide, farming productivity faces a big challenge to feed the growing global population, specifically in developing and emergent economies where the system of food productivity is dominated by small farm-holders [90]. To fulfill the anticipated demand for food in 2050, there is a need for 0.2 to 1 billion hectares of extra land for agricultural farming. Around the globe, plenty of attention must be paid to meeting the world's food demand and farmers' income, as well as the provision of raw materials and support for bioenergy production by increasing farming land to marginal zones [91]. There is an increase in land demand, not only for food productivity but also for bioenergy food stock supply to non-provisioning ecology services, leading to the urbanization of protected areas [92,93]. Because of the globalization of the food supply and the rise in world trade for agrarian products, the position of food production is changing [94,95]. As growth in the world population requires additional food, shelter, and fuel [11], the food consumption arrangement of the population is changing towards products that are extra land-intensive to supply, mainly due to an increase in wealth [85,87]. The enhanced demand for agricultural products can be fulfilled by advanced agricultural inputs, fertilizers, pure water, pesticides, proper agrarian management, and agriculture expansion [13]. The enhancement in agricultural productivity has lessened the influence of these demands [11], but still, changes in land use have happened [87]. Since the last century, the Earth's surface has been transformed mainly due to agricultural productivity. There is consensus over the capability of the global food production system to fulfill the present and upcoming food demands of the world's population while meeting ecological and environmental needs [88].

The land values of agriculture are primarily determined by, among other factions, prospects of upcoming earnings that are themselves connected to the prolific volume of the Earth and anticipated cost-effective revenues from agrarian production [96,97]. Therefore, soil situations and richness stages influence agricultural land values over the rent proportion or the price of the sale (or evaluated value) of land for agriculture. Conversely, soil may be less productive due to constant contact with erosion that may harm the soil structure and lessen the quality of nutrients and organic matter [98,99]. As a result of a decline in productivity, the quality of food productivity and the farmland capacity may decline and affect agricultural productivity profits. Adopting sound soil management practices can positively influence soil condition and reduce damage and the soil erosion cost. Therefore, it is regarded as the significant driver for the rate of agricultural land [100]. It is hard to quantify the association between possessions and practices of land for agriculture and practices of soil arrangements since empirical evidence for this concept is limited [101,102]. In conclusion, discussion of the hypothesis suggests that an increase in agricultural land ensures sustainable food productivity. Hence, the hypothesis is stated as follows:

H1. *Agricultural land significantly positively influences food production.*

2.1.2. Agricultural Land and Crop Production

The land for agriculture is an essential individuality and the final requirement for social presence in the biosphere, and it establishes agricultural possessions where management portrays central mechanisms essential in disparities in the spreading of farmland capabilities [103]. The suitability estimate of agricultural land is the method that predicts the land's appropriateness in a specific location for harvesting different crops to project

the limitations and the potential of the crop production area [104]. Entry to possession and land management is frequently challenging in societies dependent on it [105]. Prominent agricultural land management depicts the primary participants' collaboration choices [106] and establishes the vital background for human growth in insights into challenging environmental behaviors [107]. This is linked to environmental concerns, overriding operational and organic techniques to increase the economic and societal standing of the rural public grounded on the sustainable manipulation of farmland for living. This is accomplished by contract methods regulating attainment, proprietorship, and land use [108].

Land for agriculture is vital for food production and further crops, and its preservation is essential for preserving the production of crops [109]. Streamlined agrarian lands with small elements of the natural environment and herb varieties are augmented for crop production [110,111]. However, they are related to soil deprivation, environmental damage, declining water value, and harm to species variety [112–117]. These adverse ecological influences, in turn, wear away the environmental procedures necessary for the production of crops, such as fertilization, pest management, aquatic retention, and nutrient resources [118]. This denotes that over a certain period, agriculturally focused land overview may reduce agrarian productivity [119]. Numerous studies have established crop diversity as being related to a drop in harvest volatility over a certain period [120–122]. Research advocates that this harvest progress is determined by the optimistic influence of divergence on the ecology services crucial to crop production, as well as on pest organization [123–125], soil well-being [126,127], and pollinator variety [128,129]. Agriculture uses 11% of the Earth's terrestrial surface for the production of crops and is accomplished by several players with supervision, such as NGOs and global organizations [130,131]. The main tendencies in agricultural land structure have been recognized in the emergent world, with 70% of land used for agricultural expansion by agriculturalists [132,133]. This is recognized in the key opinion that land is the basis of capital and control [134]. Such social opinions hosted on geopolitical dismay, social cultures, and technologies are barely unidirectional and, in most circumstances, create management clashes [135]. Studies around the world, for instance, [136] in India, [137,138] Pakistan, [139,140] China, [141] Kenya, and [142] Vietnam, noted that agrarian training, the suitable handling of agrarian land, and the appropriate use of food and agriculture resources are of leading prominence in attaining the aim of optimum harvest efficacy and sustainable agricultural productivity. Furthermore, it was also recommended that the suggested claims of the kernel, irrigation, and primary and trivial nutrients were central influences in acquiring projected crop yield [143]. Also, agriculture may have proficiency and practical awareness to accomplish farmhouse responses proficiently in order to acquire optimum harvest productivity. In that regard, many farmers in the economy of Pakistan have been unsuccessful in attaining targeted crop output because agriculturalists do not have adequate information to make rudimentary farm contributions at an optional level [144–146]. Collectively, the discussion shows that expansion in the area of agricultural land positively influences crop production. Hence, the hypothesis is stated as follows:

H2. *Agricultural land significantly positively influences crop production.*

2.1.3. Agricultural Land, Environmental Sustainability, and Food Production

Developments in food production over recent periods have shown leaps with human population evolution; these developments have originated at a price to equal the atmosphere and social well-being, while straight adverse responses to agrarian systems from environmental degradation these days threaten long-term agronomic productivity [140]. Corresponding investigation plans are required to direct people into a harmless, adequate space for farming. In the current period, the growth of agriculture marked with increas-

ing productivity has raised unintentional concerns [147]. Not a single investigation plan has been headed towards the damage of bio assortment; nonetheless, it has also caused enhanced CO₂ discharges and ecological deprivation [148]. The maximum worldwide food creation is derived from areas with significant environmental deprivation and allied social well-being costs [149]. A current significance for agronomy is recognizing resolutions for how additional food is produced, whereas the importance of natural assets has not declined. The ecological possessions of agronomic assets need to be evaluated and clarified as a cure [150–153].

Environment variation and ecological deprivation, with biodiversity damage, persist as the prime tests that current and future groups face. The up-to-date statement of the Intergovernmental Panel on Climate Change (IPCC) forms the extensive and prevalent influences of environmental variation over people and communal schemes of environment schemes and states that we agreed to exceed the 1.5 °C edge by 2040 [154]. During a similar period, in several areas of the biosphere, natural capital such as land, forestry, and aquaculture have been gradually tainted or curtailed [155], and additional classes are more vulnerable to worldwide loss than ever before [156]. Additional land is required to work as a CO₂ drop to lessen environmental variation by pulling CO₂ from the troposphere. Nonetheless, the preservation of bio-assortment needs additional land to be saved and re-established. This problem of environmental variation and ecological deprivation increases numerous safety worries as it considerably raises the probability of nutrition uncertainty [157], clashes, and criminalities [158] in the absence of faith and collaboration [159] and relocation and enforced dislocation [160,161]. This endangers individual, public, nationwide, and global safety [162–164].

Moreover, additional nutrition must be created from agricultural land structures to feed the growing world population. Resolutions to harvest further nutrition with fewer resources while lessening contrary ecological and environmental concerns entail supportable agricultural land usage in addition to progressive biotechnology and agriculture [6]. Referring to the sustainability of the environment [165] shows that the potential for carbon sequestration through ecosystem restoration and extensive use of land to meet dietary preferences creates a “carbon opportunity cost”. Here, they plan the scale of this prospect and find that a move in worldwide food production to shrub-grounded feeds through 2050 might be a clue to the seizure of 332–547 Gt CO₂, equal to 99–163% of the CO₂ release budget consistent with the 66% chance of regulating heating to 1.5 °C. The literature [166] examines the environmental influence of agricultural land redeployment in China. Forecasts show that by 2050, additional retrieval of marginal land under present policies will worsen environment-associated costs. Farmland safety threats will be considerably intensified in the future due to the clash between nutriment farming and conservational sustainability. Their paper shows that emergent marginal land repossession worldwide must be constrained and encouraged to increase harvest yields to attain food security and environmental assistance. Accordingly, [167] shows that the adaptation of Sustainable Development Goals (SDGs) in 2015 relocated attention to the issues linked to sustainability in both emerging and advanced states. They show how agrarian productivity—a primary driver for attaining many of these Sustainable Development Goals—is disturbed by emissions of CO₂, deforestation, consumption of renewable energy, nature properties, and local incorporation in the 10 Association of Southeast Asian Nations (ASEAN) nations. Their empirical results show that ecological deprivation (as in CO₂ emission) decreases agrarian yield over the area. Moreover, [62] shows that agrarian production is the basis of China’s state economy, and green agricultural productivity is the driving power for the growth of a green economy and the precondition for recognizing green performance and sustainable ecology. They also conclude that, dissimilar to customary agrarian creation, the notion

of green agrarian harvest too widely reflects several aspects such as state economy, atmosphere, and communal growth. It points the way to the future of the Chinese agricultural economy. Thus, overall, we expect that high environmental sustainability will increase the provision of agrarian land to contribute to a growth in food-level productivity. Hence, the hypothesis is stated as follows:

H3. *In the presence of environmental sustainability, an increase in agricultural land increases food production.*

2.1.4. Agricultural Land, Environmental Sustainability, and Crop Production

Agricultural productivity has declined due to climate issues, such as rainfall, CO₂ emissions, and temperature deviation [168,169]. These issues damage the agronomy sector, increasing the exposure among small, semi-medium, and medium agriculturalists whose welfare and customs of existence rest on agrarian actions in emergent economies [166]. Climate variation's upshot might differ from economy to economy, being reliant on topographical sites, and reduces the output of the agronomy sector and its associated undertakings in emergent economies [170–172]. Emergent economies are more reflective than advanced states due to a significant dependence on food production for nutrition, a shortage of practical novelty, and an absence of environment ambiguity edition approaches for agronomic productivity [173]. Farming productivity is directly impacted by variations in atmospheric components such as temperature (AT), CO₂, and rainfall.

Global warming and temperature waves have posed challenges for emergent nations due to the absence of ecological approaches and guidelines [174,175]. A pragmatic model views raising biodiversity as advancing the productivity of crops and the security of food, and backs environment-resistant farming. Impending struggles should expand harvests that mark land out as more multi-efficient than monocultures. Land usage is an anthropogenic element influencing soil responses and other biochemical factors. The constantly rising demand for additional agrarian land and the deprivation of prevailing's create the necessity to address the issue of the growth of sustainable technologies and the formation of satisfactory supporting ecological sustainability [176].

Worldwide, in the late 1960s, the demand for marketable crops grown in rigorously managed structures enlarged, backing a lessening of crop types and genomic assortment globally [177]. Prevailing data demonstrate the adverse environmental influences of this transfer, generally due to rigorous yearly crop production and land simplification [178–183]. Basic agrarian land is related to the deprivation of primary ecology services or the remunerations that are easily obtained from the atmosphere; this is vital to agricultural productivity, and includes soil productiveness, food cycling, and genomic bio-diversity, as well as modifying amenities with soil retention, fertilization, common pest resistance, and aquatic sanitization. Ecological services produced by agrarian structures are mainly attained through over-provisioning amenities, i.e., nutrition, fiber, and production of fuel, over traditional amenities, such as increasing land aesthetics, constructing societal setups, and market involvement, and further amenities, such as natural environment conservation and these approaches response into subsidiary and regulating facilities. Environmental factors that disturb agricultural manufacture (denoted as damages), for instance, damage to crops or aquatic life from natural hunters and influences, may add to disservices caused by farming, with nutrient runoff or environmental damage [184]. Management of agronomy enhances ecological well-being and the provisioning of significant ecology services for agronomy, whereas lessening disservices can raise the firmness and amount of production over a given period, leading to a declining necessity for external inputs, and enhancing the transfer of ecological services to the broader ecology [185–188]. Thus, In conclusion, we expect that high environmental sustainability increases the provision of agricultural

land, which results in a rise in the efficiency rate of crops. Hence, the hypothesis is stated as follows:

H4. *In the presence of environmental sustainability, an increase in agricultural land increases crop production.*

3. Materials, Methods, and Study Data

3.1. Econometric Model Specification

The key aim of the present study is to evaluate the influence of diverse key variables of agricultural undertakings such as food production, crop production, and environmental sustainability as a moderator on the agricultural land of China. As per the chief objective of the research, the following models are planned:

$$FP_t = f(AGL_t, CO_2t, GDPG_t, UP_t, INF_t) \quad (1)$$

$$CP_t = f(AGL_t, CO_2t, GDPG_t, UP_t, INF_t) \quad (2)$$

$$FP_t = f(AGL_t, AGL_t * ES_t, CO_2t, GDPG_t, UP_t, INF_t) \quad (3)$$

$$CP_t = f(AGL_t, AGL_t * ES_t, CO_2t, GDPG_t, UP_t, INF_t) \quad (4)$$

Equations (1) through (4) can be further extended as follows:

$$FP_t = \beta_0 + \beta_1 AGL_t + \beta_2 CO_2t + \beta_3 GDPG_t + \beta_4 UP_t + \beta_5 INF_t + \varepsilon_t \quad (5)$$

$$CP_t = \beta_0 + \beta_1 AGL_t + \beta_2 CO_2t + \beta_3 GDPG_t + \beta_4 UP_t + \beta_5 INF_t + \varepsilon_t \quad (6)$$

$$FP_t = \beta_0 + \beta_1 AGL_t + \beta_2 AGL_t * ES_t + \beta_3 CO_2t + \beta_4 GDPG_t + \beta_5 UP_t + \beta_6 INF_t + \varepsilon_t \quad (7)$$

$$CP_t = \beta_0 + \beta_1 AGL_t + \beta_2 AGL_t * ES_t + \beta_3 CO_2t + \beta_4 GDPG_t + \beta_5 UP_t + \beta_6 INF_t + \varepsilon_t \quad (8)$$

where FP_t presents the annual level of food production in models 5 and 7; CP_t presents the yearly level of crop production in models 6 and 8; AGL_t represents the quantity of agricultural land available for the productivity of crop in models 5 through 8; the annual emission level of CO_2 is represented by variable CO_2t in models 5 through 8; the variable $GDPG_t$ shows yearly GDP growth level in models 5 through 8; the variable UP_t shows the annual growth of the urban population level in models 5 through 8 and the variable INF_t shows the yearly level of inflation in the economy in models 5 through 8. The study has used environmental sustainability (ES_t) as the moderator in models 7 and 8. The dummy variable (ES_t) is 1 for high environmental sustainability and 0 for others. It is measured by the median split of variable CO_2 emissions and is considered above the median high CO_2 emission and below the median low CO_2 emission. Therefore, low CO_2 emission is 1, and high CO_2 emission is 0. The environmental sustainability (ES) moderator is a dummy variable computed from the CO_2 emission variable by taking a median split and below the median. Low CO_2 emission is considered as 1, and is termed environmental sustainability (ES). The term $AGL_t * ES_t$ shows the interaction variable in models 7 and 8. The term ε_t represents the error variable in models 5 to 8. The model's parameters (β_0 – β_6) reveal the influence of independent constructs over dependent constructs, and the term t in models represents the time measurement.

3.2. Econometric Methodology and the Research Design Strategy

The paper aims to find the potential influence of agricultural land on food and crop productivity, with environmental sustainability as a moderating element. In the initial

phase, we followed the studies of [189–196]. We used the advanced techniques of time series analysis, particularly the autoregressive distributed lag model (ARDL) of [197,198].

Accordingly [199] have projected the theory of the ARDL bounds test, which predominantly uses Wald statistics in the model to regulate whether the construct's lag factor is substantial. Refs. [138,198], grounded on the ARDL theory of the bounds test and the VAR (p) model, have consecutively projected the ARDL cointegration technique to identify several study factors' long- and short-term dynamic relations. Compared to the traditional cointegration model, the ARDL cointegration model has several benefits. As variables could be in the order of I(0) or I(1), the outcomes lead the research to ARDL-bounds testing [200]. The ARDL model has several benefits over other test approaches to check cointegration. First, this technique is most suitable when factors combine I(0) and I(1). Second, we can simultaneously evaluate both short- and long-term relationships between variables with the ARDL bounds test methodology. Moreover, the ARDL model also handles the endogeneity problem by adding lags in independent and dependent constructs. The particular arrangement of the ARDL model, in the context of Equations (5) through (8), can be illustrated as follows. The model for ARDL model is formulated as:

$$\Delta \hat{y}_t = b_0 + \sum_{i=1}^m \beta_i \Delta \hat{y}_{t-i} + \sum_{i=0}^n \delta_i \Delta X_{t-i} + \hat{a}_1 \hat{y}_{t-1} + \hat{a}_2 X_{t-1} + \mu_t \quad (9)$$

where β and δ show the short-term estimation information and $\hat{a}_1$ and $\hat{a}_2$ represent the factors of the long-term relations. Δ indicates the first difference of constructs. The m and n represent the lags of the model's variables. The term μ shows an error variable in the model.

The bounds test technique of cointegration requires us to perform an F-test on the nominated ARDL bounds test model with a suitable length of lags. We apply a requirement of up to lag three at the variable level and then choose the optimum lag length according to the Criterion of Akaike Information (AIC). The regular F test establishes cointegration [201,202], which provides two groups of critical values (i.e., upper and lower bounds) for the bounds test. The upper and lower thresholds contain expectations that all factors are I(0) and I(1). This delivers a constraint of a bound that contains all likely orderings of the constructs. If the F-statistic produced from the test of the bound equation is over the higher bound, the hypothesis of the null of no cointegration is excluded. The test cannot reject the null hypothesis if it is lower than the lesser bound. Conversely, if the rate of the F-statistic is within the lower upper bounds, the results are indecisive. In a situation of cointegration among variables, the second phase takes in the valuation of a model in the long term with the equation as follows:

$$\hat{y}_t = b_0 + \sum_{i=1}^p \beta_i \hat{y}_{t-i} + \sum_{i=0}^q \delta_i X_{t-i} + \varepsilon_t \quad (10)$$

where β and δ signify the variable's coefficients and p and q represents the periods of slowdown for constructs. The statistical notion ε_t denotes the error variable or white noise term at the t period.

If the constructs in Model 10 have a relation of cointegration, around an (ECM) [203]; therefore, we can review the optimum term of lag in the model using one or extra data values (AIC, SIC, HQ, etc.), and the standards of p and q , and vice versa for Model 10. So, we examine the hypothesis of null of whether there is a relation of cointegration among the series of constructs in the model, that is:

Hypothesis of null H_0 : $\beta_i = 0$

Hypothesis of alternate H_1 : $\beta_i \neq 0$; ($i = 1; 2; 3; 4$)

According to [204], whether or not to discard the hypothesis of null is decided by linking the correlation coefficient's F-statistic in the test of F-statistics by the critical rate of the ARDL cointegration constant of the acute rate of the extreme asymptotic extent of the F-statistic [205]. However, as the nominated sample extent is somewhat minor, we associate the rate of the model F-statistic with the beginning rate of the asymptotic dispersal of the F-statistic proposed by [206].

(1) If the F-statistic of the projected model is superior to the equivalent maximum critical rate in the acute standards table, it stands that a relation of cointegration happens among the constructs, and the hypothesis of null is not accepted. Equally, once it is a smaller quantity than the lowermost level in the criteria table, it stands that that no cointegration occurs among the factors.

(2) If the projected model's F-statistic lies in the maximum and minimum bounds in the critical values table, it is essential to suppose that the construct is a random combination of $I(0)$ and $I(1)$. Conferring to the pertinent description, if the model of ARDL (p, q, r, m, n) cointegration passes the criteria test of the F-statistic assessment of the asymptotic distribution, a formerly cointegrating or long-term link occurs among the constructs [207].

As seen in [40], the short-term economic action constraints result from assessing an ECM model regarding the long-term estimate, and there is at least one causality between the constructs resolved by the F-statistic of the long-term approximation and the ECM lag. So, we are obliged to reconsider the ECM matter in the model. Conferring to [208], the model of ARDL-VECM is recognized for the constructs in the model, and the grouping of causality and ECM is cast off to more investigation in the short-term dynamics among the constructs in the model. After the long-term relationship is recognized, we can acquire the short-term dynamics by altering Model 8 to the arrangement of an Error Correction (ECM) model following [209,210] as:

$$\Delta \hat{y}_t = C + \sum_{i=1}^p \beta_i \Delta \hat{y}_{t-i} + \sum_{i=0}^q \delta_i \Delta X_{t-i} + \phi \hat{y} ECT_{t-1} + \mu_t \quad (11)$$

where ECT_{t-1} is the limit of ECM, i.e., totally, the constants of the short-term model are the factors associated with the short-term dynamics through which the model is merged to the state of equilibrium, and the term ϕ signifies the factor of error correction for the processes of the speed of adjustment at which the imbalance of instability is attuned in the short run towards the direction of long-term equilibrium. The error correction model (ECM) bounds testing, cointegration test method, and Toda–Yamamoto causality analysis technique require a series of standard statistical tests that will be discussed in subsequent sections.

3.3. Unit Root Tests

All the pragmatic research using time series data adopts the idea that these sequences have steadiness characteristics. Without steadiness characteristics, estimating each variable among the time series factors or among the time series data is usually wrong. Over further arguments, each construct must pass through a time (termed the lagged break), so its influence seems to be the dependent factor, which is linked to psychosomatic, procedural, and legitimate aspects. For instance, once agricultural land is increased, it takes some time for the outcomes of this rise to be reflected in food and crop production enhancement. The variability of the time series for variables under investigation is because it contains a unit root, so the test of the unit root needs to be implemented to confirm the firmness of the study's variable, the data for the time series, and the degree of integration of variables. Though there are various unit root tests, we will count on the precision and generality of the following two tests:

3.4. The Augmented Dickey–Fuller Test (ADF)

In the Augmented Dickey–Fuller (ADF) test [211], the equation of the model is assessed in its comprehensive system (by the existence of track breaker and period route restrictions) as follows:

$$\Delta \hat{y}_t = b_0 + b_1 t + b_2 \hat{y}_t - 1 + \sum_{i=1}^{\hat{g}} b_i \Delta \gamma \hat{y}_t - i + \varepsilon_t \quad (12)$$

where the term t shows the figure of time or years; i shows the gap of time; $\hat{g}$ shows gap length; $\hat{y}_t$ shows the variable's values to be analyzed in t year; and b_i , b_2 , b_1 , and b_0 indicate coefficients in the model. The notation ε_t specifies the error term at t year. In the ADF test, the null hypothesis is projected as $b_2 > 0$ and assumes that the time series variable is not stationary. In contrast, the alternate proposition is $b_2 = 0$, which assumes that the time series variable is not stationary.

3.5. The Phillips and Perron (PP) Test

The Phillips–Perron unit root test marks an additional common postulation to the Augmented Dickey–Fuller (ADF) test, that is, the data in the time series are produced by manner of autoregressive integrated moving average (ARIMA), which contracts with the issue of serial correlation by a nonparametric correction, in which the model equations are assessed (with the trend and cutter):

$$\Delta \hat{y}_t = b_0 + b_1 t + b_2 \hat{y}_t - 1 + \varepsilon_t \quad (13)$$

The time series research considers PP tests superior and more exact than ADF tests, particularly with sample size. The PP test is recommended if there are contradictions or variations between the two tests' results.

3.6. Sources of Data

In the present study, we use yearly data from 1990 to 2021 and use the ARDL technique to inspect the long- and short-term dynamic relations among China's agricultural land (AGL), food production (FP), CP, the interaction term (AGL*ES), carbon dioxide emission (CO₂), GDP growth (GDPG), urban population (UP), and inflation (INF). In the present paper, to maintain focus on the long- and short-term dynamic associations among China's agricultural land, food production, and crop production, we have selected the World Bank's World Development Indicator (WDI) series for China (see Table 1). Concurrently, the study's model presents further constructs of manufacturing economic progress, such as inflation, urban population, and gross domestic product growth, to alleviate the problem of disregarding factor deviations. Additionally, taking into account the values of inclusiveness and usage devoted to the study data, the total professed factors in the model were altered to a dual logarithmic setup, and this alteration assisted in achieving a comparatively steady data spread and in amending the issue of heteroskedasticity, the issue of heteroskedasticity, making the assessed outcomes clear and easy to understand.

Table 1. The main variables of the research and sources of data.

Study Variables	Notation	Description Detail	Data Source
Agricultural Land	AGL	Agricultural land (% of land area)	WDI
Food Production	FP	Index of food production (taken as 2014–2016 = 100)	WDI
Crop Production	CP	Index of crop production (taken as 2014–2016 = 100)	WDI
CO ₂ Emission	CO ₂	Emissions of CO ₂ (calculated as metric tons per capita)	WDI

Table 1. Cont.

Study Variables	Notation	Description Detail	Data Source
Environmental Sustainability	ES	The (ES) is the dummy variable indicated by 1 for high environmental sustainability and zero otherwise. It is measured by the median split of the variable CO ₂ emission and considered above median high CO ₂ emission and below median low CO ₂ emission. Therefore, low CO ₂ emission is regarded as 1 to compute the dummy variable (ES) environmental sustainability variable.	WDI
GDP Growth	GDPG	GDP growth (calculated as annual %)	WDI
Urban population	UP	Urban population (calculated as % of total population)	WDI
Inflation	INF	Inflation, GDP deflator (annual %)	WDI

Source: World Bank's World Development Indicator (WDI) series for China from 1990 to 2021.

4. The Results

4.1. The Results of Descriptive Statistics, Correlations, and Preliminary Investigation

As stated, the key objective of the paper is to investigate the relations among agricultural land, food production, crop production, and environmental sustainability as moderating elements. Table 2 presents the outcomes of the descriptive statistics of the study variables. The outcomes of summary statistics confirm that averages of agricultural land, food production, crop production, environmental sustainability, and other control variables (GDP growth, urban population, and inflation) are all positive. In particular, the urban population (UP) is less on average than the other variables. The CO₂ is high on average among all variables. Additionally, as shown in Table 3, the pairwise correlation analysis shows that agricultural land positively correlates with food production, crop production, and CO₂ emission. In contrast, GDP growth, urban population, and inflation negatively correlate with agricultural land. The correlation analysis estimation also shows a correlation of positive means for GDP growth, urban population, and inflation.

Table 2. The results of the descriptive statistics.

Variables	Mean	SD	Min	Max
AGL	5,249,922	51,972.09	5,065,920	5,290,386
FP	75.5422	22.0192	37.14	103.25
CP	75.8363	22.0445	41.61	108.35
CO ₂	6,329,919	3,243,210	2,173,360	1.10 × 10 ⁷
GDPG	9.0808	2.7434	2.2397	14.2309
UP	3.5062	0.7274	1.8385	4.6017
INF	4.6640	4.8554	−1.2631	20.6170

Note: Table 2 presents a summary of the statistics of the study's main variables utilized in empirical models. Mean, SD, Min, and Max show the average value, standard deviation, minimum value, and maximum values of the study's variables, respectively. All the variables of the study are reported in Table 1.

Table 3. Correlation analysis.

	AGL	FP	CP	CO ₂	GDPG	UP	INF
AGL	1						
FP	0.8115 ***	1					
CP	0.7638 ***	0.9950 ***	1				
CO ₂	0.7084 ***	0.9706 ***	0.9827 ***	1			
GDPG	−0.0729	−0.4422 ***	−0.4752 ***	−0.4354 ***	1		
UP	−0.6339 ***	−0.9204 ***	−0.9458 ***	−0.9376 ***	0.5494 ***	1	
INF	−0.2871	−0.4612 ***	−0.4451 ***	−0.3509 **	0.6111 ***	0.3952 **	1

Notes: Table 3 presents the results of the correlation analysis. See Table 1 for variable definitions. Subscripts **, and *** indicate the level of significance at 5%, and 1%, respectively.

Moreover, to further examine the correlation between agricultural land and food production, and between agricultural land and crop production, this study uses the main analysis variables for explicit research. Figures 2–4 demonstrate that all three indicators—food production, crop production, and carbon dioxide emission (CO₂)—positively correlate with agricultural land. Moreover, Figures 4–7 demonstrate that all three indicators—GDP growth, urban population, and inflation—are negatively correlated with agricultural land.

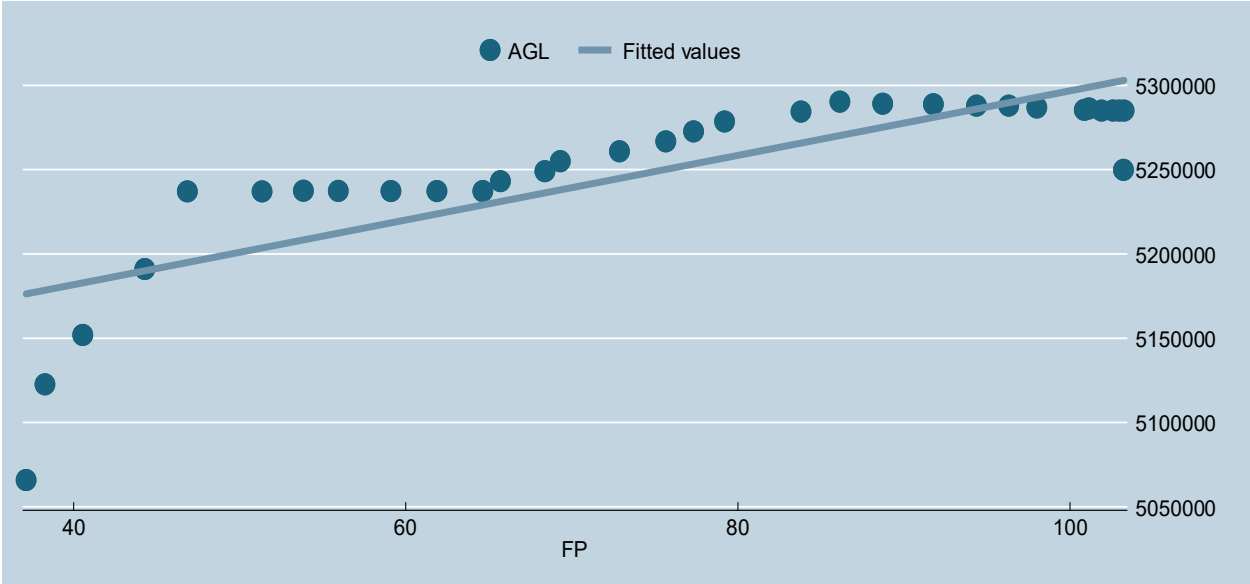


Figure 2. Food production and agricultural land.

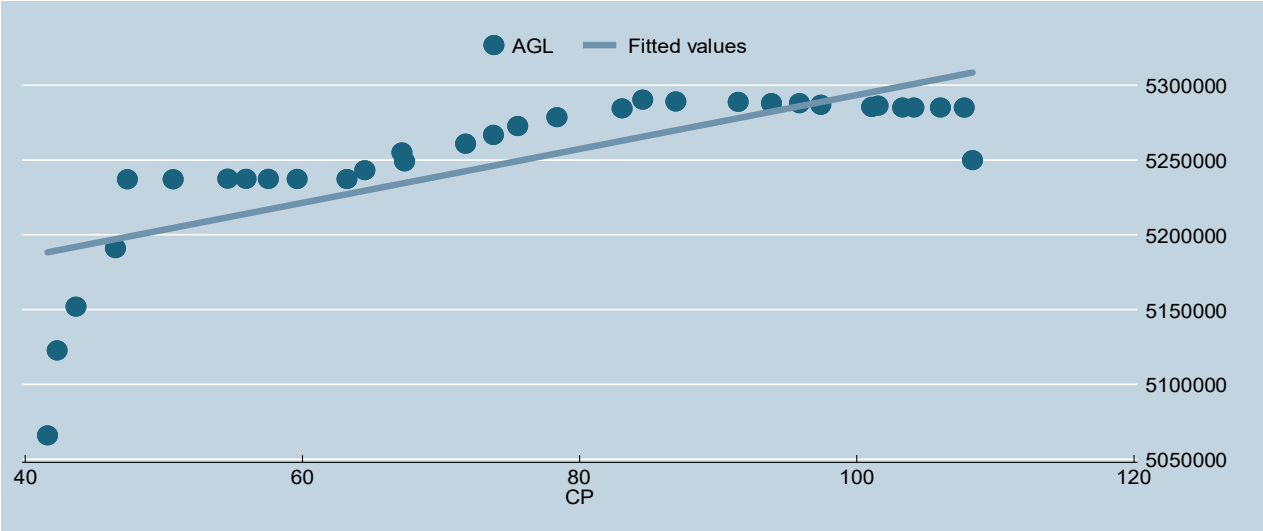


Figure 3. Crop production and agricultural land.

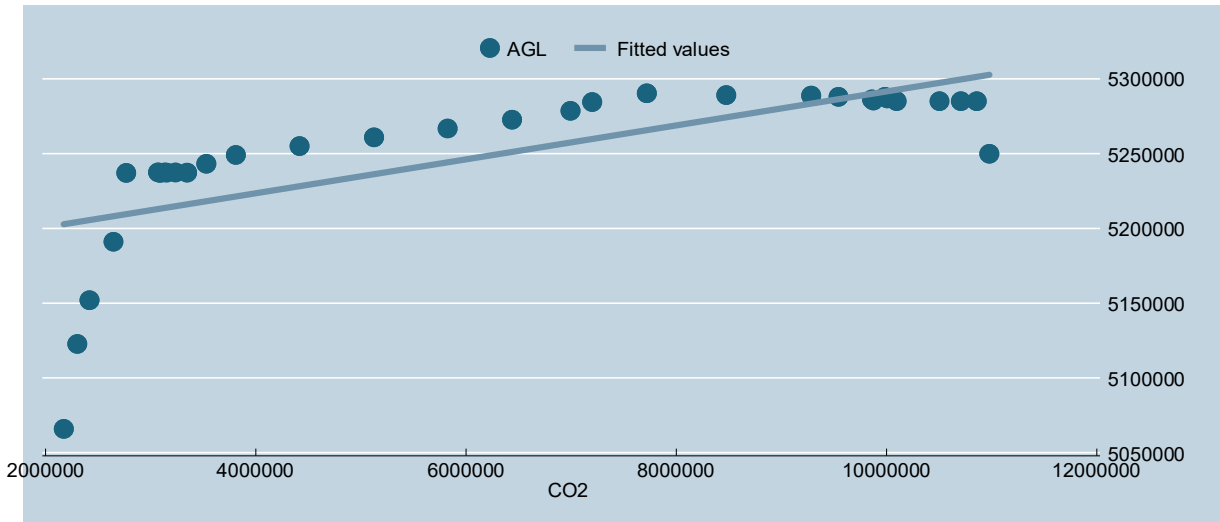


Figure 4. Carbon dioxide emission (CO₂) and agricultural land.

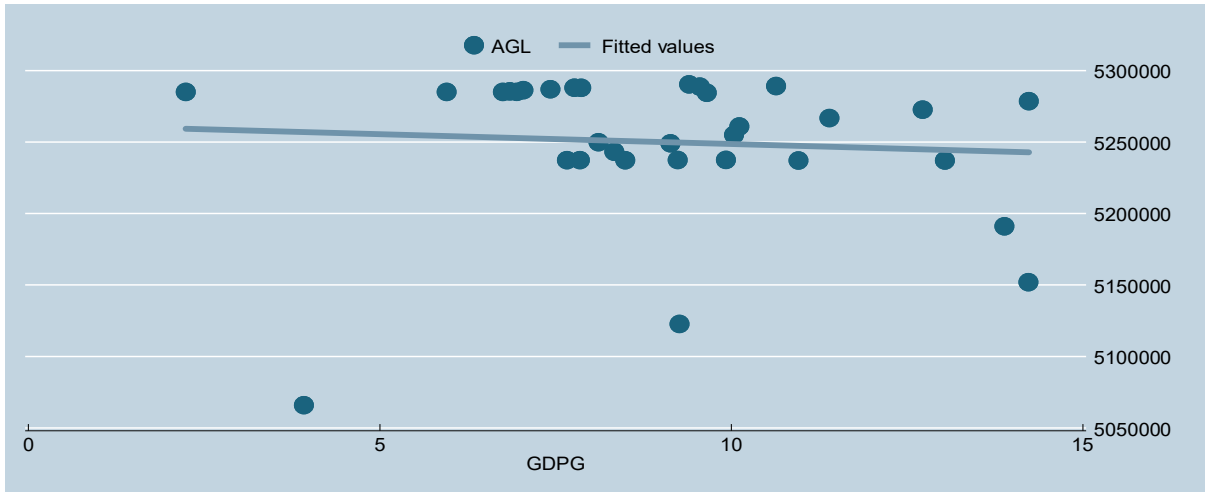


Figure 5. GDP growth and agricultural land.

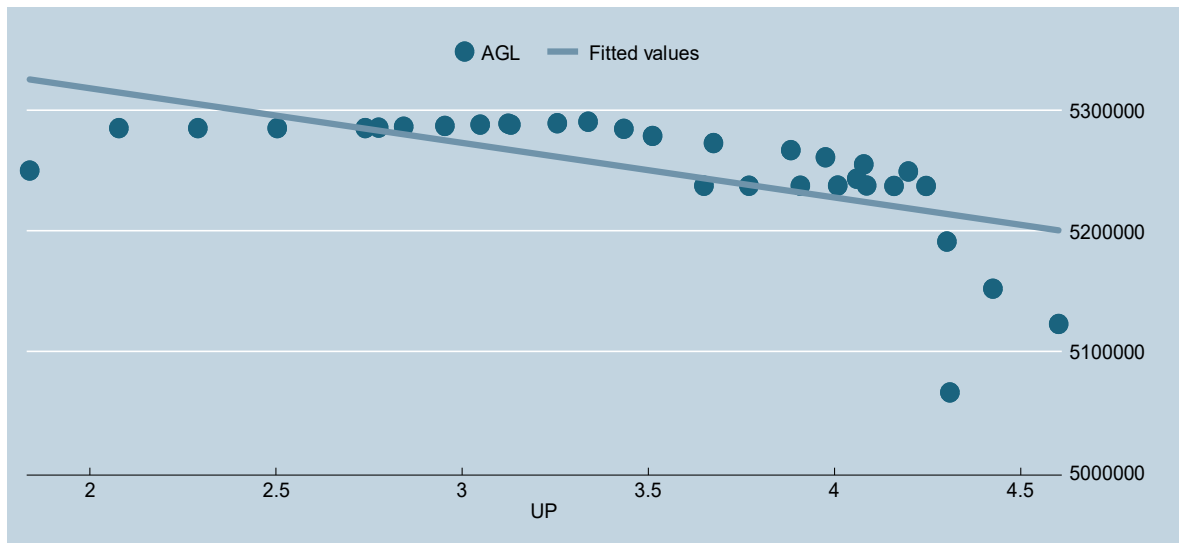


Figure 6. Urban population and agricultural land.

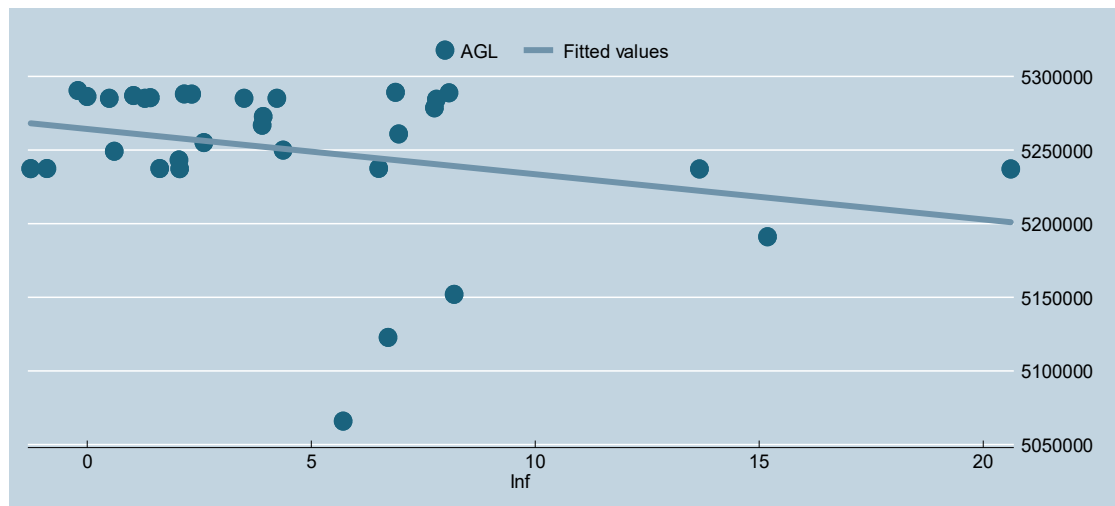


Figure 7. Inflation and agricultural land.

4.2. Ordinary Least Square (OLS) Regression

The estimated outcomes for the models of baseline (Equations (5) and (6)) are offered in Table 4. Columns 1 and 3 depict the estimation outcomes with the primary explanatory variable AGL and control variables. The coefficients of AGL are statistically significant at the 1% level and show positive association in columns 1 and 3. To test the effect of the moderating element, we use the environmental sustainability (ES) with AGL as (AGL*ES) interaction term in models (Equations (7) and (8)) shown in Table 4. Columns 2 and 4 show the outcomes of the estimated coefficients for (AGL*ES). The coefficient of (AGL*ES) is significant and positive at the 1% significance level in columns 2 and 4. In conclusion, the findings of the empirical investigation for environmental sustainability show that in China, low CO₂ emissions enhance food and crop production due to an increase in the efficiency of agricultural land.

Table 4. Results of ordinary least square (OLS) regression.

Variables	Dependent Variable: FP		Dependent Variable: CP	
AGL	0.0001 *** (3.81)	0.0001 *** (7.69)	0.0001 *** (5.69)	0.0001 *** (4.40)
AGL*ES		9.98×10^7 ** (2.12)		8.72×10^7 * (1.93)
CO ₂	2.78×10^6 *** (9.84)	4.81×10^6 *** (7.94)	4.15×10^6 *** (11.20)	5.47×10^6 *** (9.05)
GDPG	−0.5588 *** (−3.53)	0.5081 (1.46)	−0.4956 * (−1.81)	−0.0875 (−0.33)
UP	2.9798 ** (2.44)	−5.7270 ** (−2.38)	−5.6367 *** (−2.92)	−4.5641 ** (−2.41)
INF	−0.1047 (−1.58)	−0.5603 *** (−4.70)	−0.2874 *** (−2.77)	−0.3757 *** (−3.18)
Constant	−485.6142 *** (−6.61)	−606.0189 *** (−7.17)	−486.2795 *** (−4.92)	−254.785 *** (−3.68)
F-test	912.25	413.05	672.79	448.81
Prob.	0.0000	0.0000	0.0000	0.0000
R ²	0.9979	0.9904	0.9926	0.9908
Obs.	32	32	32	32

Notes: Table 4 presents the results of the ordinary least square (OLS) estimates of Equations (1)–(4). See Table 1 for variable definitions. Subscripts *, **, and *** indicate the level of significance at 10%, 5%, and 1%, respectively.

4.3. Stationary/Unit Root Test

The primary purpose of the stationary or unit root test is to check the evenness of long-term direct associations of primary variables and to elude counterfeit estimations due to pseudo-regression. As shown in Table 5, the actual data series is nonstationary conferring to ADF and PP tests, but the chain of variables (AGL, CP, FP, CO₂, GDPG, UP, INF) is stationary at less than a significance level of 1% with first-order differences. Hence, all the variables scrutinized for the study show first-order integration I(1) [212,213]. Since the unit root tests have ensured first-order differences for a series of data, it is now safe to emphasize finding the presence of cointegration among a selected series of variables in the study. As per the specification, finding the maximum lag length is necessary. Therefore, the present study emphasizes the criterion (AIC) of Akaike's information selection of lag at a minimum level. The selected maximum lag order is set to $p = 3$, based on AIC [214]. Since the selected series of the variable show orientation of I(0) or I(1), it is safe to make a further estimation with the ARDL model for bounds testing.

Table 5. Stationary/unit root test.

Variables of the Study	(Test of ADF)		(Test of PP)	
	I(0)	I(1)	I(0)	I(1)
AGL	−2.6301 (0.0983)	−6.0738 *** (0.0000)	−2.8447 (0.0641)	−6.1327 *** (0.0000)
CP	0.8849 (0.7791)	−7.1586 *** (0.0000)	−0.5358 (0.8708)	−7.2308 *** (0.0000)
FP	−2.7952 0.0706	−7.7141 *** (0.0000)	−2.4831 (0.1291)	−4.3910 *** (0.0016)
CO ₂	−0.5934 (0.8577)	−6.1612 *** (0.0000)	−0.0413 (0.9474)	−6.6650 *** (0.0000)
GDPG	−2.8453 (0.0637)	−4.6580 *** (0.0008)	−3.1310 (0.0345)	−4.7027 *** (0.0007)
UP	1.4077 (0.9985)	−4.8629 *** (0.0005)	1.8590 (0.9996)	−4.8629 *** (0.0005)
INF	−2.8845 (0.0591)	−4.8944 *** (0.0005)	−2.4923 (0.1270)	−4.7076 *** (0.0007)

Notes: Table 5 presents the results of the unit root test. See Table 1 for variable definitions. Subscript *** indicates the level of significance at 1%.

4.4. Autoregressive Distributed Lag (ARDL) Bounds Test for Cointegration Analysis

Usually, researchers use the ARDL bounds test to examine the long-term cointegration between the nexus of constructs used in study [215]. The study first uses the lag order selection criterion grounded on the minimum (AIC) value to identify the best lag length. Secondly, a general F-test based on Wald statistics is executed for each primitive variable (first-order lagged). Moreover, the determined critical values from the F-statistics from the model of conditional error correction ARDL contingent at the bounds test of cointegration are applied as a final point to define the long-term relationship between the factors used in the study models [216], rendering results for the model of ARDL cointegration estimation (shown in Tables 6 and 7), and establishing that the standards of the F-Test Statistics are more significant than the upper limit at both the 1% significance level for Models 5, 6, and 8, and at the 5% significance level for Model 7, indicating that there is the cointegration between variables is in the long term of all of the study's models, which is consistent with the study of [206].

Table 6. Results of the ARDL bounds test.

Models Selected	F-Value	Sig.	I(0)	I(1)	Cointegration
FP = f (AGL, CO ₂ , GDPG, UP, INF) (2, 1, 0, 2, 0, 2) K = 5, AIC = 2.7007	6.8319	10%	2.26	3.35	Accepted
		5%	2.62	3.79	
		2.5%	2.96	4.18	
		1%	3.41	4.68	
CP = f (AGL, CO ₂ , GDPG, UP, INF) (3, 2, 2, 3, 3, 3) K = 5, AIC = 1.4670	14.9564	10%	2.26	3.35	Accepted
		5%	2.62	3.79	
		2.5%	2.96	4.18	
		1%	3.41	4.68	
FP = f (AGL, AGL*ES, CO ₂ , GDPG, UP, INF) (2, 1, 2, 1, 2, 0, 2) K = 5, AIC = 2.8277	3.9967	10%	2.26	3.35	Accepted
		5%	2.62	3.79	
		2.5%	2.96	4.18	
		1%	3.41	4.68	
CP = f (AGL, AGL*ES, CO ₂ , GDPG, UP, INF) (2, 3, 3, 3, 3, 3, 1) K = 6, AIC = 0.9670	9.5680	10%	2.26	3.35	Accepted
		5%	2.62	3.79	
		2.5%	2.96	4.18	
		1%	3.41	4.68	

Notes: Table 6 presents the results of the ARDL bounds test. See Table 1 for variable definitions.

Table 7. Long-term coefficient estimation analysis results (cointegration test).

	Dependent Variable (FP)		Dependent Variable (CP)	
AGL	0.0001 *** (6.9940) [1.71 × 10 ⁵]	0.0001 *** (3.9539) [1.50 × 10 ⁵] 9.71 × 10 ⁷ **	7.33 × 10 ⁵ *** (3.9539) [1.85 × 10 ⁵]	6.21 × 10 ⁵ *** (3.9788) [1.56 × 10 ⁵] 1.24 × 10 ⁶ ***
AGL*ES		(2.2401) [4.33 × 10 ⁷]		(2.7604) [4.50 × 10 ⁷]
CO ₂	4.36 × 10 ⁶ *** (9.5781) [4.55 × 10 ⁷]	5.35 × 10 ⁶ *** (9.7160) [5.51 × 10 ⁷]	4.30 × 10 ⁶ *** (8.7222) [4.93 × 10 ⁷]	5.57 × 10 ⁷ *** (9.7240) [5.72 × 10 ⁷]
GDPG	−0.2534 (−0.8592) [0.2950]	−0.0858 (−0.3041) [0.2822]	−0.2560 (−0.8016) [0.3194]	−0.0236 (−0.0804) [0.2933]
UP	−2.1702 (−0.8592) [2.0269]	−1.8714 (−1.0517) [1.7795]	−5.7365 ** (−2.6137) [2.1948]	−5.2745 *** (−2.8520) [1.8494]
INF	−0.5314 *** (−4.2834) [0.1241]	−0.5336 *** (−4.8674) [0.1096]	−0.3995 *** (−2.9741) [0.1343]	−0.4090 *** (−3.5901) [0.1139]
C	−567.9489 *** (3.9539) [88.2387]	−526.9110 *** (−6.7869) [77.6371]	−6.4365 *** (−6.7868) [77.6371]	−268.0355 *** (−3.3219) [80.6875]

Notes: Table 7 presents the results of the cointegration test. See Table 1 for variable definitions. Subscripts **, *** indicate the significance level at 5%, and 1%, respectively.

4.5. The Estimation of Long-Term Coefficients

Since the ARDL bounds test endorses the permanency of long-term cointegration among the constructs of all the models used in the study, it is now required to utilize the ARDL model for p, q, r, m, and n by assessing long-term coefficients of cointegration at every descriptive variable to analyze the AGL effect at FP and CP (see Tables 7 and 8). Table 7 displays long-term cointegration outcomes aimed at diverse ARDL models at p, q, r, m, and n. Table 7 shows that agricultural land has a positive and significant relation with FP and CP at a 1% significance level and vice versa, which backs the feedback hypothesis. Moreover, environmental sustainability (ES) as a moderating construct significantly impacts agricultural land. As a result, it has increased food and crop production in China. As can be seen in Table 7, AGL*ES has a significant and positive impact at FP and CP at the 5% and 1% levels of significance, respectively.

Table 8. The diagnostic test for the ARDL model estimation results for long-term coefficients.

Model	Test	Parameters	Value	Probability
CP = f (AGL, CO ₂ , GDPG, UP, INF)	LM Test	F-Test	0.0081	0.9311
		Obs*R ²	0.0392	0.8431
	ARCH	F-Test	0.4497	0.5084
		Obs*R-squared	0.4760	0.4902
	RESET Test (Ramsey)	t-test statistic	0.1227	0.9063
		F-statistic	0.0151	0.9063
	Jarque–Bera		0.6179	0.7342
	f (AGL, CO ₂ , GDPG, UP, INF)	LM Test	F-Test	1.6194
Obs*R ²			5.3274	0.0697
ARCH		F-Test	0.0404	0.8423
		Obs*R-squared	0.0433	0.8352
RESET Test (Ramsey)		t-test statistic	2.1770	0.0763
		F-statistic	4.7393	0.0948
Jarque–Bera			0.3776	0.8280
FP = f (AGL, AGL*ES, CO ₂ , GDPG, UP, INF)		LM Test	F-Test	2.3611
	Obs*R ²		3.4265	0.0642
	ARCH	F-Test	0.0704	0.7928
		Obs*R-squared	0.0752	0.7839
	RESET Test (Ramsey)	t-test statistic	1.2331	0.2326
		F-statistic	1.5206	0.2326
	Jarque–Bera		0.1432	0.9309
	CP = f (AGL, AGL*ES, CO ₂ , GDPG, UP, INF)	LM Test	F-Test	1.5776
Obs*R ²			2.6925	0.1008
ARCH		F-Test	0.2889	0.5953
		Obs*R-squared	0.3070	0.5795
RESET Test (Ramsey)		t-test statistic	1.2353	0.2403
		F-statistic	1.5261	0.2403
Jarque–Bera			0.7654	0.6820

Notes: Table 8 presents the results of the ARDL model for coefficients in the long term. See Table 1 for variable definitions.

4.6. The ARDL ECM Coefficient Estimation of Short-Term Dynamics

After inspecting the long-term relations for the allocated models, it is applicable to examine the short-term subtleties of individual means rendering to the ECM-ARDL model (see Table 8). Conferring to [206], the ECM term formerly postulates the amount at which the model regulates long-term equilibrium, and there is a shock period in the model. Moreover, it is presumed that ECM is likewise refuted and has an arithmetical significance by the significance level to interpret the long-term association among the constructs [214]. After investigating the long-term links among constructs in different models of the present study, it is safe to pursue further investigation with short-term dynamics using the ECM-ARDL model, as shown in Table 8. Conferring to [206], the (ECM) shapes an amount at the model that alters to the long-term symmetry, and the model has a period of shock. Moreover, it is considered that the ECM is also refuted at the significance level. It has statistical relevance in accounting for the correlation among variables in the long term. Table 9 presents the results for ECM (−1) of all the models, and shows significant and negative outcomes at the 1% level of significance, which denotes that the rates of adjustment to every shock period in long-term equilibrium models are 1.337%, 53.6%, 133.5%, and 37.4%, respectively. These results also indicate that the equilibrium rate of the adjustment of models is a good post-shock association process.

Table 9. Error correction model results (short-term coefficients).

Variables (Dependent_	Variable	Coefficients of Estimation	Std:_Error	t-Test Statistic	Prob.
FP	C	−1349.174	41.3004	−32.6674	0.0001
	D(AGL)	0.0001	8.59×10^6	15.3559	0.0006
	D(CO ₂)	2.81×10^6	1.90×10^7	14.8005	0.0007
	D(GDPG)	0.2809	0.0317	8.8736	0.0030
	D(UP)	2.5890	0.3349	7.7311	0.0045
	D(INF)	−0.0044	0.0129	−0.3441	0.7535
	ECM(−1) *	−1.3375	0.0410	−32.6464	0.0001
	R-squared	0.9972			
	Adj. R ²	0.9906			
	S.E.R	0.1276			
	S.S.R	0.1302			
	F-value	151.5496			
	Prob.	0.0000			
	DW	3.2018			
CP	C	55.5896	4.4780	12.4139	0.0000
	D(AGL)	−0.0001	1.84×10^5	−6.9557	0.0002
	D(CO ₂)	2.04×10^6	4.59×10^7	4.4419	0.0030
	D(GDPG)	−0.0562	0.0733	−0.7676	0.4678
	D(UP)	−1.7542	0.7310	−2.3998	0.0475
	D(INF)	0.5472	0.0589	9.2966	0.0000
	ECM(−1) *	−0.5358	0.0432	−12.4031	0.0000
	R-squared	0.9674			
	Adj. R ²	0.9240			
	S.E.R	0.3668			
	S.S.R	1.6147			
	F-Test	22.2781			
	Prob.	0.0000			
	DW	2.0392			

Table 9. Cont.

Variables (Dependent_	Variable	Coefficients of Estimation	Std:_Error	t-Test Statistic	Prob.
FP	C	−1916.038	158.4831	−12.0899	0.0001
	D(AGL)	0.0002	2.00×10^5	10.3814	0.0001
	D(AGL*ES)	-7.62×10^7	1.49×10^5	−5.1057	0.0038
	D(CO ₂)	5.58×10^6	7.20×10^7	7.7576	0.0006
	D(GDPG)	0.2024	0.0972	2.0833	0.0917
	D(UP)	0.4921	0.9202	0.5348	0.6157
	D(INF)	−0.1203	0.0415	−2.9032	0.0337
	ECM(−1) *	−1.3345	0.1103	−12.1006	0.0001
	R-squared	0.9535			
	Adj. R ²	0.8817			
	S.E.R	0.4576			
	S.S.R	2.3035			
	F-Test	13.2793			
CP	Prob.	0.0001			
	DW	2.5609			
	C	−350.6142	27.3093	−12.8386	0.0002
	D(AGL)	6.91×10^5	6.18×10^6	11.1896	0.0004
	D(AGL*ES)	1.33×10^6	1.10×10^7	12.0819	0.0003
	D(CO ₂)	-4.94×10^6	5.41×10^7	−9.1338	0.0008
	D(GDPG)	1.2264	0.1005	12.2080	0.0003
	D(UP)	−2.0718	0.6775	−3.0578	0.0377
	D(INF)	0.1546	0.0362	4.2692	0.0130
	ECM(−1) *	−0.3740	0.0289	−12.9398	0.0002
	R-squared	0.9844			
	Adj. R ²	0.9563			
	S.E.R	0.2822			
	S.S.R	0.7964			
	F-Test	35.0263			
	Prob.	0.0000			
	DW	3.0821			

Notes: Table 9 presents the results of the error correction model. See Table 1 for variable definitions. Subscript at ECM (−1) * indicates the significance level at 1%.

In conclusion, it is evident from Table 9 that agricultural land significantly positively affects food and crop production. The moderating effect of environmental sustainability (ES) has a significant positive impact, which leads agricultural land to influence food production and crop production positively. This shows that from the viewpoint of land structures, the approaches related to agricultural land structures in China are divided into three cooperative areas where agrarian land systems can contribute to a rise in future food production, namely agricultural land expansion, crop growth, and agrarian strengthening. Agricultural land structures deliver the main bio-geophysical base for sustainable food production. Meanwhile, farmland plays a central part, and over food production and fodder yields, they currently constitute a significant part of the worldwide food supply [217]. Recent global warming has lengthened the growing crop season and reduced cold strictness in some high-altitude areas in the north, such as northeast China [218]. It is widely believed that climate trends alone will hurt crops in northeast China; however, after the earlier few periods, the approval of long-season cultivators has led to a significant increase in yields, ranging from 13% to 38% [219].

4.7. Stability Test for Robustness Checks

To confirm the constancy of ARDL models recognized for the present paper, an arithmetic investigation of recursive CUSUM and recursive CUSUMSQ for the stated model assessment factors is utilized [206]. The outcomes of the test to check the robustness of the CUSUM and the CUSUMSQ for the models of the study of ARDL are depicted in Figures 8–11. Parameter steadiness and model consistency are attained once the stages of the CUSUM and the CUSUMSQ persist in 5% of the critical range, visible in dashed red lines. The overall models depicted in Figures 8–11 are primarily practical, and the present research outcomes are informative. Moreover, Figures 10 and 11 also confirm the relevance and stability of environmental sustainability with agricultural land as a moderator to enhance food and crop productivity.

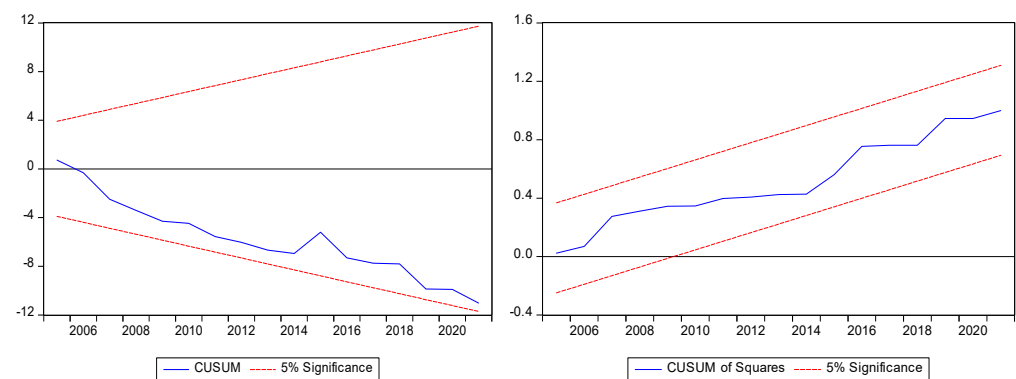


Figure 8. Plots of cumulative sum (CUSUM) and cumulative sum of square (CUSUMQ) for the model $FP = f(AGL, CO_2, GDPG, UP, INF)$.

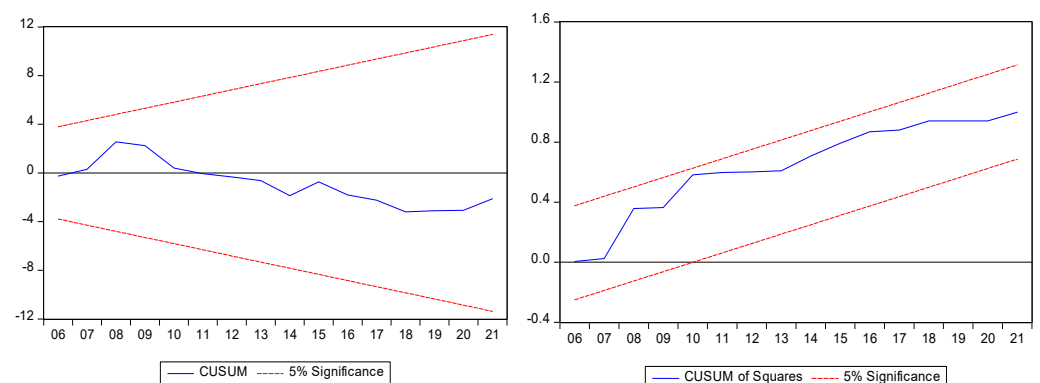


Figure 9. Plots of cumulative sum (CUSUM) and cumulative sum of square (CUSUMQ) for the model $CP = f(AGL, CO_2, GDPG, UP, INF)$.

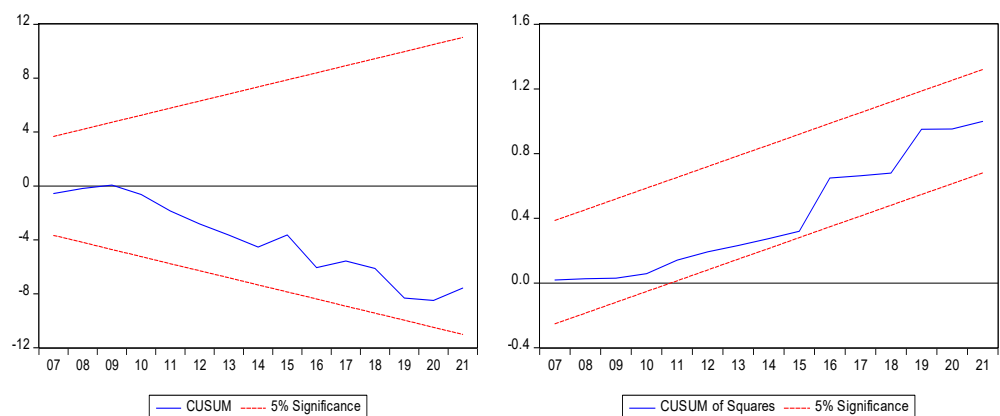


Figure 10. Plots of cumulative sum (CUSUM) and cumulative sum of square (CUSUMQ) for the model $FP = f(AGL, AGL*ES, CO_2, GDPG, UP, INF)$.

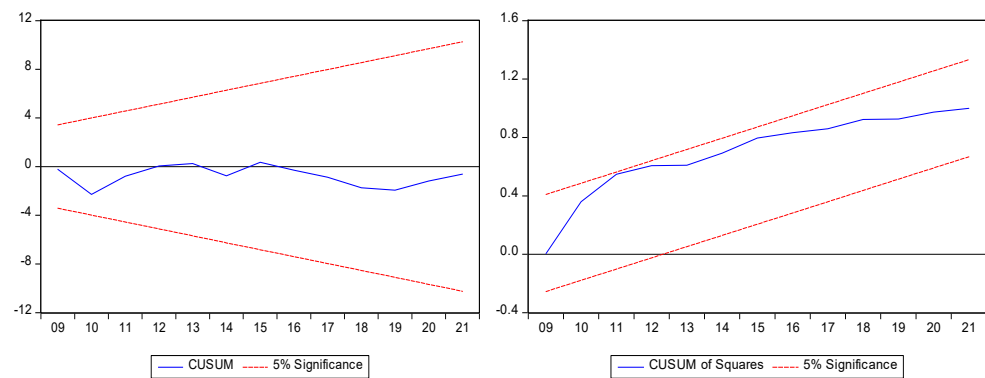


Figure 11. Plots of cumulative sum (CUSUM) and cumulative sum of square (CUSUMQ) for the model ($CP = f(AGL, AGL \cdot ES, CO_2, GDPG, UP, INF)$).

4.8. Toda–Yamamoto Causality Test

Subsequently, to estimate long-term outcomes, we perform a causality test. Grounded in the Toda–Yamamoto Granger causality test results, as shown in Table 10, the study obtains vibrant results. We find reverse causality among food production (FP) and CP, supporting the conservation hypothesis. The study finds bidirectional causality between food production (FP) and agricultural land (AGL), giving evidence for the feedback hypothesis. Moreover, the study finds bidirectional causality between CP and agrarian land (AGL), which verifies the feedback hypothesis.

Table 10. Toda–Yamamoto causality test.

Cause	→	Effect	Test Statistics	Significance Value
FP	→	CP	10.8814	0.1439
CP	→	FP	21.8312	0.0027
FP	→	AGL	72.8310	0.0000
AGL	→	FP	23.3955	0.0015
CP	→	AGL	65.1300	0.0000
AGL	→	CP	13.6004	0.0288

Notes: Table 10 presents the results of the Toda–Yamamoto causality test. See Table 1 for variable definitions.

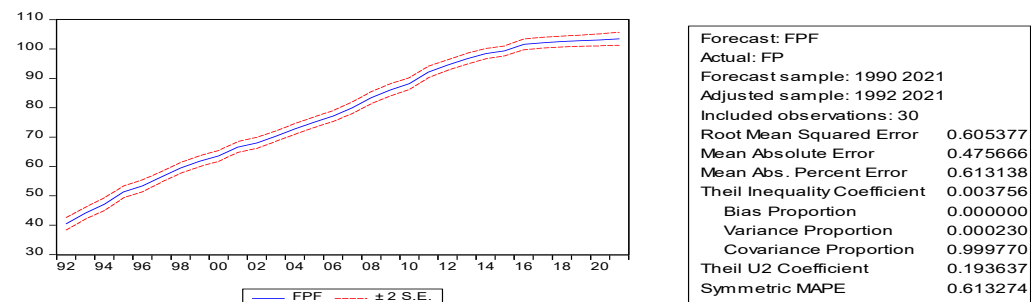
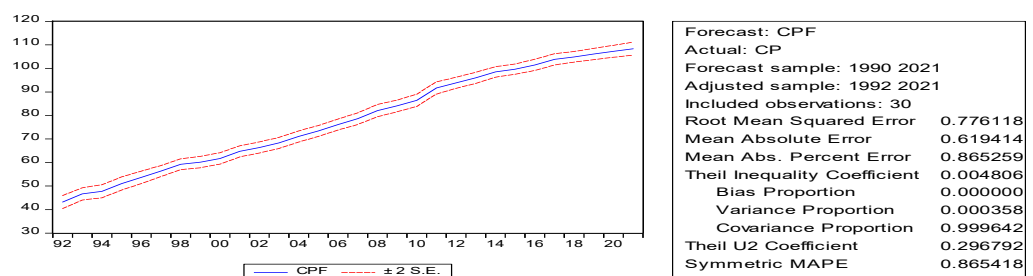
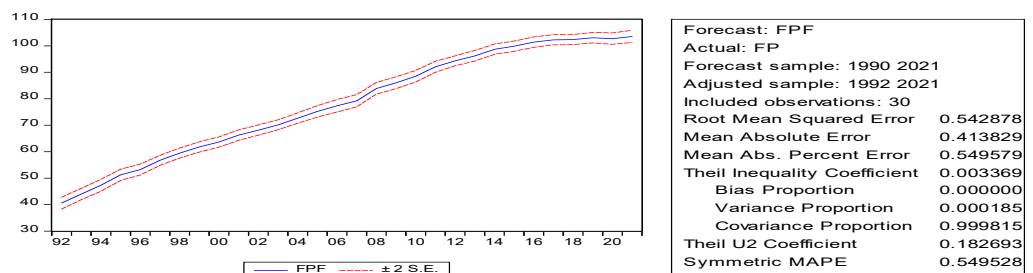
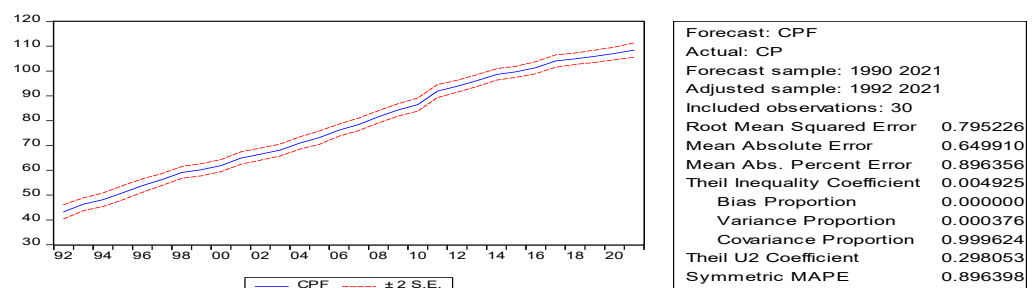
4.9. The Unrestricted Error Correction Model (ECM)—The Performance Testing of Forecasting

As the excellence of the projected outcomes rests on the excellence of the extrapolative enactment of the expected unrestricted (ECM) model, it is essential to confirm that the model is worthy of predictability for the estimation period. To attain that, the most significant methods for forecasting the performance of typical models of macroeconomics over the assessment period are utilized, which include the measurement of inequality projected over Theil (U) and the inequality ratio containing three ratios: the first is the bias proportion ratio (U^M); the second is the variance proportion ratio, (U^S); and the third is the covariance proportion ratio (U^C). Table 11 and Figures 12–15 show the results of using the ARDL model to evaluate the extrapolative presentation of an unrestricted ECM model. It is evident from Table 11 that in all the models, the value of U is low and a smaller amount than the accurate value, U^M is an assessment equivalent to (0), the U^S rate is near to (0), and U^C is a rate near to the integer (1). Therefore, it could be declared that the unrestricted ECM models have worthy predictive presentation through the dates in the investigation, which display the performance of the genuine and projected standards for all the dependent variables of the estimation models accordingly, as unrestricted error correction models. Therefore, the outcomes of these models can be applied to the resolution of economic policy.

Table 11. The unrestricted (ECM) model results in predictive performance.

Study Models	Theil (U)	Bias Proportion Ratio (U^M)	Variance Proportion Ratio (U^S)	Covariance Proportion Ratio (U^C)
1	0.0038	0.0000	0.0002	0.9997
2	0.0048	0.0000	0.0003	0.9996
3	0.0034	0.0000	0.0002	0.9998
4	0.0049	0.0000	0.0004	0.9996

Notes: Table 11 presents the results of the unrestricted (ECM) model. For variable definitions, see Table 1.

**Figure 12.** Chart of actual and estimated value for the model $FP = f(AGL, CO_2, GDPG, UP, INF)$.**Figure 13.** Chart of actual and estimated value for the model $CP = f(AGL, CO_2, GDPG, UP, INF)$.**Figure 14.** Chart of actual and estimated value for the model $FP = f(AGL, AGL*ES, CO_2, GDPG, UP, INF)$.**Figure 15.** Chart of the actual and estimated value for the model $(CP = (f AGL, AGL*ES, CO_2, GDPG, UP, INF))$.

4.10. Robustness Check: FMOLS and DOLS Estimations

To further confirm the key analysis, our paper also applies the estimation of the fully modified ordinary least square method (FMOLS) and the technique of dynamic ordinary least square (DOLS) estimates to check the brevity and robustness of the primary analysis. Since both (FMOLS and DOLS) estimation techniques follow the same asymptotic distribution as proposed by [220,221], the present paper uses both FMOLS and DOLS estimates. Moreover, the FMOLS is a non-parametric estimation technique that addresses serial correlation issues. In addition, the DOLS technique also follows the parametric cointegration estimation method and has the power and robustness to solve the endogenous effect problem. The results of both FMOLS and DOLS methods are consistent with estimating the main conclusions of ARDL estimation in the long term and ensure the rationality and robustness of the main findings. The long-term results for both estimators for model valuation are presented in Table 12.

Table 12. The FMOLS and DOLS estimate results.

Variables and Statistics	FMOLS				DOLS			
	FP		CP		FP		CP	
AGL	0.0001 *** (6.99)	0.0001 *** (7.30)	7.33×10^5 *** (3.95)	6.21×10^5 *** (3.97)	0.0002 *** (6.13)	0.000288 *** (8.14)	0.0002 ** (2.78)	0.0001 *** (1.58)
AGL*ES		9.71×10^7 ** (2.24)		1.24×10^6 *** (2.76)		3.84×10^7 *** (5.71)		2.98×10^6 * (2.36)
CO ₂	4.36×10^6 *** (9.578)	5.35×10^6 *** (9.71)	4.30×10^6 *** (8.72)	5.572×10^7 *** (9.72)	3.30×10^6 *** (6.91)	3.03×10^7 *** (5.95)	3.34×10^6 *** (3.87)	5.37×10^6 *** (5.15)
GDPG	−0.2534 (−0.85)	−0.0858 (−0.30)	−0.2560 (−0.80)	−0.0236 (−0.08)	−0.7233 * (−2.13)	−2.2693 * (−2.21)	−1.0715 (−1.75)	2.3948 (1.14)
UP	−2.1702 (−1.0707)	−1.8714 (−1.05)	−5.7365** (−2.61)	−5.2745 *** (−2.85)	−3.8727 * (−1.85)	−0.4625 (−0.15)	−6.6308 (−1.76)	−1.8287 ** (−2.98)
INF	−0.5314 *** (−4.28)	−0.5336 *** (−4.86)	−0.3995 *** (−2.97)	−0.4090 *** (−3.59)	−0.2228 (−1.65)	−0.014871 (−0.08)	0.01644 (0.07)	−0.6610 (1.80)
Constant	−567.9489 *** (−6.43)	−526.9110 *** (−6.78)	−311.6432 *** (−3.26)	−268.0355 *** (−3.32)	−1188.867 *** (−5.91)	−1434.071 *** (−7.87)	−949.1216 ** (−2.61)	−521.0299 ** (−2.40)
R-Squared	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
Adj. R-Squared	0.98	0.98	0.99	0.99	0.99	0.99	0.99	0.99
obs	31	31	31	31	29	29	29	29

Notes: Table 12 presents the results of the (FMOLS) and (DOLS) estimates of Equations (1)–(4). See Table 1 for variable definitions. The t-statistics are in brackets. Subscripts *, **, and *** indicate the level of significance at 10%, 5%, and 1%, respectively.

5. Discussion

In this study, we propose that an increase in agricultural land is attributed to high productivity in food and enhanced productivity volume in crop yield. Our empirical analysis has also indicated that food and crop production in China has increased gradually over time. In the 30 years from 1990 to 2020, overall agricultural land demand for the creation of food and consumption in China grew fast from 84.22 million hm² in 1990 to 121.74 million hm² in 2020 [222]. Hence, the traditional food system and crop production through the expansion of agricultural land area have sustained food and crop productivity yield with advanced agrarian-based technology and industrial inputs [223]. Due to speedy technological and economic growth in China, the observed increase in food productivity and farming output is attributed to the sustainability of agricultural land. Agricultural land is an essential component of sustainable agriculture and is directly linked to the formation of food based on plant feeds and supply feed for cattle and aquaculture [4].

The empirical outcomes also validate the proposed hypotheses of the study and present a positive and significant association amid an increase in agricultural land and food and crop production. These findings show that enough food and crops could be produced to fulfill the nutritional demands of the population of China. Our empirical findings are also supported by the present literature, which indicates that, with 8% of the biosphere's agricultural land to feed 20% of the biosphere's population, China faces a plain scarcity of agrarian land capital compared to its big general residents base [222]. At

one point, from the side of supply, the work of cultivating terrestrial possessions and the damage of farming creation roles have carried immeasurable weight to China's cultivated terrestrial possessions [224,225]. On the contrary, from the side of demand, the change in the populace's nutrition feeding arrangement has put forward a severe test for the demand for cultivated land [226]. Therefore, to fulfill the public's diet requirements, China's agricultural economy is utilizing advanced technology of agriculture and industry inputs such as Nano fertilizers technology, renewable energy resources, advanced water management technology for irrigation, and availability of sustainable agricultural land.

We have predicted that high environmental sustainability builds sustainable agricultural land, which contributes to high productivity and availability of food and increases resilience in crop productivity and general productivity over the short and the long term. For instance, prior literature argues that a rise in the rate and severity of risky climate actions (e.g., droughts, high temperature, CO₂ emissions) drives variations in overall nutrition creation over interrelating possessions on harvest yield and harvest area. Therefore, it is underlined that agriculture production is significantly linked to the issue of climate change due to the result of CO₂ emissions [81]. Thus, against the background of a surge in economic development restrictions, energy and resources of the environment, and hardships to lessen climate change, the world community has put a premium on agricultural CO₂ emission reduction and emphasized low-carbon agriculture [79,80]. The current paper proposes substantial intuitions around the flexibility-based effect of environmental sustainability. It has often been established in the long and short term since ecological sustainability depends on economic capability that incurs agricultural growth in food and crop productivity and ends the desired advantage of expanding agricultural land. Even though environmental sustainability cannot be quantifiable, the paper has adopted methodologically sound practices in that principles regarding sustainable food and crop productivity are linked to sustainable agricultural land expansion. Specifically, higher environmental sustainability leads to greater amounts of agrarian land, which enhances food and crop production in the long and short term, as shown by data from 1990 to 2021. The standpoints of empirical findings are argued in prominent features as follows:

Empirical findings show that increases in agricultural land increase food and crop productivity in the long and short term. We assume that economies that expand their agricultural land for high productivity of food and crop output growth are able to be self-sufficient in the dietary demand of the population and may experience high agricultural economic development. These empirical findings support those of [227] in the case of the economy of Ghana; they find that food productivity has steadily risen in Ghana over the past two decades and has a high correlation with agricultural land and population growth. They further indicated that the sustainability of food production is linked to sufficient farmland to see food demand for an increased populace in the long term. Moreover, our study is related to several streams of literature. For instance, the study by [23] declared that agriculture is dynamic for nutrition safety and backs the Sustainable Development Goal (SDG 2—Zero Hunger) like other SDGs. SDG-2 appeals for sustainable systems of food production. As mentioned earlier, metropolitan farming usually contains extra agro-environmental creation procedures and additional labor, with less usage of artificial fertilizers and insecticides, the manufacture of which accounts for a significant portion of agriculture-related GHG releases [228], and leads to environmental pollution and harm to wildlife [229]. Additionally, for fitness and well-being assistance, green spaces inside and near cities contribute to reducing warming [230] and air pollution [231], protecting urban areas from extreme climate events. However, few attempts have been made to measure the precise influence of metropolitan and peri-metropolitan agriculture on the environment [232]. Meanwhile, natural ecosystems typically absorb more CO₂ than farmland [233];

metropolitan farming might also indirectly support the Environmental Act by reducing pressure to convert additional untouched areas into agricultural land. In conventional agriculture, transporting nutrition from the farm to the customer often consumes much more energy than the cultivation process [234]; thus, growing food near the customer can decrease discharges through transportation [235].

Additionally, the empirical results of the present study showed that high environmental sustainability increases agricultural land and enhances food and crop production. We have found that in the presence of the moderator (ES), the associations among agricultural land, food production, and crop production show a significant positive impact. These empirical findings support those of [236,237]; they conclude that an outpouring in nutrition claims caused by populace growth is putting massive pressure on worldwide agrarian production levels. So, meeting the growing food demand could lead to increased CO₂ emissions and other greenhouse gas emissions from agriculture unless farming output is not increased. This is mainly because crop agronomy consumes large amounts of energy, directly or indirectly, significantly increasing global greenhouse gas emissions. Moreover, effectual methods of agriculture are also considered necessary not merely to cause a surge in harvest yields but also to help guarantee a satisfactory environmental effect. In conclusion, using partial energy and GHG discharges resourcefully is a vital driver to advance agricultural sustainability and minimize ecological issues.

Moreover, the present study also estimates long-term outcomes by performing a causality test based on the Toda–Yamamoto estimation of the Granger causality test. It shows causality in reverse between food production (FP) and CP, supporting the conservation hypothesis. The study finds bidirectional causality running between food production (FP) and agricultural land (AGL) and between CP and AGL, which is a verification of the feedback hypothesis. Since agrarian terrestrial usage in the reference line setups (i.e., assuming no sustainability approaches) and the growth of the agriculture land zone would entail additional agricultural land. Therefore, these empirical findings confirm the findings of the present literature's results. These studies conclude that increasing biological agriculture would require additional agricultural land that enhances food and crop productivity [234–237].

Finally, the empirical findings of the present paper likewise offer the need for wider opinions assessing the influence of agricultural land on the sustainability of food and crop production. Moreover, environmental sustainability as a moderating element has shown that a sustainable environment is the primary driver to increase agricultural land, which ultimately increases crop yield and food productivity and leads to resilient and sustainable agricultural economic growth. In that respect, our observations of data and empirical methodology entirely meet the requirements and maintain all of the propositions of our paper. To the best of our knowledge, our study is among the few works that take environmental sustainability variables as a moderator with the linkage to the relationships among agricultural land, food, and crop production for the economy of China. Prior work is mainly based on finding long- and short-term dynamics using the most conventional and repeated methodologies.

Unlike other research, our paper has employed several econometric techniques, i.e., ordinary least square estimation (OLS), which is robust enough to investigate the parameters' relationships. To find whether variables are stationary, we employed two tests for unit root, namely the PP and the ADF tests; both are robust in finding the unit root in the model's factors. Specifically, the present study uses the ARDL cointegration model as the key model of the paper. It is grounded in the Pesaran and Shin theory of the ARDL bounds test. The ARDL model is robust as it mainly utilizes Wald statistics for vigorous estimation to conclude whether the lag coefficient of the variable is significant. The present study also

uses the unrestricted error correction model (ECM). Conferring to Engle and Granger and Kalai and Zghidi, the grouping of ECM and causality is more significant in investigating the short-term changing aspects among the variables in the model. Furthermore, our study also uses the Toda–Yamamoto causality test, which then evaluates the long-term causality results between the study's key factors.

6. Conclusions

This paper delivers empirical evidence for the association between agricultural land and food production, and between agriculture and crop production by considering environmental sustainability as a moderator for the Chinese economy. The study incorporates panel data on China's agricultural land, food production, crop production, GDP growth, urban population, inflation, and environmental sustainability as a moderator from 1990 to 2021. To this end, several econometric models were employed, i.e., ordinary least square estimation (OLS), the unit root test, the autoregressive distributed lag model for cointegration (ARDL), the unrestricted error correction model (ECM), and the Toda–Yamamoto causality test.

Our study has found a positive and significant association between agricultural land and crop and food production. First, the ordinary least square (OLS) estimation investigation confirm the significance of the four hypotheses of the present study. Second, the bounds test of the ARDL model approves the existence of a long-term cointegration relationship in the projected present models. Especially when the critical values are at a 5% significance level, the result of F-test statistics for all tested models shows a value more significant than the higher acute limit value. This finding of outcomes shows decisive confirmation for long-term associations among agricultural land (AGL), food production (FP), CP, environmental sustainability (AGL*ES), carbon dioxide emission (CO₂), GDP growth (GDPG), urban population (UP), and inflation (INF) in all the tested models. Third, to check long-term and short-term elasticity, the results' findings depict the positive and significant associations between agricultural land and food production, and between agricultural land and crop production. Additionally, with the existence of the moderator of environmental sustainability, the associations among agrarian land, food, and crop production display a significant positive impact. Fourth, the present study also estimates long-term outcomes by performing a causality test grounded on the estimation of the Toda–Yamamoto approach to the Granger causality. The Toda–Yamamoto analysis test of Granger causality shows reverse causality among food production (FP) and CP, supporting the conservation hypothesis. The study finds bidirectional causality running between food production (FP) and agricultural land (AGL) and between CP and agrarian land (AGL), which shows verification of the feedback hypothesis. Finally, the study investigates performance for forecasting analysis of the projected unrestricted (ECM) model and shows that unrestricted (ECM) models have worthy projecting performance.

This study used the ARDL method to investigate the impact of driving China's agricultural economic growth, but there are still relevant limitations. In addition, regarding data assortment, we did not consider the regional differences in China, which may lead to bias in the analysis. Of course, for this study, this may also be a way in which future models or analytical methods can be improved. Our paper has cast off the secondary data. However, primary data can also be used to comprehend and develop the applicable information by relating both archival and survey data to enhance the vigor of the study and its outcomes. Moreover, further research is required to recognize the additional societal and environmental liaisons of the agricultural land, food, crop productivity, and ecological sustainability relationships. These constructs could be market dynamics, cost and capital of agriculture inputs, institutional constraints, and climate change.

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