A multiobjective DEA model to assess the eco-efficiency of major cereal crops production within the carbon and nitrogen footprint in China

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A multiobjective DEA model to assess the eco-efficiency of major cereal crops production within the carbon and nitrogen footprint in China

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Abstract:

[Background]Agricultural production systems are facing the challenges of increasing food production while reducing environmental cost, particularly in China. Understanding the eco-efficiency of the staple food crop production contributes to sustainable agriculture. In this study, the eco-efficiency of rice, wheat and maize production within the carbon (C) footprints (CF) and nitrogen (N) footprint (NF) at a province scale based on 555 farm survey data from China was measured in which a combination of life cycle assessment (LCA) and data envelopment analysis (DEA) was used. [Results] The results showed that the synthetic N fertilizer applications and CH_4 emissions dominated the CF of crop production, while NH_3 volatilization was the main contributors to the NF in the grain crop production process. Based on DEA-based sustainability performance assessment results, the eco-efficiency of major cereal crops production were all found to be inefficient (eco-efficiency <1). An increase in yields had only limited effects on improvement in eco-efficiency of rice, wheat and corn production because the yield increase potential rates were very small (0.1~3.4%), and there were no significant differences in increase potentials of yields between provinces. From a perspective of environmental impact reduction potential rates, GWP (22.7~25.1%) was more important for the environmental mitigation target than Nr (10.9~17.9%) in rice production, but the opposite scenario appears in wheat and corn production. [Conclusions] Improving crop management practices by reducing N fertilizer use and adopting water-saving irrigation technology could be strategic options to mitigate climate change and eutrophication and improve the eco-efficiency of the staple food crop production in Chinese agriculture.

Keywords:

Carbon footprint;

Nitrogen footprint;

Eco-efficiency;

Life cycle assessment;

Data envelopment analysis;

Grain crops

Background

Climate change and eutrophication pollution are one of the most important environmental problems [1], threatening significantly the well-being of humankind and other creatures on earth. Agriculture is one of the principal contributors to anthropogenic greenhouse gas (GHG) emissions, especially non-CO_2 emissions [i.e., methane (CH_4) and nitrous oxide (N_2O) emission].On the contrary, with economic development and population growth, people began to increase energy, fertilizers, pesticides and agricultural film to maintain food production, through which more greenhouse gas emission was produced. Moreover, a significant proportion of the nitrogen (N) annual application of fertilizer as reactive N (Nr; all N species except N_2) is released into the environment, causing a series of environmental problems such as air pollution, stratospheric ozone depletion and eutrophication [2]. Therefore, modern intensive agricultural and food markets have been demanding better products with less impact on the environment. Eco-efficiency is a concept used to analyze farm sustainability, which relates the economic value of an activity to how the environment is influenced. It is playing a more and more important role in evaluating the efficiency of economic activities related to natural resources and ecological deterioration and has begun to attract academic attention [3].

In agricultural production as well as in other areas, the environmental impacts can be quantified by different indicators, which can be measured by the Life Cycle Assessment (LCA) [4], which has been proven to be a valuable tool for addressing the environmental impact of various agriculture production systems, in which the identification of the subsystems that contribute most to the environmental impact overall and the comparison of products and processes with the same function was involved. Among the different environmental burdens, global climate change and local eutrophication pose a serious threat to the well-being of humankind and other organisms on earth. The LCA indicator that evaluates these burdens was the carbon (C) footprint (CF) and N footprint (NF). The CF is widely used in comparing the impacts of different products on climate change, and is used to explore mitigation measures for greenhouse gas emissions [5]. While the NF indicates the total amount of Nr lost to the environment due to human activities [6]. To understand tradeoffs or synergies and possible simultaneous mitigation practices, integrated assessments are preferred. Several of these attempted to establish a single score for the environmental impact of wheat production using weighting, which aggregates the results of standardized indicators for each environmental impact category and assigns weighting factors based on their relative importance [7]. However, weight factors based on value selection are subject to subjective and political influences, as well as lack of knowledge on resource consumption and pollutant emission, which complicates the derivation of weight factors [7].

Eco-efficiency gathers the economic and environmental dimensions to relate a product to environmental impacts. A primary challenge of eco-efficiency measurement is the integration of several different environmental impact categories with different measurement units into a single environmental damage index. The eco-efficiency set is a collection of economic and environmental dimensions, linking products to environmental impacts. One of the main challenges of eco-efficiency measurement is the integration of several different environmental impact categories and different units of measurement into a single environmental damage index. As a linear programming based frontier estimation tool, data envelopment analysis (DEA) is used to quantify and measure relative efficiency of a set of similar entities of Decision Making Units (DMUs) having multiple inputs and/or outputs. Furthermore, this union provides quantitative benchmarks to guide the performance of any system in terms of environmental sustainability. At present, different methodologies were proposed to implement the LCA + DEA approach, aiming at assessing performance of multiple input/output for a large number of entities on the operational and environmental levels. The most commonly used methods are the three-step method [8] and the five-step method [9]. Recently, Rebolledo-leiva et al. [10] proposed a four-step method which focuses on increasing output and decreasing CF through DEA model, and then determines the target of resources contributing to CF. However, in all these methods, the DEA model used only identifies an inefficient DMUs, which may not be feasible from an operational or management perspective. Through a multiobjective DEA model, more flexibility is allowed in searching for feasible efficient targets in the decision-making process which is more applicable to agricultural systems, and has been widely applied in various fields. There is a large amount of literature that evaluates eco-efficiency based on DEA models, which is available at a range of scales, spanning the micro level to the macro level. At a regional scale, Otsuka [11] evaluated eco-efficiency with a DEA model to confirm the Porter hypothesis in Japan's manufacturing sector and concluded that GHG emissions, which can be reduced by increasing funding for technological innovation, are the major factor accounting for inefficiency. In order to determine the level of operational input efficiency of each farm, Iribarren et al. [8] conducted a study using the LCA+DEA method on 72 dairy farms. They benchmarked potential reductions in inputs while calculating the environmental benefits associated with these reduction targets, and concluded that a total of 31 farms were considered effective. The focus of existing literature in China is mainly directed to ecological efficiency on the national and provincial levels. The spatial distribution of 273 cities in China from 2003 to 2015 was explored by Huang et al. [12] with urban agglomeration as the index, and the urban ecological efficiency was evaluated by DEA method. The ecological efficiency of 281 prefecture-level cities in China from 2006 to 2013 was measured by Bai et al. [13] through the envelopment analysis model of super-efficiency data, and a new comprehensive evaluation index system of urbanization was proposed. However, it is still unclear the eco-efficiency of major cereal crops production in China.

In China, agriculture is one of the most predominant GHG emission sources globally, including 50% of the total CH_4 and 92% of the total CO_2 emissions in 2010 [14]. In addition, China is the greatest consumer of N fertilizer alt 45 Mt, accounting for 37.6% of world consumption in 2014, about 27 Tg yr^{-1} of N fertilizer was applied for crop production during 2001~2010 in China [5], mainly to produce rice, wheat and maize. At present, the large input and low efficiency of resources and energy in food production aggravate the degradation of climate and environment [15]. To make matters worse, grain yields in China has stagnated since 2010, with 79% of its rice crop, 56% of its wheat and 52% of its maize. Meanwhile, the use of various related resources, such as pesticides and fertilizers, is likely to continue to increase in any case [16]. In other words, many Chinese farmers may buy (and use) more and more agricultural materials, but their net economic benefits have not been significantly improved [17]. Producers are more concerned with eco-efficiency, which, according to the world business council for sustainable development (WBCSD), means producing more products with less environmental impact and fewer resources. Therefore, the objectives of the present investigation were: (1) to estimate the CFs and NFs of rice, wheat and maize from farm survey data using LCA assessment; (2) to analyze the prime driving forces of CFs and NFs of three grain crops on province levels for the first time; (3) to assess the eco-efficiency of rice, wheat and maize on province levels using a multiobjective LCA+DEA model.

Material and methods

Study region

Study sites that represent the major crop production areas of China were selected (Fig. 1). Generally, the typical provinces of rice growing were selected in Jiangxi and Hunan with a warm and humid climate in southern China. The water management in local rice in this area was irrigated normally under intermittent flooding conditions during the rainy season. Meanwhile, we chose Jiangsu and Anhui provinces to conduct research on winter wheat. Corn was a typical grain crop production system in Jilin and Hebei, where there was a humid climate, while maize rotation in summer and winter was a typical sub-humid climate in Hebei. Sites of the farm survey across these representative crop production areas are shown in

System boundary

The focus of this study is directed to the environmental impact and GHG emissions of the three grain crop production in the surveyed region. For this purpose the input/output items of the model DMU shall be established within an LCA+DEA framework. Fig. 2 shows the elements involved in the LCA +DEA study of the farms was assessed for the entire production chain of crop. For LCA analysis, the GHGs and Nr emissions included the following: 1) electricity generation, gasoline and diesel production from mechanical jobs (tilling, seeding, irrigating, harvesting, and packing); 2) manufacturing, storage, and transportation of agricultural materials (including N fertilizers, phosphate fertilizers, potassium fertilizers, pesticides, seeds and film); (3) total CH_4 and N_2O seasonal emissions from fields, as well as NH_3 volatilization, and NO_3^- and NH_4^+ leaching during crop growing periods. For DEA, labor, machinery, diesel fuel, water for irrigation, electricity, chemical fertilizer, pesticides, seeds and film were considered as the inputs. Direct GHG emissions, crop yields and Nr emissions to air are the main outputs at the system boundary assuming that all selected analysis items are independent of each other

Data sources

The farmer survey is a multiphase survey of major cereal crops farms in six provinces of China. In this study, stratified random sampling was adopted. The questionnaire consisted of four parts: (1) amounts of N, phosphate, potassium fertilizers, and pesticides used for each crop production; (2) farm mechanical operations (e.g. methods of soil tillage, harvesting); (3) water management practices such as tube or well irrigation; and (4) farm area and grain yield of each crop. There were 40 representatives were conducted as pre-tested at Swan village, Ningxiang county of Hunan in order to test the reasonability of the questionnaire. Finally, effective improvements were made to the questionnaire based on the evaluation and recommendations. During the predictive test, farmers reported that they had encountered considerable problems in answering questions about their financial status. Therefore, to avoid motivational questions, questions related to the financial status of the farm were removed from the list. Two towns and villages in each county and 2 village in each town were selected for field investigation. 20 households were randomly selected from each village and head of households (farmers) was interviewed face to face. Household farms were divided into two categories of small sized (<0.7 ha), middle sized (2~7 ha) and large sized household farms (>20 ha) according to the farm size data obtained in the survey based on the land planning standards of the ministry of agriculture and village of the People's Republic of China. Overall, A 600 investigate dataset was collected with farmers from all six province. Of this sample, about 555 surveys were fully completed and could be used.

Carbon footprint calculation

With the application of farm-gate principles of agricultural life cycle assessment that are generally accepted, researchers established the system boundary concerning cereal crops from sowing to harvesting. Using the global warming potential (GWP) for a timespan of a century, the GHG emissions were estimated [18]. According to the life cycle inventory, the CF ($kgCO_2eq\ kg^{-1}$) for each crop in each of the provinces concerned was calculated using the following equation:

$$CF_y = CE_t/Y \quad (1)$$

$$CE = CE_{input} + 25 \times CH_4 + 298 \times N_2O \quad (2)$$

$$CE_{input} = \sum I_n \times C_n \quad (3)$$

Where CF_y is the total CF for each kg of the rice, wheat, and maize produced ($kgCO_2$-eq kg^{-1}); yield is the grain yield of grain produced (t ha^{-1}). CE_t is the GHG emissions for 100 years of all the trace gases with an impact on radiative forcing [19] associated with the entire life cycle concerning the production of rice, wheat, and maize ($kgCO_2$-eq ha^{-1}). CE_{input} is the amount of indirect emissions of agriculture inputs; I_n and C_n are the each item of agricultural input and its GHG emissions coefficient (Table 1), respectively. For most of inputs, the conversion coefficients of CO_2 equivalent were retrieved from the Chinese Life Cycle Database (CLCD v0.7, IKE Environmental Technology CO., Ltd, China). In the meantime, those of pesticides and seeds were retrieved from Ecoinvent v2.2 (Swiss Centre for Life Cycle Inventories, Switzerland). CH_4 and N_2O are the amount of average non-CO_2 emissions on an annual basis. The constants 25 and 298 represent the GWP coefficients for CH_4 and N_2O (based on a 100-year time frame).

Guided by the 2006 IPCC Guidelines for National Greenhouse Gas Inventories, the CH_4 and N_2O emissions from paddy fields were estimated [19]. Using the following equation, the CH_4 emissions released directly from submerged paddy field were estimated:

$$CF_{CH_4}=EF_{i,\ j,\ k}\times t_{i,\ j,\ k}\times 25 \qquad (4)$$

$$EF_{i,\ j,\ k}=EF_C\times SF_W\times SF_P\times SF_O \qquad (5)$$

$$SF_O=(1+\textstyle\sum_i ROA_i \times CFOA_i)^{0.59} \qquad (6)$$

$$ROA_i=Y\times 0.623\times 0.5\times 0.85 \qquad (7)$$

In the above equations, CF_{CH4} represents the annual per unit methane emission from rice cultivation ($kgCO_2$-eq ha^{-1}); $EF_{i\,j\,k}$ is a emission factor on a daily basis ($kgCH_4$ ha^{-1} day^{-1}); t_{ijk} is the growing timespan of rice (day); i, j, and k stands for different ecosystems, water regimes, organic amendments' type and amount, and other conditions influencing CH_4 emissions from rice production; and 25 is CH_4 's relative molecular warming forcing of in a 100-year time horizon [19]. While EF_c is the baseline emission factor for fields without organic amendments that are continuously flooded, 1.30 kg CH_4 ha^{-1} day^{-1}. SF_w and SF_p, serves as a scaling factor that is used in accounting for the differences in water regime both during the rice growing period and before rice transplantation. SF_o serves as the scaling factor which varies with regard to both type and amount of organic amendment that is used. ROA_i represents organic amendment' application rate. $CFOA_i$ in (6) is the conversion factor, which is concerned with organic amendment i; 0.623 is rice's residue/grain ratio, 0.5 is the coefficient of rice straw retention, this figure indicates the percentage of the amount of straw retention compared with total straw under the framework of present technological level [20], 0.85 is the conversion coefficient, which indicates the ratio of fresh weight to dry weight for rice straw [21].

As is shown in the following equation, the estimated N_2O emissions released directly from N fertilizer application is depicted

$$CF_{N_2O}=N\times\varepsilon\times\frac{44}{28}\times 298 \qquad (8)$$

In the above equation, N is the amount of N fertilizer that applied during a single crop season; Ɛ is the default emission factor of N_2O emission of applied N fertilizer. Emission factors of synthetic N fertilizer use in dry crops and submerged rice paddies were adopted respectively from IPCC (2006) [19] and Zou et al. [22] (Dry cropland, 0.01 kg N_2O-N kg^{-1}, Rice paddy, 0.0073 kg N_2O-N kg^{-1}); 44/28 is the molecular conversion factor of N_2 to N_2O; 298 reveals the global warming potential (GWP) of N_2O relative to CO_2 over a 100-year time horizon.

Nitrogen footprint calculation

In this study, the NF served as an indicator of the total direct N-losses to the environment that occur for the production of one unit of (food) product, measured in g N/kg food product. The eutrophication potential was chosen to assess the impact which is associated with Nr emissions and losses during the period of grain crop production. Based on ISO 14044 [23], the NF of grain crop produced was calculated.

$$NF_y = NE_t/Y \qquad (9)$$

$$NE_t = NE_{input} + NV_{NH_3} + NE_{N_2O} + NL_{NO_3^-} + NL_{NH_4^+} \qquad (10)$$

$$NE_{input} = \sum I_n \times N_n \qquad (11)$$

As is shown above, NE_t is the total Nr emission which is linked with the entire life cycle of the production of grain crop (gN-eq ha^{-1}). The Nr emission during the process of production of kinds of agricultural inputs and the field during the process of grain crop production was included; NE_{inputs} is the indirect total amount of Nr emissions. It is associated with agricultural input applications and is calculated through multiplying the factual use amount of kinds of agricultural inputs (I_n) by those emission factors (N_n) from IKE eBalance v3.0 (IKE Environment Technology CO., Ltd, China) (Table 1); The Nr emission from field consists of NH_3 volatilization, N_2O emission, NO_3^- and NH_4^+ leaching. The amount of emission was calculated through multiplying pure N use amount by relative loss coefficient. Guided by the manual published internationally, the eutrophication potential value is converted into by multiplying the eutrophication potential value by the eutrophication potential factor.

$$NE_{N_2O} = N \times \varepsilon \times 44/28 \times 0.476 \times 1000 \qquad (12)$$

$$EV_{NH_3} = N \times \varnothing \times 17/14 \times 0.833 \times 1000 \qquad (13)$$

$$NL_{NO_3^-} = N \times \sigma \times 62/14 \times 0.238 \times 1000 \qquad (14)$$

$$NL_{NH_4^+} = N \times \gamma \times 18/14 \times 0.786 \times 1000 \qquad (15)$$

In the four equations above, ϕ is the NH_3 volatilization loss coefficient. For rice, wheat and maize, it's 0.338, 0.275 and 0.226 respectively [24]; σ is the NO_3^- leaching coefficients. For rice, wheat and maize, it's 0.305, 0.606 and 0.175 respectively; γ is the NH_4^+ leaching coefficients. For rice, it's 0.339. For wheat, it's 0.190. For maize, it's 0.043. 17/14, 62/14 and 18/14 are the molecular weight ratios of NH_3

to NH_3-N, NO_3^- to NO_3-N, and NH_4^+ to NH_4^+-N, respectively; For NH_3 (kgN-eq kg^{-1} of NH_3), N_2O (kgN-eq kg^{-1} of N_2O), NO_3^- (kgN-eq kg^{-1} of NO_3^-) and NH_4^+ (kgN-eq kg^{-1} of NH_4^+), 0.833, 0.476, 0.238 and 0.786 are eutrophication potential factors, respectively, those related applied eutrophication potential factors were sourced from the CML2002 methodology [25]; 1000 is a unit conversion factor (g kg^{-1}).

SBM-Undesirable Super efficiency model

On the basis of previous work, this study adopts the slack efficiency measure DEA (SBM-DEA) model, which can take into account the influence of poor output (such as pollution) on efficiency [26]. Compared with the traditional CCR and BCC models, in the SBM model, relaxation variables are directly added to the objective function of the undirected SBM-DEA model with bad output [26] is used to measure efficiency, which is indicated by ρ of decision-making units (DMU_s) under evaluation (xik, $y^g{}_{rk}$, $y^b{}_{tk}$) (where o = 1, …, k). This model provides for minimization of the following fractional objective function, which therefore implies the maximization of slack variables The model provides minimization of the following fractional objective function, which means maximization of the relaxation variable s_i^- , s_r^g , s_t^b. Assuming that the DMU_s set is j = {1, 2, …, n}, where each DMU has m inputs, S_1 desirable outputs, and S_2 undesirable outputs.

$$\begin{cases} \rho^* = min\dfrac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{ik}}}{1-\frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}\frac{s_r^g}{y_{rk}^g}+\sum_{t=1}^{s_2}\frac{s_t^b}{y_{tk}^b}\right)} \\ s.t.\quad \sum_{j=1,j\neq k}^{n} x_{ij}\lambda_j - s_i^- \le x_{ik} \\ \qquad \sum_{j=1,j\neq k}^{n} y_{rj}^g\lambda_j + s_r^g \ge y_{rk}^g \\ \qquad \sum_{j=1,j\neq k}^{n} y_{tj}^b\lambda_j - s_t^b \le y_{tk}^b \\ \qquad 1-\frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}\frac{s_r^g}{y_{rk}^g}+\sum_{t=1}^{s_2}\frac{s_t^b}{y_{tk}^b}\right) > 0 \\ \qquad s^- \ge 0, s^g \ge 0, s^b \ge 0, \lambda \ge 0 \\ \qquad i = 1,2,\dots,m; r = 1,2,\dots,s_1 \\ \qquad t = 1,2,\dots,s_2; j = 1,2,\dots,n (j \neq k) \end{cases} \quad (16)$$

where: ρ, s_i^- , s_r^g , s_t^b are the efficiency score, excess input, good output deficit, and excess of undesirable output, and the DMU_o is defined as efficient in the presence of the eco-environment when ρ=1 and consequently $s_i^- = s_r^g = s_t^b$ =0. When there is an efficiency loss in the DMU ($\rho^* < 1$), based on the relaxation variables s^-、s^g、s^b, the sources of ecological efficiency loss can be decomposed into: (1) Input redundancy ($IE_x = \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{ik}}$), represents the reducible proportion of input factors. (2) Insufficient expected output ($IE_{y^g} = \frac{1}{s_1+s_2}\sum_{r=1}^{s_1}\frac{s_r^g}{y_{rk}^g}$), indicates the expansion ratio of expected output,

(3) Unexpected output redundancies ($IE_{y^b} = \frac{1}{M+I}\sum_{i=1}^{I} s_i^u / u_{i0}$), indicate a reduction in the proportion of undesired output. The objective function is normalized, allowing for comparison of the efficiency scores between the observations. In addition, the bad output, even though it is not transferred, is treated as input in the constraint, but as output in the target function, which is in the denominator.

Statistical analysis

Data processing was performed using Microsoft Office Excel 2010 and all statistical analyses were conducted using IBM SPSS Statistics, windows Version 22 (IBM Corp., Armonk, NY, USA, 2013). One-way ANOVA and the least significant difference test (LSD) were used to check the differences between farm size classes and regions. The standard $P<0.05$ was used as the confidence level for statistical significance.

Results

Farm size, grain yield and agricultural input

There were significant differences in crop yield, farm size and input of agricultural capital among the different crop production. The main farm size from the surveyed farms was 0.1~ 0.5 ha in size for rice, wheat and maize, accounted for ~80% of total farmers, which showing the great fragmentation of China's croplands. The farm size of the rice and wheat were larger than those of the maize in the surveyed farms. Among the rice, wheat, and maize production, the CF and NF of three crops all showed an increasing trend with the increase of crop farm size classes (Table 4). The average yields from surveyed farms ranged from 4.9 to 6.5 t ha^{-1} for the rice, 4.9 to 6.7 for wheat and 6.1 to 8.4 t ha^{-1} for maize, respectively. The highest of yields of grain crop production was found in the maize production. Grain yield of rice was higher in Hunan than in Jiangxi, and those of wheat and maize were no significant difference between Jiangsu and Anhui, Hebei and Jilin. The life cycle inventory dataset, consisting of agricultural inputs and fields, was presented, in detail, based on the above defined system boundaries (Table 2). The input from diverse forms of synthetic fertilizers followed the order: N fertilizers >P_2O_5 fertilizers > K_2O fertilizers for rice and wheat. N fertilizer use ranged from 141.7 kg N ha^{-1} to 460.6 kg N ha^{-1} across the farms surveyed. The mean N application rate was the highest for rice (363.2 kg N ha^{-1}) and the lowest for maize (172.8 kg N ha^{-1}). For wheat production, N was applied in a higher rate in Jiangsu than that in Anhui. While for maize, the N application rate was higher in Jilin province than in Hebei (Table 2). Diesel fuel is also a large input of agricultural resources, in the range of 61.8~163.3 kg ha^{-1} were used in over 80% of the total farms surveyed. Film was not used for crop production but in rice, where 5.5~8.5 t ha^{-1} films were used in Jiangxi and Hunan.

Carbon footprint

The CF for rice, wheat and maize were 0.87, 0.30, and 0.24 kgCO_2-eq kg^{-1} at yield-scale, respectively. The CF of rice production was 2.9 and 3.6 times that of wheat and maize, respectively, largely attributable to higher CH_4 emissions from paddy fields, which comprised 63% of the total value of CF. The GHGs emissions associated with agricultural inputs were the second largest contributor to the CF of rice production, accounting for 27.4%, while the N_2O emissions from paddy fields had a small impact on the CF that it is negligible. Agricultural inputs were the secondary contributor to the CF of rice production, but was the largest secondary contributor to wheat and maize production, accounting for 65.4 and 74.5%, respectively (Fig. 3). The GHGs emissions of synthetic fertilizers production and application (including N fertilizers, P_2O_5 fertilizers, and K_2O fertilizers) were the most significant fractions of the total agricultural inputs, accounting for 40.2, 47.3 and 42.7% for rice, wheat and maize, respectively. The GHGs emissions from diverse forms of synthetic fertilizers followed the order: N fertilizers > P_2O_5 fertilizers > K_2O fertilizers for all grain crops. In addition, GHGs emissions from N fertilizers of rice were higher than that of wheat and maize, but the opposite trend was found in P_2O_5 fertilizers. Following synthetic fertilizers, diesel oil consumption was the second largest contributor to GHGs emissions, accounting for 36.9, 47.2, and 40.9% for rice, wheat and maize, respectively. The GHGs emissions from seeds were significantly greater for the rice than that of wheat and maize. The GHGs emissions from pesticides, associated with herbicides, insecticides and fungicides were lowest, only accounting for 1.4, 2.4, and 3.1% for rice, wheat and maize, respectively. With regard to the different sources, field cultivation contributed the most to the CF of rice, while the production of agricultural inputs dominated the CF of wheat and maize. As seen in Table 4, the CF varied with farm size for among rice, wheat and maize, and rice and wheat were produced with a significantly lower CF (by 20~40%) in large contractors than that in general household contractor, while no difference was observed for maize production in Hebei province.

Nitrogen footprint

The NF for the rice, wheat, and maize were 17.1, 14.3, and 6.8 g N-eq kg^{-1} $year^{-1}$ at yield-scale, respectively. The NF of maize was obviously less than that of wheat and rice, and similar between wheat and rice. Different to GHGs emissions, the Nr emissions of diesel oil consumption shared the largest percentage of agricultural inputs, being 471.4, 547.3, and 447.6 gN-eq ha^{-1} $year^{-1}$ for rice, wheat and maize, respectively. Next to diesel oil consumption, synthetic fertilizers emitted 278.7, 227.3, and 222.7 gN-eq ha^{-1} $year^{-1}$ for rice, wheat and maize, accounting for ~ 30.0%. The pesticides were still the least contributor of Nr emissions in all grain crops, accounting for less than 2% of total Nr emissions from agricultural inputs. NH_3 volatilization dominated NF from fields associated with N fertilizer applications for the all grain crop, accounting for 96.5, 94.8, and 96.0% for the rice, wheat, and maize, respectively. The NH_4^+ leaching from maize fields had a small impact on the NF, was only 81.1 gN-eq kg^{-1} $year^{-1}$ at yield-scale. The NF for production of the three staple foods was linearly correlated with the CF (Fig. 4). In other words, the surveyed farms that produced higher GHG emissions also had higher Nr discharges. As such, the NF of rice production in Jiangxi province, wheat production in Jiangsu province, and maize production in Hebei province, were also higher than that in the other respective provinces (Table 3). The significant linear relationship between the CF and NF of food production from all the surveyed farms, attributed to the large contribution of N fertilizer to both Nr and GHG releases (Fig. 2). N fertilizer additions are known to promote the releases of various Nr species, linearly or exponentially, and it is widely accepted that N fertilizer use is a substantial source of GHG emissions during the life-cycle of cereal grain production. The synthetic N fertilizer inputs contributed more to the CF of the wheat and maize than to that of rice (Fig. 2); as a result, the linear relationship between the CF and NF was stronger for wheat (R_2 = 0.69) and maize (R_2 = 0.52), than for rice (R_2 = 0.45) production (Fig. 4).

Eco-efficiency analysis

As shown in Table 5, the eco-efficiency score of rice, wheat and corn production at a province level were 0.53, 0.66, and 0.89 based on a cumulative average, respectively. There was no significant difference in eco-efficiency scores between different provinces of the same crop. Corn in Jilin had the highest eco-efficiency score (0.91), which was significantly higher than that of wheat in Anhui (0.62) and corn in Hunan (0.51) by 45% and 76%, respectively. When the eco-efficiency value is less than 1, the numerical value of relaxation variable can reflect the cause of eco-efficiency loss. There was significant difference in operational targets of rice, wheat and corn production based on cumulative averages of SBM-DEA window analysis. The redundancy rates of yield, resources input and undesired output are all negative, which indicates that insufficient output is not the cause of eco-efficiency loss, but mainly lies in the excess of resources input and unexpected output. An increase in yields had only limited effects on improvement in eco-efficiency of rice, wheat and corn production because the yield increase potential rates were very small (0.1~3.4%), and there were no significant differences in increase potentials of yields between provinces. Among the resources input factors, the main causes of crop eco-efficiency loss for rice are diesel consumption of harvest, electricity for irrigation and N fertilizer input. Inputs of diesel consumption of harvest, herbicides and N fertilizer are too much for the wheat production, and that of seed production, herbicides and N fertilizer for the corn production. From a perspective of environmental impact reduction potential rates, GWP (22.7~25.1%) was more important for the environmental mitigation target than Nr (10.9~17.9%) in rice production, but the opposite scenario appears in wheat and corn production.

Discussions

Carbon and nitrogen footprints from grain crop production

The CF for the rice, wheat and maize in the study ranged from 0.84 to 0.90, 0.27 to 0.34 and 0.23 to 0.26 kgCO_2-eq kg^{-1} among provinces from all the surveyed farms, respectively. The corresponding CF for grain production in China were similar to wheat (0.3 kgCO_2-eq kg^{-1}) and maize (0.3 kgCO_2-eq kg^{-1}) production in Canada [18, 27], respectively. In our study, the estimated CF for rice is lower than in India, where rice yields are relatively low but energy costs for irrigation are high (Pathak et al., 2010). However, The CF for rice in the surveyed farms were little higher than the amounts of rice production in Japan (0.8 kgCO_2-eq kg^{-1}) [25]. It may be due to the levels of agricultural inputs in China were generally larger than those in developed countries. Xu et al. [29] showed that the CF of rice production was 2.50, 2.33, 1.89, 1.54, and 1.34 kg CO_2-eq kg^{-1} on yield-scale in Guangdong, Hunan, Heilongjiang, Sichuan and Jiangsu of China, respectively. Differences in crop carbon footprints are mainly attributed to differences in the sources of data collection and the emission factors of agricultural inputs at quality system boundaries as well as the calculation methods between studies. For example, different provinces have different requirements for irrigation. Compared with the agricultural areas in northern China where water resources are scarce, the Yangtze River basin has a smaller demand for irrigation due to its natural superior climate resources. In addition, due to the superior geographical features and climatic conditions, the yield of the Yangtze River basin is generally higher than that of other agricultural areas, resulting in a small CF per unit yield. The data presented herein indicate that average GHGs emissions from agricultural inputs were higher for the rice than those for wheat and maize, which may be due to greater applications of diesel oil, electricity, seeds, fertilizers and films for the rice, in spite of larger pesticide for the wheat and P_2O_5 fertilizers for the maize (Table 3). What is more, paddy rice cultivation is a primary contributor to global CH_4 emissions, which was necessarily performed for rice cultivation in the farms surveyed. The CH_4 emissions from paddy fields are the main component of CF in this study, similar to other studies [30]. Xue and Landis [31] estimated that the NF was ~2.65 gN-eq kg^{-1} of cereals production by using the LCA method in the Gulf of Mexico. Regarding the value of NF, our values are several orders of magnitude higher than the values obtained by Xue and Landis [31], which is similar to Pierer et al. [32], but this is due to the use of different sets of characterization factors for the calculation method. In addition, differences in nitrogen management during grain production are also possible reasons for differences in Nr loss. NH_3 volatilization is the main NF source in food crop production, which is similar to the results reported by Leip et al [33]. The NH_3 volatilization increased linearly with the N fertilizer application rates in among rice, wheat and maize seasons [24]. What is more, the NF of rice production were larger than that of wheat and maize production, primarily attributed to higher levels of NH_3 volatilization during the rice growing seasons [15]. This trend may be due to the higher moisture and urea content in rice growing period, which is conducive to the improvement of soil urease activity, leading to the increase of NH_4^+ concentration in paddy soil [24]. Moreover, compared to small sized household farms, the CF and NF in large sized farms were significantly lower (Table 4). The main reason is that farmers with large scale of land planting generally have a higher level of farmland management, which can more effectively control the production and application of agricultural materials, thus improving the utilization efficiency of water and fertilizer. Huang et al. [12] further proposed that planting scale has a negative impact on the fertilizer application of farmers, and land transfer should be increased to promote the concentration of land to some farmers so as to reduce the fertilizer application per unit area. This is consistent with the findings of Feng et al. [34], who reports that large farms (> 0.7 ha, 10 mu) may have 30 more topsoil organic carbon reserves than small farms (less than 0.7 ha)

Eco-efficiency of crop production

Using DEA model and eco-efficiency assessment of LCA adopted by different research institute, as Beltran-Esteve et al. [35], although only a few examples of eco-efficiency of economic angle of view has always been the hot spot of the planting industry research, but it is not the focus of this study pointed out in this study, we have some DEA model to consider the economic aspects of the production process, such as Sahoo et al. [36] and Cherchye et al [37]; However, these models do not take into account environmental impacts or the definition of ecological efficiency of the WBCSD. It should be highlighted that we have focused the eco-efficiency assessment on producing more with fewer resources and less environmental impacts as done initially by Lozano et al. [38]. Our results of eco-efficiency assessment considering the whole agricultural input from major cereal crops of China are reported in Fig.2. The eco-efficiency score of rice, wheat and corn production at a province level were 0.53, 0.66, and 0.89 based on a cumulative average, respectively (Table 5). A direct comparison among the results from different studies is not always straightforward, due to the different system boundaries definition and assumptions. Zhu et al. [39] performed the eco-efficiency of rice cultivation in China during 1995-2014 based a DEA index method. Due to different modeling assumption (e.g. straw mulching and its economic impact on grain and straw distribution), their eco-efficiency score of rice production are higher compared to our results by 33%. With regard to Japan, our eco-efficiency score of wheat is lower by 11.5%, respectively. This is mainly due to the differences in wheat yield, i.e. 6.0 t ha^{-1} in our study and 9.7 kg ha^{-1} in Japan, and differences in input, i.e. fertilizer, diesel oil and pesticide. With regard to the contribution of unit processes, our findings are consistent with previous studies that identified field emissions and fertilization as the main factors influencing the impact [40]. What is more, our study the impact on eco-efficiency was also dominated by diesel consumption of harvest and electricity for irrigation, the deviation is probably due to the different contribution of these input flows. With the rapid development of rural land transfer and agricultural mechanization in China in recent years, problems such as excessive land management scale, mismatched management capacity and scale, excessive investment in agricultural machinery, and low utilization efficiency have occurred in some areas, leading to the loss of agricultural eco-efficiency.

Mitigation scenarios and the possibility of their realization

Our result showed that CF and NF can be reduced by Nr emission reduction, combined with increased food production and reduced CH_4 emissions (Table 2). Reduction of rice paddy field CH_4 emissions would be an efficient solution toward lowering the CF of rice production. The use of appropriate farming practices could reduce CH_4 emissions from paddy rice cultivation, in ways that tillage practice is optimized and water and fertilizer management is improved. Rational water resource management (such as intermittent irrigation, intermittent irrigation-drainage in mid-season-frequent waterlogging, non-waterlogging-drainage in mid-season-intermittent irrigation) was adopted to reduce CH_4 emission compared with continuous flooding in rice growing season [41]. To both cut N inputs and enhance the grain yields, there is a need to greatly improve the N partial factor productivity (PFPN) on a national scale [42]. Chen et al.[15] found that the PFPN could approach 54, 41, and 56 kg grain kg^{-1} N in the main agroecological areas, respectively, for rice, wheat and maize production in China; these levels are 3.6, 2.9 and 2.5 times than our values of 15.1, 13.9 and 22.8 kg grain kg^{-1} N. In addition, for rice, the total nitrogen application should be divided into at least three stages: base fertilizer, early tillering and heading, which are effective in maintaining or even increasing rice yield, and can save 20~30% nitrogen fertilizer (Zhao et al., 2015). Concerning proper nitrogen management for wheat and maize, compared with the current one topdressing, two topdressing (one topdressing at the later stage of wheat and maize growth) was carried out, promoting the deep application of maize topdressing. Even in the case of reduced nitrogen application, it can also greatly increase the grain yield [15, 42]. Other measures, for example, soil tests such as a preplanting NO_3 test is an effective method also can help avoid excessive use of N fertilizer [44]; the incorporation of N fertilizer into soil and banded N fertilizer placement minimize N losses such as NH_3 volatilization and increase fertilizer efficiency; and the effect of the preceding stubble on nitrogen supply in grain pods reduced the amount of nitrogen applied to the next crop [46].

Main uncertainties of the study

In this study, CF and NF related environmental impacts and eco-efficiency of major cereal crops production is quantified with an integrated LCA and DEA approach. However, LCA results are strongly affected by the modeling assumptions and the inherent uncertainty connected with the definition of system boundary. Some of the limitations of our study are that, due to ignorance, certain aspects of planting have not been addressed, such as the impact of crop residues on crop rotation management, changes in the timing of current and new management practices, and the indirect effects of climate change on feed composition, fertilizer quality and irrigation. There was no information on the preceding crops in rotation, and thus the environmental benefits, such as N fertilizer reduction resulting from introducing grain legumes were unclear. In addition, NH_3 volatilization loss rate under the same grain cropping system were used the same loss rate in the NF calculation of farmers' survey in each province, which may lead to some differences from the actual value due to the influence of soil properties, climatic conditions and farm management practices between regions [45]. Despite the above limitations, trends in NH_3 contributions would likely not change for the NF of all grain crops. Further, toxicity to humans and various ecosystems and biodiversity, which were important environmental impact categories [46], were excluded because the sources of pesticide data are complex. However, despite these limitations, the fact remains that the environmental characteristics of rice, wheat and maize produced throughout China are best represented in this paper, using unified evaluation criteria

Conclusion

In this study, a combination of LCA and DEA was used to measure ecological efficiency, that is, crop yields under a single environmental impact index such as global warming and water eutrophication. The focus was on a comparison in rice, wheat and corn production at a province level in China by a farmer survey. The results showed that compared with those from the developed countries, the CFs for the three major grain crops in China were higher. Moreover, N fertilizer use was seen as the most important contributor (44~79%) to the total CF of crop production, which was significantly correlated with N fertilizer application rate. Rice had a higher PCF (0.87 kgCO_2-eq kg^{-1}) than wheat (0.30 kgCO_2-eq kg^{-1}) and maize (0.24 kgCO_2-eq kg^{-1}), mainly due to the high CH_4 emission from rice fields. Meanwhile, the product NFs were 17.11, 14.26, and 6.83 g N-eq kg^{-1} for rice, wheat, and maize, respectively. In contrast to global production, the greater contributions of NF mean that cereal production depends more on NH_3 volatilization in China. Furthermore, the significantly positive relationships between CF and NF indicate the potential for simultaneous mitigation in the regions with high agricultural inputs, e.g. fertilization amounts. On the basis of the above analysis, optimization of synthetic fertilizers application is necessary to reduce the NF of cereal production. The results of LCA-DEA indicated that the eco-efficiency of major cereal crops production was found to be inefficient. Additionally, based on DEA-based sustainability performance assessment results, major cereal crops production is found to be as the major driver of CF and NF with an approximate share of

17~22% of the total impact. It also identified the target operational input for environmental measures when practicing eco-efficient crop production. These findings should contribute to achieving sustainable agriculture. Redundancy rate analysis is also provided, which indicated that diesel consumption of harvest, electricity for irrigation, herbicides and N fertilizer input value dramatically changes the overall eco-efficiency score. Based on previous studies, this study proves that the combined application of LCA and DEA is a method suitable for the comprehensive ecological efficiency evaluation of agricultural production

Abbreviations

C: carbon; CF: C footprints; N: nitrogen; NF: N footprints; LCA: LCA life cycle assessment; DEA: data envelopment analysis; GHGs: greenhouse gases; CH_4: methane; N_2O: nitrous oxide; Nr: reactive N; DMUs: decision-making units

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Authors' contributions

Zhongdu Chen designed the study and writed the first draft; Chunchun Xu and Long Ji provided data and carried out formula analysis and performed the data analyses. Fuping Fang discussed the results and contributed to improving the manuscript.

Availability of data and materials

The dataset supporting the conclusions of this article is included within the article.

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare that they have no competing interests

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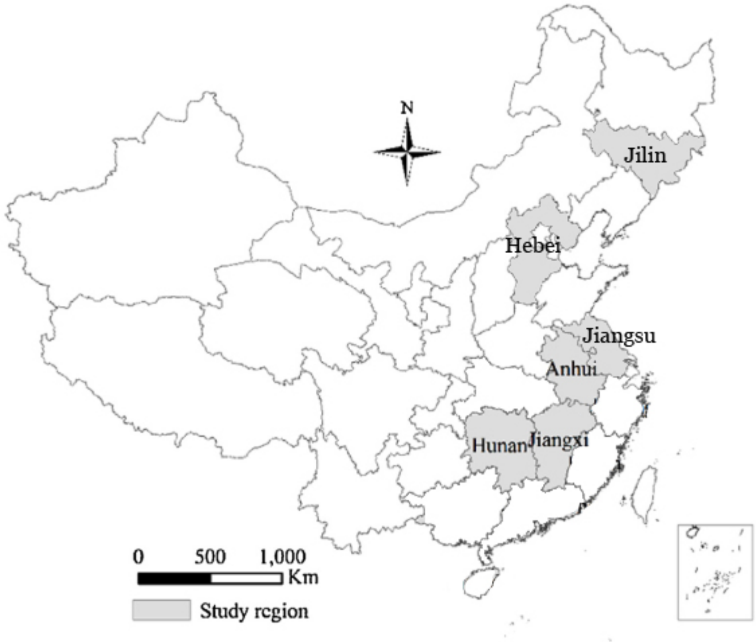
Figures

Fig.1 Geographical distribution of sites surveyed in China (The value in parenthesis is the number of farms surveyed).

Fig.2 A simplified flow chart of rice, wheat and corn production. When measuring the DEA-based eco-efficiency scores, GWP and Nr were selected as the DEA inputs by a grouping procedure based on the correlation analysis.

Fig.3 The average carbon footprint (CF) and nitrogen footprint (NF) of rice, wheat, and maize production base on a farms survey in China.

Fig.4 Correlations between the average carbon footprint (CF) and nitrogen footprint (NF) of staple food (a, rice; b, wheat; c, maize) production in China (*P* <0.01 in all plots). Each data point represents a farmer.


N
Jilin
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0 500 1,000
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Study region

Fig. 1.

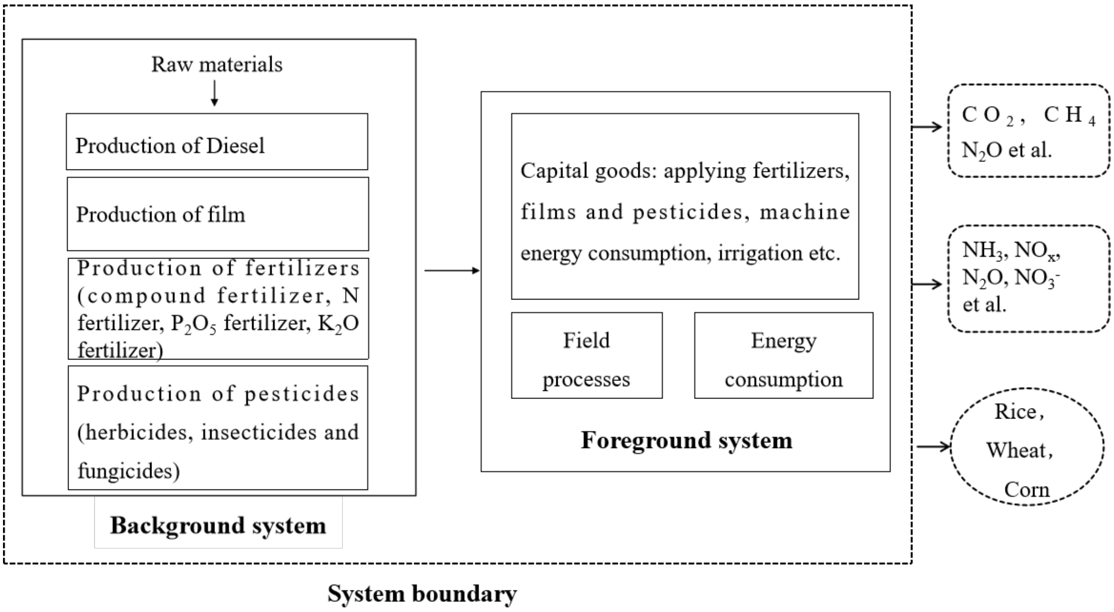
Raw materials
Production of Diesel
Production of film
Production of fertilizers (compound fertilizer, N fertilizer, P_2O_5 fertilizer, K_2O fertilizer)
Production of pesticides (herbicides, insecticides and fungicides)
Background system
Capital goods: applying fertilizers, films and pesticides, machine energy consumption, irrigation etc.
Field processes
Energy consumption
Foreground system
CO_2, CH_4 N_2O et al.
NH_3, NO_x, N_2O, NO_3^- et al.
Rice, Wheat, Corn
System boundary

Fig.2

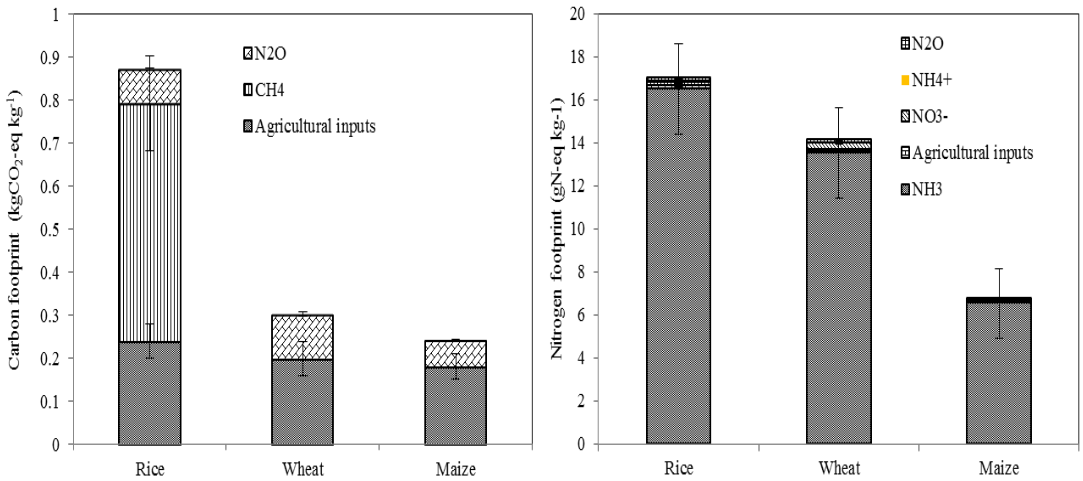
Carbon footprint (kgCO2-eq kg-1)
N2O
CH4
Agricultural inputs
Rice
Wheat
Maize
Nitrogen footprint (gN-eq kg-1)
N2O
NH4+
NO3-
Agricultural inputs
NH3
Rice
Wheat
Maize

Fig.3

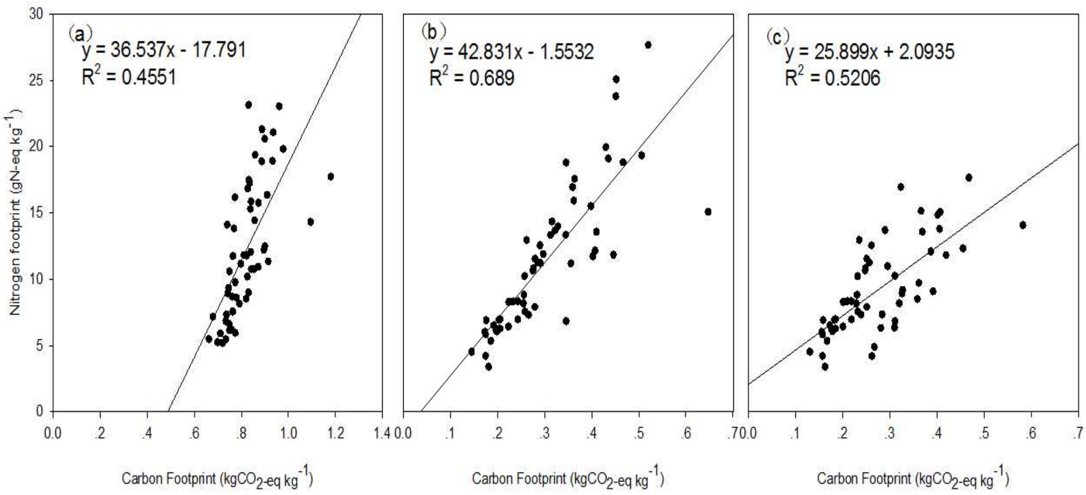
(a)
y = 36.537x - 17.791
R2 = 0.4551
(b)
y = 42.831x - 1.5532
R2 = 0.689
(c)
y = 25.899x + 2.0935
R2 = 0.5206
Nitrogen footprint (gN-eq kg-1)
Carbon Footprint (kgCO2-eq kg-1)
Carbon Footprint (kgCO2-eq kg-1)
Carbon Footprint (kgCO2-eq kg-1)

Fig.4

Tables

Table 1 Independent variables and emissions factor of farm inputs for rice, wheat, and maize production in China.

Indicators	Independent variables	Description of independent variables	Coefficient	
			GHGs emission ($kgCO_2$-eq kg^{-1})	Active nitrogen emission (kgN-eq kg^{-1})
Resources Input	N	N-fertilizer application rate per unit area (kg ha^{-1})	1.53	0.89×10^{-3}
	P_2O_5	P_2O_5-fertilizer application rate per unit area (kg ha^{-1})	1.63	0.54×10^{-3}
	K_2O	K_2O-fertilizer application rate per unit area (kg ha^{-1})	0.65	0.03×10^{-3}
	Herbicides	Herbicides application rate per unit area (kg ha^{-1})	16.61	3.53×10^{-3}
	Insecticides	Insecticides application rate per unit area (kg ha^{-1})	10.15	4.49×10^{-3}
	Fungicides	Fungicides application rate per unit area (kg ha^{-1})	10.5	7.05×10^{-3}
	Diesel	Diesel consumption from machinery operation per unit area(kg ha^{-1})	4.99	4.66×10^{-3}
	Electricity	Power consumption from irrigation per unit area (kWh ha^{-1})	0.82	0.12×10^{-3}
	Film	Film application rate per unit area (kg ha^{-1})	22.72	12.03×10^{-3}
	Rice seed	Rice seed application rate per unit area (kg ha^{-1})	1.84	0.76×10^{-3}
	Wheat seed	Wheat seed application rate per unit area (kg ha^{-1})	0.58	0.24×10^{-3}
	Maize seed	Maize seed application rate per unit area (kg ha^{-1})	1.93	0.88×10^{-3}
Expect output	Grain yield	Total crop yield per unit area (kg ha^{-1})		
Undesired output	Global warming	Standardized global warming potential per unit area ($kgCO_2$-eq ha^{-1})		
	Eutrophication pollution	Standardized eutrophication potentials per unit area (kgN-eq ha^{-1})		

The conversion coefficients of CO_2 equivalent for most of inputs were from the Chinese Life Cycle Database (CLCD v0.7, IKE Environmental Technology CO., Ltd, China), except those of pesticides and seeds which were from Ecoinvent v2.2 (Swiss Centre for Life Cycle Inventories, Switzerland). The Nr emission factors (N_n) from IKE eBalance v3.0 (IKE Environment Technology CO., Ltd, China).

Table 2

The life cycle inventory dataset of farm size, grain yield, agricultural inputs and fields of rice, wheat and maize production in the surveyed regions (mean ± S.E.)

Item	Rice		Wheat		Corn	
	Jiangxi	Hunan	Jiangsu	Anhui	Hebei	Jilin
Farm size (ha)	2.1±0.5	2.6±0.9	2.4±1.1	1.6±0.3	0.6+0.2	0.8+0.2
Grain yield (t ha^{-1})	6.0±0.4	5.4±0.5	5.7±0.8	6.0±0.7	6.7±0.6	7.7±0.7
Diesel oil (L ha^{-1})	107.1±27.1	95.2±33.4	131.9±31.4	103.0±29.0	104.1±19.2	88±10.3
Electricity for irrigation (kW h ha^{-1})	27.3±8.5	33.2±7.1	-	-	91.8±14.4	80.1±10.9
Seeds (kg ha^{-1})	78.6±14.0	36.0±17.8	44.2±9.7	55.5±6.6	44.6±7.6	35.5±5.1
Films (kg ha^{-1})	7.4±1.1	7.0±1.5	-	-	-	-
Herbicides (kg ha^{-1})	0.3±0.1	0.3±0.2	0.5±0.2	0.3±0.1	1.9±0.4	1.4±0.7
Insecticides (kg ha^{-1})	0.4±0.2	0.3±0.2	0.6±0.2	0.5±0.1	0.7±0.2	0.6±0.3
Fungicides (kg ha^{-1})	1.1±0.4	0.8±0.5	1.1±0.5	1.0±0.4	0.3±0.1	0.2±0.1
N fertilizers (kg ha^{-1})	363.2±97.4	217.0±96.3	272.4±83.1	197.3±57.1	172.8±31.1	200.3±37.0
P_2O_5 fertilizers (kg ha^{-1})	31.5±14.1	36.1±7.8	25.1±9.7	35.2±9.7	93.7±30.1	107.6±39.7
K_2O fertilizers (kg ha^{-1})	67.0±23.0	86.9±30.0	56.2±18.6	78.1±25.7	63.86±16.7	91.1±26.7
CH_4 (kg ha^{-1})	131.3±19.5	121.1±29.5	-	-	-	-
N_2O (kg ha^{-1})	1.9±0.5	1.2±0.5	2.0±0.4	1.4±0.3	1.3±0.2	1.5+0.3
NH_3 (kg ha^{-1})	149.04±39.5	89.07±40.0	90.9±34.1	65.9±23.1	47.2±13.2	55±21.2
NO_3^- (kg ha^{-1})	4.9±0.5	2.9±0.9	7.3±1.0	5.3±0.7	1.4±0.1	1.6±0.2
NH_4^+ (kg ha^{-1})	1.6±0.4	1.0±0.5	0.7±0.01	0.5±0.01	0.1±0.02	0.1±0.03

Table 3

The average hidden greenhouse gases (GHGs) and reactive nitrogen (Nr) emissions from agricultural inputs of grain crop production in China (mean ± S.E.)

Input	GHGs emission (kg CO_2-eq ha^{-1})			Nr emission (g N-eq ha^{-1})		
	Rice	Wheat	Corn	Rice	Wheat	Corn
Diesel oil	504.7±134.1	451.3±149.7	479.3±134.1	471.4±139.8	547.3±140.1	447.6±77.1
Electricity for irrigation	24.8±6.6	-	70.7±13.1	3.6±0.9	-	10.3±1.8
Seeds	105.4±25.8	28.9±4.6	77.3±11.6	43.5±10.6	12.0±1.9	35.2±5.8
Films	163.6±23.8	-	-	86.6±11.8	-	-
Herbicides	5.0±1.7	6.6±3.1	27.4±8.3	1.1±0.4	1.4±0.7	5.8±1.8
Insecticides	3.6±1.6	5.6±1.1	6.6±2.1	1.6±0.8	2.5±0.6	2.9±1.2
Fungicides	10.0±5.0	11.0±4.8	2.6±1.2	6.7±2.1	7.4±2.8	1.8±0.8
N fertilizers	443.9±144.4	359.3±107.1	285.4±52.2	258.2±86.3	209.0±62.3	166.0±30.6
P_2O_5 fertilizers	55.1±17.1	49.1±5.2	164.1±18.9	18.3±6.1	16.3±1.6	54.4±6.6
K_2O fertilizers	50.0±17.1	43.6±14.3	50.4±14.1	2.3±0.8	2.0±0.7	2.3±0.7
Totals	1366.0±234.1	955.6±194.4	1163.8±224.1	893.2±187.2	797.9±104.7	726.4±100.7

Table 4

Variation of product carbon footprint and nitrogen footprint with farm size classes (Mean ± S.E.).

Crop	Region	Carbon Footprint ($kgCO_2$-eq kg^{-1})			Nitrogen footprint (gN-eq kg^{-1})		
		LZF	MZF	SZF	LZF	MZF	SZF
Rice	Jiangxi	0.80±0.12b	0.89±0.15b	1.12±0.07a	17.47±3.11b	20.44±1.31b	24.07±2.01a
	Hunan	0.78±0.11a	0.82±0.13a	0.98±0.14a	12.05±2.11a	13.85±3.08a	16.03±3.21a
Wheat	Jiangsu	0.26±0.04c	0.35±0.01b	0.40±0.02a	14.17±2.01c	17.01±1.41b	19.12±1.11a
	Anhui	0.22±0.04c	0.28±0.01b	0.31±0.01a	9.88±3.22c	11.64±1.42b	15.87±1.33a
Corn	Hebei	0.25±0.02a	0.27±0.02a	0.30±0.02a	5.96±2.37a	6.86±1.41a	8.61±2.13a
	Jilin	0.20±0.03b	0.24±0.02b	0.29±0.01a	5.46±0.67b	6.84±0.44b	7.94±0.53a

Household farms were divided into two categories of small sized (SZF, <0.7 ha), middle sized (MZF, 2-7 ha) and large sized household farms (LZF, >20 ha) according to the farm size data obtained in the survey. Different letters indicate significant differences between farm size classes at $p < 0.05$.

Table 5

The eco-efficiency and redundancy rate of grain crop production on province levels in China (mean ± S.E.)

Item	Rice		Wheat		Corn	
	Jiangxi	Hunan	Jiangsu	Anhui	Hebei	Jilin
Eco-efficiency						
	0.55±0.15	0.51±0.13	0.69±0.24	0.62±0.21	0.87±0.15	0.91±0.13
Undesired yield redundancy rate						
Labor	0.4%	0.3%	-0.2%	-2.6%	-1.1%	2.0%
Seeds	-7.3%	-5.7%	-8.8%	-9.3%	-10.4%	-10.9%
Tillage	-10.6%	-12.0%	-10.0%	-15.4%	-9.9%	-14.5%
Sowing	-2.8%	-5.4%	-1.9%	-6.1%	-7.9%	-4.5%
Harvest	-17.7%	-19.9%	-17.4%	-16.8%	-7.9%	-4.5%
Electricity for irrigation	-17.9%	-15.0%			-7.7%	-4.6%
Herbicides	-8.7%	-4.3%	-12.5%	-14.1%	-16.8%	-23.3%
Insecticides	-8.1%	-4.2%	-1.3%	-1.7%	-19.1%	-15.3%
Fungicides	-0.2%	-0.6%	-2.9%	-9.9%	-2.7%	-9.2%
N fertilizers	-17.9%	-20.9%	-24.6%	-32.9%	-31.7%	-31.3%
P_2O_5 fertilizers	-3.9%	-2.0%	6.8%	-0.5%	-7.9%	-3.4%
K_2O fertilizers	-2.6%	-4.9%	4.0%	-0.7%	-11.0%	-5.5%
Grain yield	-0.4%	-0.1%	-1.3%	-2.7%	-3.4%	-1.1%
GWP	-25.1%	-22.7%	-12.5%	-13.1%	-14.0%	-13.5%
N_r	-17.9%	-10.9%	-24.5%	-23.0%	-20.2%	-20.6%

Figures

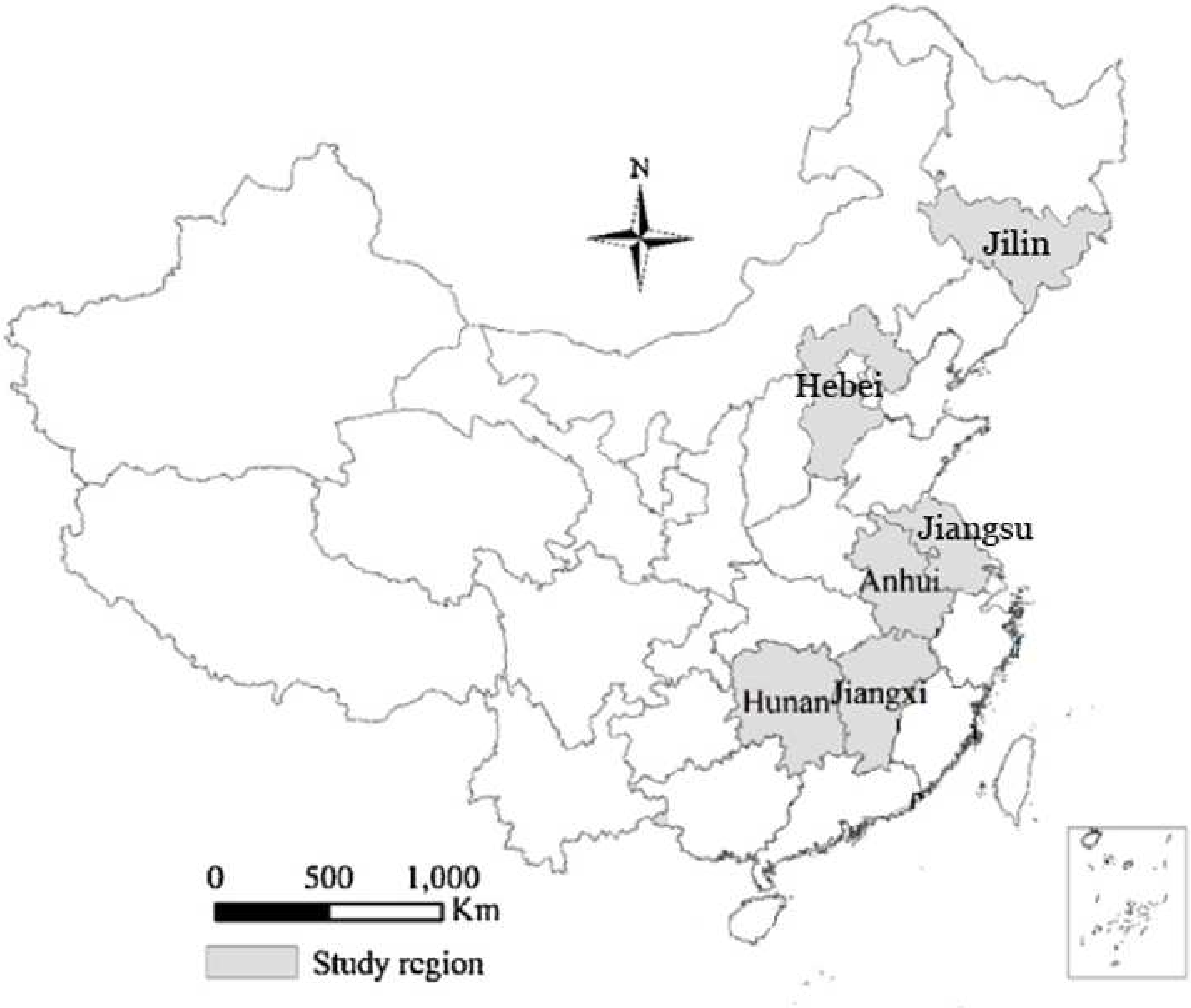

Figure 1

Geographical distribution of sites surveyed in China (The value in parenthesis is the number of farms surveyed). Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

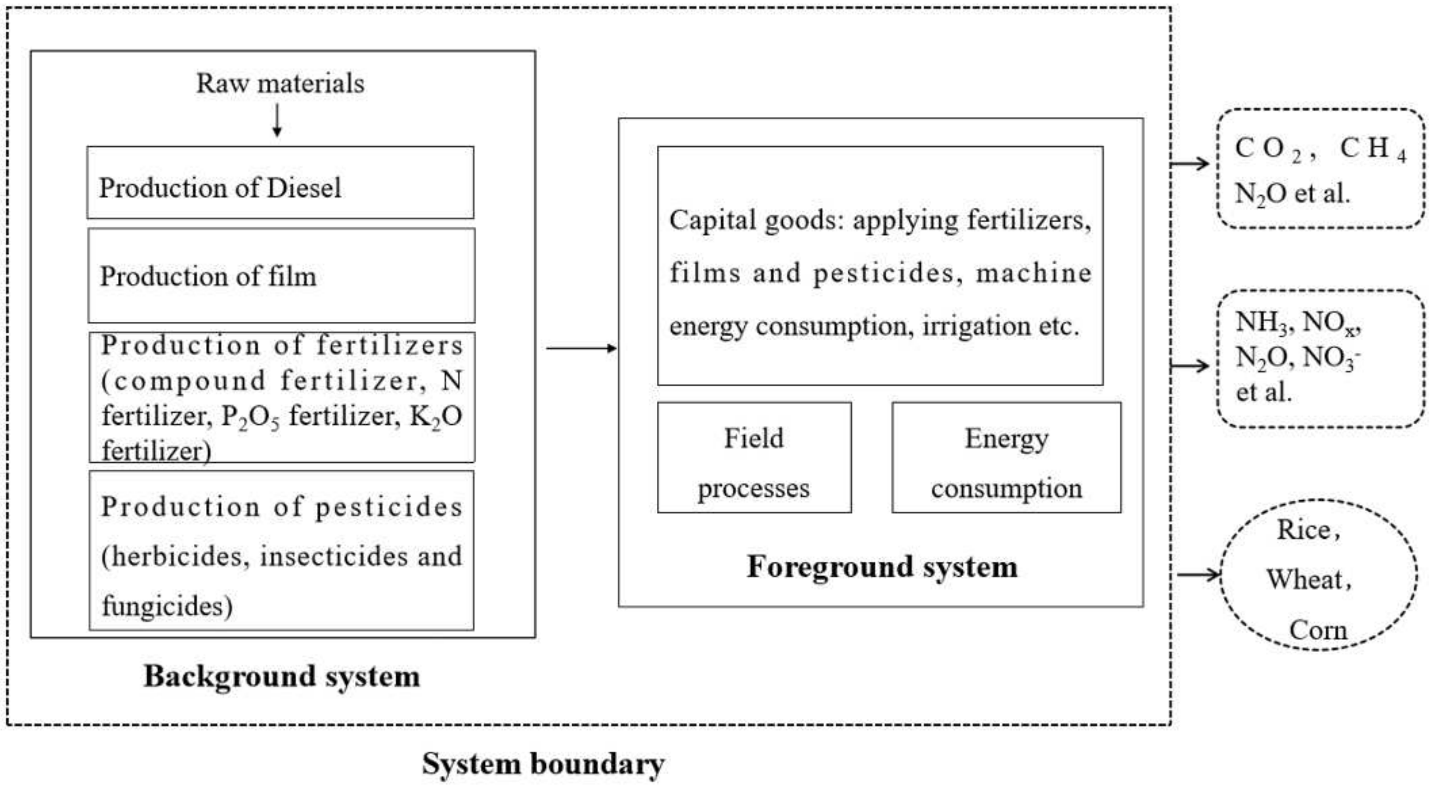

Figure 2

A simplified flow chart of rice, wheat and corn production. When measuring the DEA-based eco-efficiency scores, GWP and Nr were selected as the DEA inputs by a grouping procedure based on the correlation analysis.

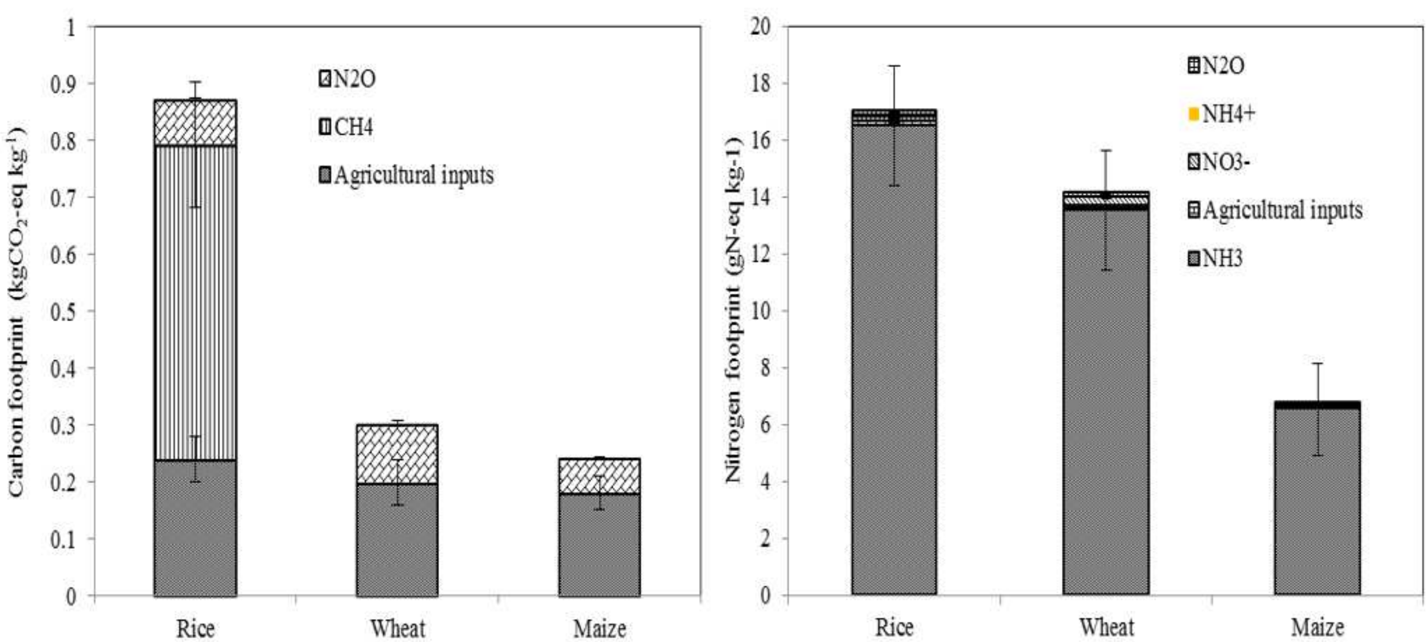

Figure 3

The average carbon footprint (CF) and nitrogen footprint (NF) of rice, wheat, and maize production base on a farms survey in China.

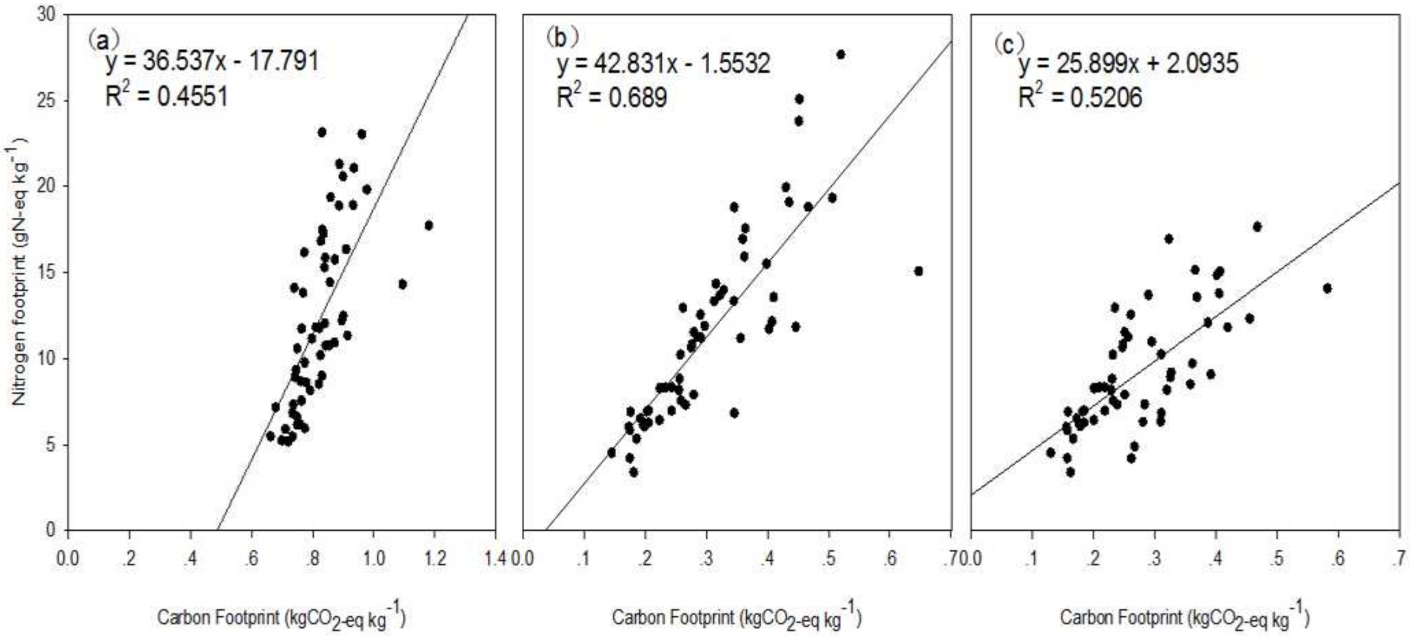

Figure 4

Correlations between the average carbon footprint (CF) and nitrogen footprint (NF) of staple food (a, rice; b, wheat; c, maize) production in China (P <0.01 in all plots). Each data point represents a farmer.