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Composite effects of human, natural and social capitals on sustainable food-crop farming in Sub-Saharan Africa

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ABSTRACT

This study analyzes the spontaneous impact of human, social and natural capital on food crop technical efficiency (TE) in Sub-Saharan Africa (SSA). Our study contributes to the literature by adopting the meta-analysis method to investigate the relationship between TE and the three groups of capitals to better shed light on the TE in SSA regions. Our results highlight that social capital is the most critical factor among the three groups of capitals in promoting farming productivity. In particular, agriculture efficiency benefits from increasing people's trust in institutions and the frequency of extension visits. Natural capital like temperature and elevation is essential in determining the farming TE in SSA regions. Outstandingly, our results also indicate that calorie intake, a proxy of labor quality, should be improved to achieve better productivity.

1. Introduction

Africa is the most vulnerable continent to food security, where 20% of its population is undernourished, of which the majority is from Sub-Saharan Africa (SSA) (Food and A. O. E. C. on Agriculture; African Union Commission, 2020). This happens even though the main economic activities and livelihoods of people in SSA revolve around agriculture production, which significantly contributes to economic growth and social welfare (Johnston and Mellor, 1961; Johnson, 1993; Gollin et al., 2002; Timmer, 2002). Malnutrition due to food insecurity is a severe problem in SSA because it results in detrimental health and development consequences to subsequent SSA generations (Gundersen and Ziliak, 2015). Existing literature has suggested that food insecurity in SSA is caused by both the insufficient quantity and the poor quality of nutrient intakes (Abdulai and Hazell, 1996; Sasson, 2012). Thus, in this paper, we aim to tackle the reasoning that improving agricultural production, especially food crops such as wheat or maize, could at least solve the quantity part of the problem since these products have been staple foods that provide essential carbohydrates for human activities for millenniums.

Our study applies technical efficiency (TE) to measure and analyze the agriculture productivity in SSA. This concept is defined as "the degree to which the actual output of a production unit approaches its maximum" (Färe and Lovell, 1978). To put it simply, TE is the measurement of how efficient a production unit is with given production inputs. Studies of Hoang-Khac et al. (2021) and Ehui and Pender (2005) have confirmed that Africa, especially the SSA regions, is known as one of the least efficient agricultural production areas in the world, which traps people in a vicious circle of poverty and malnutrition. Thus, promoting African agriculture productivity via improving TE in farming is imperative to solve this conundrum. Therefore, our study aims to examine the driving factors that could help improve the farming efficiency of the SSA regions.

Previous studies have decomposed TE to discover its driving factors from various perspectives. A review article reported that farmers' education and experience, extension contacts, credit access and farm size are significant driving forces that explain farming TE (Bravo-Ureta and Pinheiro, 1993). Researchers pointed out that experience and level of formal education have a positive impact on TE (Djomo and Sikod, 2012). Other studies suggested that the differences in TE among farms could be explained by household demographic characteristics, such as household size, income, land size, education, gender, age, etc. (Hakim et al., 2021). Moreover, religious beliefs and interpersonal

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trust are social factors that could also be significant determinants of TE (Barro and McCleary, 2003). Besides the socio-demographic characteristics, nature-related factors, such as precipitation, irrigation and altitude, could also significantly impact the TE (To-The and Nguyen-Anh, 2021; Anang et al., 2017; Pindiriri et al., 2016; Poudel et al., 2017). Hence, our study categorizes the agricultural efficiency-driving factors mentioned above into three different groups: (1) human-related factors, such as demographic characteristics, namely human capital; (2) society-related factors, such as beliefs, trusts, or social contacts, namely social capital; (3) nature-related factors, such as climate or location characteristics, namely natural capital (Dasgupta, 2021).

Since sustainable development is a more desired path for humanity, it is necessary to include human, social and natural factors in the analysis, especially in agricultural production. Thus, we conduct a meta-analysis to assess the impacts of different groups of capitals, including human, social and natural capitals, on agricultural TE in SSA. Meta-analysis is "the analysis of the results of statistical analyses for the purposes of drawing general conclusions" (Hedges, 1992; Glass, 1977). In other words, meta-analysis can be considered a quantitative form of a literature review using statistical testings and econometric methods (Guzzo et al., 1987). This method allows us to collect the results and findings from independent studies in a systematic manner, then use these results to estimate variations and correlations between drivers via a regression model (Stanley et al., 2013).

In appraising agriculture TE, several meta-analysis studies have been conducted in various geographical areas: Thiam et al. (2001) reviewed TE of the agriculture sector (mainly on food crops such as maize, wheat, and rice) in 15 developing countries in Asia and South America; Moreira Lopez and Bravo-Ureta (2009) used meta-regression to examine TE of dairy farms in different developed countries, such as Europe, Oceania and North America; Minviel and Latruffe (2017) studied the effect of public subsidies on farming TE based on 195 papers in mainly Europe and America from 1986 to 2014; Bravo-Ureta et al. (2007) did include African countries in their meta-analysis, but with a small number of observations or narrow areas. However, there is only a handful of evidence focusing on this three-way interaction, especially in the context of Africa. For instance, in a meta-regression analysis, the authors investigated how social and natural capital, along with human capital, could explain TE (Hoang-Khac et al., 2021). Moreover, their study only mentioned the role of social and natural capital and had not delved into the relationship between our three capitals or their composite impacts on TE. Therefore, this paper also contributes to the literature by adopting the meta-analysis method to investigate the relationship between TE and the composite effects of the three groups of capitals (i.e., human, social and natural capitals) to better shed light on agricultural TE in the SSA regions.

The rest of the paper is organized as follows: Section 2 presents the literature review. Section 3 explains the methodology and summarizes our data collection and variable description. Section 4 presents the estimation results and discussions. Section 5 discusses the policy implications. Section 6 concludes the paper.

2. Literature review

2.1. Human capital and technical efficiency

Human capital is not a recent discovery, this concept was introduced decades ago in the works of Schultz (1961) and Becker (1962). In early studies on this concept, human capital was suggested to link directly to training and educational level (Coff, 2002). Later, *human capital* is defined as "the stock of competencies, knowledge and personality attributes embodied in the ability to perform labor so as to produce economic value" (Djomo and Sikod, 2012). Therefore, education level, farming experience, health, and technical training are three factors that are commonly considered as components of human capital in agriculture activities (Djomo and Sikod, 2012; Anderson and Feder, 2004). Furthermore, in this paper, we use calorie intake per capita per day as a proxy of farmers' ability to perform labor tasks (i.e., quality of labor input). Higher calorie intake implying higher energy suggests that farmer is capable of providing more human capital (Croppenstedt and Muller, 2000; Strauss, 1986).

The impact of education on farming TE appears to be the most widely studied. There is extensive literature on the nexus between education and TE from different areas in the world. For instance, the works of Lockheed et al. (1980), Huffman (2001), Maudos et al. (2003) have claimed that high education level has a positive and significant impact on agricultural efficiency in general. To account for the effects of education, previous studies have also used years of schooling as a proxy variable (Abdulai et al., 2013; To-The and Nguyen-Anh, 2021; Ndour, 2017; Dimelis and Papaioannou, 2014; Yang and An, 2002; Onyenweaku and Nwaru, 2005; Asadullah and Rahman, 2009). These studies indicated that an increase in the years of schooling could lead to an increase in farming TE. For instance, the authors suggested that education is vital to labor productivity by boosting Bangladesh farmers' access to advanced farming technology in rice production (Asadullah and Rahman, 2009).

In addition to education, farming experience also received much attention from research scholars in agricultural productivity. The existing studies have indicated that a farmer who has more experience in the field will likely have more efficient techniques and input allocation and thus is more efficient than other farmers who have less experience (Onyenweaku and Nwaru, 2005; Ho and Shimada, 2019; Poudel et al., 2017; Huy and Nguyen, 2019; Addai and Owusu, 2014; Bäckman et al., 2011; Nyagaka et al., 2010). For instance, one study argued that more years of farming experience results in a high conscious accumulation of know-how from farming practices that could help farmers operate their farms at a significantly higher level of profit efficiency (Addai and Owusu, 2014). Therefore, years of farming experience could be an essential determinant of farming TE.

For many years, policymakers worldwide have believed that agricultural development policies like extension programs that offer practical training to farmers could help improve farming efficiency. It should be noted that to avoid confusion about extension visits discussed in the next section (Section 2.2), this section refers to extension as a scheme of training that improves farmers' competencies in farming. Note that an extension can be in the form of technical consult or direct training courses. Indeed, via extension training, farmers could have high productivity because they have more knowledge and incentives to adopt new technology (Anderson and Feder, 2004). For instance, in one study, the authors found that sending extension workers to advise farmers on efficient farming techniques and information can help improve maize farms' productivity in Ghana. Another study argued that extension schemes could enhance farmers' ability to utilize agriculture inputs and technology more efficiently and thus improve productivity (Dinar et al., 2007).

2.2. Social capital and technical efficiency

Social capital consists of social participation (Peiro-Palomino, 2016), personal and social trust (Bjornskov, 2006), social connections with local extension officers (Hoang-Khac et al., 2021), and religious beliefs (Smidt and Smidt, 2003; Hopkins, 2011). Several previous studies have established the relationship between social capital as a whole or by single components and technical efficiency (TE). Coleman (1988), Olurotimi et al. (2018) argued that strengthening social capital could improve welfare by reducing the risk of forming a new link with others and thus lowering the transaction cost of establishing social networks. For instance, a study of TE in rural areas of South Africa found that social capital has a significant impact on rural development and TE (Chuzu, 2002). Therefore, social capital should be carefully considered in studies on growth and development.

Existing literature on social capital and growth has emphasized the role of social trust as an informal institution and formal institution in general economic growth in China from 2001 to 2009 (Cui, 2017). Their results indicated that social trust positively impacts economic growth (e.g., GDP per capita). In other words, a higher level of social trust could improve citizens' level of education and trust in institutions and thus drive economic development (Bjornskov and Meon, 2015). However, despite a strong relationship between trust and production outcome, the nexus of trust and total factor productivity (TFP) remains unclear (Bjornskov and Meon, 2013). For instance, by examining data from 67 countries in the early 2000s, the authors revealed a significant and positive impact of social trust on TFP growth. In another study, Olurotimi et al. (2018) showed the impact of social capital as the number of extension visits, the number of social organizations joined and contacts with research institutions on TE of cassava production in Nigeria. In particular, they argued that connections with researchers positively affect TE, while the number of extension visits and social organizations has a negative effect (Olurotimi et al., 2018).

Previous studies have identified that trust in institutions is a crucial factor influencing economic growth via two main channels: investment (Knack and Keefer, 1997) and schooling (Bjornskov, 2012; Dearmon and Grier, 2011). More precisely, the authors pointed out that social trust impacts economic growth through: (1) rate of productivity growth; (2) rate of factor accumulation; (3) institutions and policies that, in turn, affect relevant growth factors; and (4) elasticity of substitution (Bjornskov, 2012). Using data on 50 countries from 1976 to 2005, Dearmon and Grier (2011) proved that trust has a positive effect on human capital and a non-linear effect on physical capital. Therefore, trust in institutions is essential to promote economic growth as formal institutions could directly impose penalties or provide an incentive to encourage behavioral changes.

Agriculture extension is a transmitter of information on technologies, management and farming practices from scientists or authorities to farmers (Owens et al., 2003; Addai and Owusu, 2014). This scheme could provide farmers with information or technologies of new farming practices and thus improve or strengthen their capacity in farming (Dinar et al., 2007). For instance, some studies suggested that farming productivity can be enhanced thanks to the efficient use of production inputs with the help of extension workers and services (Kalirajan, 1984; Bäckman et al., 2011; Chiona et al., 2014; Abdul-Rahaman and Abdulai, 2018). Moreover, extension schemes could also help farmers improve TE derived from the adoption of new technologies by narrowing the gaps between technology and management (Kalirajan, 1984; Dinar et al., 2007). Extension officials could also help farmers compensate for the lack of formal education in farmers since they are more capable of identifying problems related to farming than farmers themselves (Nyagaka et al., 2010). Thus, several studies, such as the study of maize farmers in Ghana (Addai and Owusu, 2014), Zambia (Chiona et al., 2014) and Zimbabwe (Mango et al., 2015), the study of potato farms in Kenya (Nyagaka et al., 2010), rice farms in Bangladesh (Bäckman et al., 2011) and Ethiopia (Lema et al., 2017), and yam farms in Nigeria (Shehu et al., 2010), found that technical efficiency would increase with an increase in the number of extension visits. For instance, farmers who have access to extension services have 15% higher efficiency compared to those who do not (Owens et al., 2003). Therefore, extension services, via either direct or indirect contact, could have positive impacts on agriculture efficiency due to practical demonstration of farming-related issues (Bäckman et al., 2011; Chiona et al., 2014; Mango et al., 2015).

However, some studies have also established a negative relationship between extension and efficiency. For instance, Haji (2007) adopted the Data Envelope Analysis (DEA) approach on 150 mixed farming households in eastern Ethiopia and found that extension was a significant, negative determinant of technical efficiency. In his study, farmers reported not having new skills and information from extension officials. Enwerem and Ohajianya (2013) indicated a similar result which was ascribed to the low extension workers to farmers ratio in the studied area. Kalirajan and Shand (1988) argued that if extension workers do not have sufficient knowledge or information about farming techniques, extension contacts might not have a significant impact on TE.

2.3. Natural capital and technical efficiency

Natural capital is "the stock that yields the flow of natural resource; the population of fish in the ocean that regenerates the flow of caught fish that go to market, the standing forest that regenerates the flow of cut timber; the petroleum deposits in the ground whose liquidation yields the flow of pumped crude oil" (Johansson, 1994; O'Connor, 2000). In other words, *natural capital* is assets of nature that provide resource inputs (i.e., geology, soils, air, water and all living organisms) and environmental services (i.e., disposal services, productive services, consumptive services) (Nations, 1997).

However, due to the lack of available data on natural capital, there is a limited number of evidence on the impact of these factors as natural capital on TE (Alem, 2021). Literature on farming TE has commonly used climate and geographical locations as proxies for farmers' cultivating environment. This is because agricultural activities depend highly on temperature, precipitation or soil quality. The elevation is commonly used since this factor could help explain the change in soil quality and actual farming practices (Latruffe et al., 2004; Ghosh et al., 2014). Moreover, previous studies have suggested that people are highly dependent on nature in all of our economic activities, especially agriculture (Dasgupta, 2021). Thus, our paper formulates natural capital based on land size, precipitation, and elevation.

The relationship between land size and productivity has been widely studied (Bojnec and Fertő, 2013; Ogundari, 2013). In their study, the authors indicated a positive relationship between increasing total cultivated land area and farming technical efficiency among Slovenia farmhouses from 2004 to 2008 (Bojnec and Fertő, 2013). Another study suggested the vital role of the total arable land size in promoting the TE (Ogundari, 2013). However, the study of Ferreira and Féres (2020) suggested a non-linear relationship between farm size and technical efficiency. On this nexus, the research literature is divided into three different outcomes: (1) a positive association between farm size and technical efficiency and agriculture productivity (Ogada et al., 2014; Sherlund et al., 2002); (2) a "U-shape" relationship, indicating that for each farmer with different inputs and characteristics, there exists an optimal size of arable land where their farming efficiency is maximized (Ferreira and Féres, 2020; Helfand and Taylor, 2021; Looga et al., 2018; Henderson, 2015); (3) a negative correlation between farm size and technical efficiency (Herdt and Mandac, 1981).

Weather is one of the most critical factors affecting outcomes and productivity in agriculture. Therefore, studies on agricultural productivity should control for weather inputs to provide more robust results (Pindiriri et al., 2016). However, weather-related inputs or climate change-related factors have not yet been profoundly discussed in the literature on technical efficiency (Ibrahim et al., 2014; Singh et al., 2009). For instance, climate change maneuvers, including increasing temperature and decreasing precipitation, have been recorded to harm agriculture activities in Brazil (Gori Maia et al., 2021), Vietnam (To-The and Nguyen-Anh, 2021), West Nigeria (Oyekale, 2012), and many other regions in the world (Baten et al., 2009; Nauges et al., 2011).

Many studies showed that farmers in ecological zones with higher precipitation are more technically efficient than those in drier zones (Ibrahim et al., 2014; Ogada et al., 2014; Tasnim et al., 2015; Makki et al., 2012). More specially, existing studies suggested that irrigated small farms are more efficient and productive than rain-fed farms in Northern Ghana (Anang et al., 2017), Nigeria (Adekalu et al., 2009) and Brazil (Sampaio Morais et al., 2021). The study on the Volta basin, where farmers face drought and inconsistent rainfall during farming seasons, also suggested a similar result (Lemoalle and de Condappa, 2010). The study of Sampaio Morais et al. (2021) also argued that large farms are more likely to experience the differences in precipitation than small and medium farms. Moreover, irrigation may not cause a notable change in technical efficiency for farmers in a wetter climate. Studies on the technical efficiency of farmers adopting irrigation usually record this variable as binary input (irrigation vs. non-irrigation) (Anang et al., 2017; Hakim et al., 2021; Sampaio Morais et al., 2021). To consider the impact of climate on efficiency, Gadanakis and Areal (2020) accounted for climate factors such as rainfall and length of the growing season in technical efficiency computation using the data on 245 cereal farms in East Anglia from 2009 to 2010, showing that integrating these factors into the production function helps improve the robustness and reduce biases in technical efficiency estimations.

In addition to rainfall, temperature is an essential factor influencing the development of plants. Warmer temperatures due to climate change and extreme temperature events will have an impact on plant productivity (Vigh et al., 2018). In contrast, a mild composition of temperature, rainfall, humidity, and soil temperature is ideal for the growth of plant and agricultural production (Solís et al., 2009). Vigh et al. (2018) analyzed the influence of temperature and precipitation on the technical efficiency of Hungarian arable farms using climate data recorded in three different phases of cultivation, including seedling, vegetative growth and generative growth. Results showed that the increase in temperature and rainfall during the two initial farming phases leads to a positive change in efficiency. In contrast, temperature increase in the last phase has a negative effect on farming efficiency. In another study, the authors also established a negative relationship between technical farming efficiency and climate change factors, including rising temperature and falling precipitation (To-The and Nguyen-Anh, 2021).

Land elevation is a factor causing variation in climate, soil formation process and soil quality (Tsui et al., 2004; Mandal and Sharda, 2011). Moreover, soil quality or the way farms operate could be affected by farms' geographical location, such as climate and altitude (Latruffe et al., 2004). However, there is a handful of evidence on the impact of land elevation or altitude on farming efficiency. A few studies can be found in India (Ghosh et al., 2014), Turkey (Haq and Boz, 2019), and Laos (Southavilay et al., 2012). In their research, using the data in the area of the Ashti watershed of mid-hills of the northwest Himalayas regions from 2009 to 2011, the author indicated that the productivity of crops (e.g., wheat, maize, cowpea, soybean, and finger millet) are improved along with the increase in altitude from 600–1500 m (Ghosh et al., 2014). Poudel et al. (2017) studied the technical efficiency among organic coffee farms in Nepal in various altitude ranges and found that farmers in higher altitudes are more efficient than lower altitude ones. Note that Nepal is a hilly region with rugged, mountainous areas lying between 900 to 3000 m higher above the sea level (Grabowski, 1985), and coffee is cultivated at 800 m altitude or higher (Poudel et al., 2017). In contrast, Haq and Boz (2019) showed that high land slope and high altitude have a significant and negative effect on farming efficiency. Similarly, Southavilay et al. (2012) indicated that maize crops on low land (e.g., less than 360 m) would be more efficient than on the high ground. This difference may come from farmers' ability to use farming machinery on lowlands compared to human-based farming operations on highlands.

2.4. Conceptual framework of three capitals' composition on technical efficiency

The economy is referred to as an open subsystem of an ecosystem (i.e., the harmony of artificial capital and natural capital) (Johansson, 1994). For decades, many scientists have explored the relationship between human capital and natural capital driving economic growth. For instance, the modern theory of human capital and endogenous growth model emphasized that it is vital to concentrate on the improvement of the quality of labor inputs (e.g., qualifications and skills) to drive economic growth in the long term because the spillovers of knowledge across producers could benefit the improvement of human capital and thus offset the tendencies to diminishing returns (Caballé and Santos, 1993; Funke and Strulik, 2000; Le Van et al., 2018). In agricultural production, the interdependent relationship between economics and ecological efficiency in sustainable productions is referred to as the term "eco-efficiency" (Ghali et al., 2016). In their study, the authors used "energy used by production units" to assess the eco-efficiency toward sustainable farming productivity (Ghali et al., 2016). In another study, the authors found that farmers participating in "climate-smart agriculture" could notably have higher TE than non-participants (Ho and Shimada, 2019). A meta-analysis study on TE has also emphasized the critical role of human capital along with natural capital and other agricultural inputs in improving TE (Hoang-Khac et al., 2021).

While natural and human capitals are important inputs in the process of agricultural production, social capital could increase the provision of information and social participation to tackle environmental problems, such as conserving and managing natural resources (Ostrom, 1990). Fostering an environment that generates social capital (e.g., social learning, reciprocity, trusts, etc.) could help governments achieve sustainable development goals. For instance, joint and participatory forest management in India and Nepal has shown a significant improvement in generating the collective community responsibility for protecting biodiversity as well as improving productivity and income growth for local forest users (Rasul et al., 2011; Mukherjee et al., 2017).

Human and social capital has been recognized as a significant factor of growth. Existing literature has indicated that there may be a considerable substitution relationship between human and social capital. More specifically, as improving human capital, human time that is needed to create social capital will become more valuable (Fedderke and Klitgaard, 1998; Piazza-Georgi, 2002). In other words, investment in human skills may be a substitute for investment in some forms of social capital. Social capitals, such as expectations, information flow through social structure and norms, have also been found as essential factors that could improve human capitals (Coleman, 1988; Schuller, 2001) and thus benefit TE (Santarelli and Tran, 2013).

Taken together, in this study, we aim to extend this literature on the composite effects of human, natural and social capitals by investigating their impacts on food-crop TE using the meta-analysis data in Sub-Saharan African regions. Fig. 1 describes the possible interactions between three groups of capital and their impacts on agricultural TE as discussed above.

3. Data and methods

3.1. Data

We initially compiled a database of studies investigating the relationship between human capital and farming performance in agricultural production. We searched the following several keywords: "Human capital", "Social capital", "Natural capital", "Farming efficiency", "Food crop", and "Sub-Saharan Africa" in Google-scholar and JSTOR. In total, we discovered roughly 200 related articles on the technical efficiency of food-crop farming undertaken in Africa. Accordingly, we retrieved 64 studies and 122 observations conducted in Sub-Saharan Africa about food-crop technical efficiency, which are described in Fig. 2. The list of studies included in our meta-analysis is reported in Table A.1 in Appendix. Via scanning publication databases, we initially collected 170 studies, of which 30 were removed due to duplication. We then screened the titles and abstracts of 140 papers and excluded 10 for not fitting the eligibility criteria. The other eight papers were also excluded due to incomplete data after full-text assessment. Finally, we use data from the remaining 64 studies for this meta-analysis.

A qualified article should contain a measure of human and social capital. Regarding human capital, the report of at least one or a combination of the variables *Education*, *Experience*, and *Extension* are

Fig. 1. Conceptual framework of interaction impact of three capitals on TE.

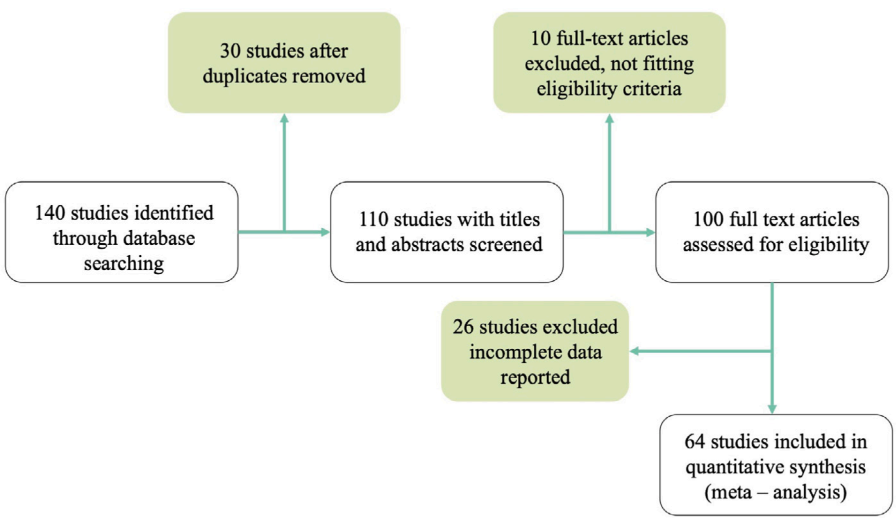

Fig. 2. Results of the paper selection process.

employed in our meta-analysis. We construct our human capital variable by employing either farmers' education, experience and extension following the results of To-The and Nguyen-Anh (2021), Lema et al. (2017). In addition to these mentioned variables, we also include a human capital variable, $CalorieIntake$, to capture the quality of labor input in farming TE. Calorie intake data is total calorie intake per capita per day, retrieved from the UN Food and Agriculture Organization (FAO) Food Balance Sheets dataset from 1961 to 2018. According to the FAO's report, $CalorieIntake$ can be treated with the same meaning as better nutrition in developing countries, especially those with food shortages (Wang et al., 2002).

Regarding social capital, the frequency of receiving local extension services and institutional trust (i.e., Corruption Perception index) is used to investigate the impact of social capital on TE. Existing literature has suggested that extension officers are representatives of the agricultural institution. Thus, the involvement of these local officers in farmers' production areas is a vital type of farmers' social capital (Takemura et al., 2014). Natural capital, surrounding nature-related factors, are described in the forms of climate or location characteristics (Dasgupta, 2021). Therefore, along with human and social capital, variables including $Rainfall$, $Temperature$, and $Elevation$ are also collected from the Transparency and World Bank database to assess the impact of natural capital on agricultural productivity.

Besides the above explanatory variables, we also investigate the impacts of other control factors that influence farmers' TE, such as types of studied crops, data type, model specifications, and the number of observations (Thiam et al., 2001; Bravo-Ureta et al., 2007). To examine the time trend effects, we code the studies as "Cross-sectional" articles wherein human capital and TE measures were analyzed using cross-sectional data that indicate no time lag effects of human capital on TE. We define those studies as "Longitudinal" based on panel data characteristics when the analysis uses panel data to estimate TE. Regarding (FAO, 2012), the types of food crops are classified to systematically partition the planted production categories to match our criteria comparing the TE between food crops. Four dummy variables are defined, namely rice, maize, beans and other types of crops (Others). The model specification, used to formulate a production function,

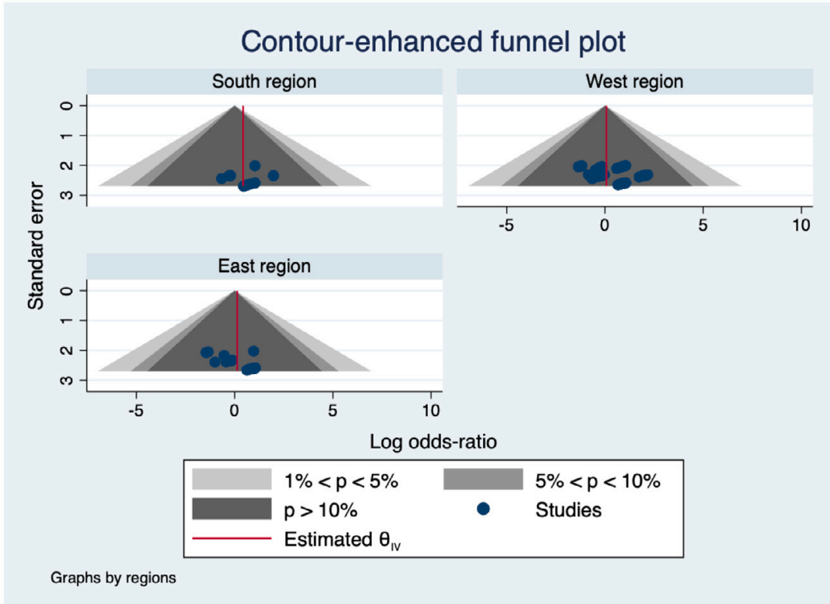

Fig. 3. Symmetric funnel plot of food crop farming efficiency.

is a fundamentally important stage before approaching the technical efficiency function. Each model specification of a production function depends on assumptions that may result in different technical efficient scores. The three most well-known and widely-used methods are the Cobb–Douglas (CD), Trans-log (TL) and Data Envelop Analysis (DEA) production functions. While the CD function stands for a more restricted function, the TL function is a more flexible method that allows the interaction between employed production factors. Several existing studies have employed both TL and CD to analyze the determinants of TE (Dearmon and Grier, 2011; Cui, 2017; To-The and Nguyen-Anh, 2021).

3.2. Method

A meta-regression model is an ideal approach to recognize the significance of the composition of human, natural and social assets on the technical efficiency of food crop farming (Hoang-Khac et al., 2021). We, accordingly, specify our regression model illustrated as below equation:

$$MTE_{ij} = \alpha_0 + \sum_{n=1}^{3} \beta_n NATURAL_{ijn} + \sum_{n=1}^{3} \gamma_n NATURAL_{ijn}^2 + \sum_{n=1}^{4} \delta_n HUMAN_{ijn} + \sum_{n=1}^{2} \lambda_n SOCIAL_{ijn} + \sum_{k=1}^{K} \eta_n CONTROL_{ijk} + \Theta_j + \varepsilon_{ij}, \quad (1)$$

where MTE_{ij} is the mean TE score of the observation i reported in j food-crop farming study and the intercept α_0 measures the mean effect size of the TE.

Firstly, the variable of interest $NATURAL_{ijn}$ represents $N = 3$ numbers of natural capital variables, including $LandSize_{ij}$ is the log of cultivated farmland size in the study area, $Rainfall_{ij}$ is the log of average precipitation in the study area, $Temperature_{ij}$ is the log of average temperature in the study area, and $Elevation_{ij}$ is the log of average elevation in the study area. We also include the square terms of natural capital variables, such as $Rainfall_{ij}^2$, $Temperature_{ij}^2$ and $Elevation_{ij}^2$, to take nonlinearities into account. Secondly, the variable of interest $HUMAN_{ijn}$ represents $N = 4$ numbers of human capital, consisting of $Extension_{ij}$, $Experience_{ij}$ and $Education_{ij}$ taking the value 1 if a study accounts for an impact of the variables, such as agricultural extension, farmer's experience and educational level, on TE. In addition to these human capital variables, $CalorieIntake_{ij}$ is also used to capture the quality of labor input in farming TE, which is measured by the log of the average level of calorie intake in the study's area. Thirdly, $SOCIAL_{ijn}$ represents $N = 2$ number of social capital variables, consisting of the frequency of visits by extension officers $ExtensionVisits_{ij}$ and the confidence of the citizens for their institution $InstitutionalTrust_{ij}$. Finally, $CONTROL_{ijk}$ represents K numbers of control variables, including "Climate zones", "Data type", "Specification of the production function", and "Types of agricultural products", is used to explain the heterogeneity among collected studies. In particular, "Climate zones" are employed to capture the differences in natural characteristics of collected studies, including Equatorial, Tropical grassland, and other climate zones (e.g., Temperature, Arid and Semi-Arid climate). Θ_j is the study-specific random effect, and ε_{ij} is the meta-regression error term. The descriptive statistics and definitions of all variables are described in Table A.2 (in the Appendix).

The analysis of TE is exchangeably selected between Tobit and fractional regression. Tobit regressions were recently employed to deal with technical efficiency in the following articles of Rezitis and Kalantzi (2016), Dalei and Joshi (2020). Meanwhile, Twumasi and Jiang (2021), Zheng et al. (2021) argued that the employment of fractional regression models could provide better goodness of fit compared to the two previous models in terms of investigating the impacts of TE determinants. Our study employs fractional and Tobit regression; then, we conduct a Reset test to test for model specification. In the fractional regression model, the fractional nature of our dependent variable MTE is the mean percentage increase in technical efficiency and thus, it could not take a value less than zero and greater than one (Papke and Wooldridge, 1996; Wooldridge, 2009; Ramalho et al., 2011). Therefore, the fractional regression model with the dependent variable MTE_{ij} as a fraction bounded between zero and one, i.e., $MTE_{ij} \in [0, 1]$, has the succeeding formula:

$$E(MTE_{ij}X_{ij}) = G(X_{ij}\delta), \quad (2)$$

where X_{ij} stands for a set of regressors consisting above explanatory variables ($HUMAN_{ijn}$, $NATURAL_{ijn}$, $SOCIAL_{ijn}$), and control variables ($CONTROL_{ij}$). For the logistic link-function $G(.)$ satisfying $0 <$

Table 1
Estimation results of the weighted fractional regressions with and without “Climate zones” interaction terms.

Variable	Without interaction terms	With interaction terms		
			Interactions with “Equatorial”	Interactions with “Others”
Natural capital				
LandSize	0.004	0.094	0.237**	1.547
	(0.131)	(0.122)	(0.110)	(2.226)
Rainfall	−0.263	−0.954	−2.133	66.940***
	(0.638)	(0.770)	(100.220)	(12.309)
Temperature	−14.491*	−4.033	124.745	317.821
	(7.577)	(2.635)	(208.337)	(211.183)
Elevation	0.502***	0.299	−5.348	−6.144
	(0.150)	(0.286)	(3.661)	(31.200)
Rainfall^2	0.036	0.087	4.129	−35.428***
	(0.048)	(0.066)	(8.437)	(8.679)
Temperature^2	2.433*	0.680	−6.785	−70.725
	(1.294)	(0.367)	(59.283)	(91.323)
Elevation^2	0.020	0.278**	8.195	2.121
	(0.174)	(0.112)	(10.822)	(16.790)
Human capital				
Education	−0.096	−0.254	0.613	2.513***
	(0.099)	(0.144)	(0.575)	(0.935)
Experience	0.262	0.735***	−1.081***	−0.447***
	(0.295)	(0.015)	(0.157)	(0.025)
Extension	−0.092	0.070***	0.026	−2.986
	(0.094)	(0.095)	(0.204)	(2.112)
CalorieIntake	2.711**	3.293*	1.151	−25.851
	(1.466)	(1.940)	(8.008)	(16.541)
Social capital				
ExtensionVisits	0.249***	0.089	0.321***	0.222
	(0.090)	(0.056)	(0.083)	(0.847)
InstitutionalTrust	−1.387***	−1.268***	3.240	−0.344
	(0.257)	(0.539)	(2.452)	(8.008)
Climate zones				
Equatorial	0.168	−21.383		
	(0.138)	(72.231)		
Others	0.428***	229.92***		
	(0.078)	(78.15)		
Types of products				
Maize	0.249	0.236		
	(0.196)	(0.223)		
Beans	0.076	−0.126		
	(0.319)	(0.293)		
Others	0.225***	0.121		
	(0.019)	(0.101)		
Other controls				
Cross-section	−0.283***	−0.363		
	(0.110)	(0.248)		
Cobb–Douglas (CD)	0.490	0.372		
	(0.373)	(0.328)		
Translog	0.603	0.391		
	(0.568)	(0.513)		
Constant	5.135	−13.140**		
	(20.804)	(6.561)		
Observations	122	122		
Log-Likelihood	−1080.63	−1063.56		

Note: Robust standard errors in parentheses.
*p<0.1.
**p<0.05.
***p<0.01.

$G(.) = \frac{exp(.)}{1+exp(.)} < 1$ (Wooldridge, 2009), the fractional logit model can be written as follows:

$$E(MTE_{ij}|X_{ij}) = \frac{e^{X_{ij}\delta}}{1+e^{X_{ij}\delta}}. \tag{3}$$

The proposed estimator for δ is the Quasi Maximum Likelihood Estimator (QMLE), which maximizes the following Bernoulli log-likelihood function (McCullagh, 1989):

$$L_i(\delta) = MTE_{ij}\log[G(X_i'\delta)] + (1 - MTE_{ij})\log[1 - G(X_{ij}'\delta)]. \tag{4}$$

Additionally, to minimize the heterogeneity between studies, a weighted regression model should be used (Stanley et al., 2013; Verbeke and Molenberghs, 2009; Little and Rubin, 2019). The weighted regression approach is a commonly used method to correct the heterogeneity in TE estimates. The homogeneity test of effect size cannot be rejected with an insignificant Chi-squared (χ^2) with p-value (0.05). Thus, the weight regression is necessary to be applied to correct the heterogeneity. Since the individual standard error is unknown, we employ weighted fractional meta-regression with weights equal to the squared root of sample size found in each study ($1/\sqrt{N_i}$) to assess our hypothesis (Stanley, 2008). In addition to the heterogeneity with moderator analysis with several control variables $CONTROL_{ij}$, since there are some observations reported in the same study, it is necessary to fit the mixed effect model with restricted maximum likelihood with Θ_j as the study-specific random effect to capture the heterogeneity of study effect sizes.

Table 2
Estimation results of the weighted fractional regressions with standardized, unstandardized variables and their marginal effects.

Variable	Unstandardized		Standardized	
	Coefficient	dy/dx	Coefficient	dy/dx
Natural capital				
LandSize	0.004	0.0009	0.004	0.0009
	(0.131)	(0.030)	(0.130)	(0.028)
Rainfall	−0.263	−0.057	0.177***	0.038***
	(0.638)	(0.138)	(0.062)	(0.013)
Temperature	−14.491*	−3.146*	0.191	0.041
	(7.577)	(1.648)	(0.131)	(0.028)
Elevation	0.502***	0.109***	0.193**	0.041**
	(0.150)	(0.032)	(0.090)	(0.019)
Rainfall^2	0.036	0.007	0.022	0.004
	(0.048)	(0.010)	(0.029)	(0.006)
Temperature^2	2.433*	0.528*	0.117*	0.025*
	(1.294)	(0.281)	(0.062)	(0.013)
Elevation^2	0.020	0.004	0.002	0.0006
	(0.174)	(0.037)	(0.023)	(0.005)
Human capital				
Education	−0.096	−0.020	−0.047	−0.010
	(0.099)	(0.021)	(0.049)	(0.010)
Experience	0.262	0.057	0.116	0.025
	(0.295)	(0.064)	(0.130)	(0.028)
Extension	−0.092	−0.020	−0.044	−0.009
	(0.094)	(0.020)	(0.045)	(0.009)
CalorieIntake	2.711**	0.588**	0.379**	0.082**
	(1.466)	(0.318)	(0.205)	(0.044)
Social capital				
ExtensionVisits	0.249***	0.054***	0.232***	0.050***
	(0.090)	(0.019)	(0.084)	(0.018)
InstitutionalTrust	−1.387***	−0.301***	−0.358***	−0.077***
	(0.257)	(0.056)	(0.066)	(0.014)
Climate zones				
Equatorial	0.168	0.036	0.168	0.036
	(0.138)	(0.029)	(0.138)	(0.029)
Others	0.428***	0.088***	0.428	0.088
	(0.078)	(0.014)	(0.078)	(0.014)
Types of products				
Maize	0.249	0.054	0.249	0.054
	(0.196)	(0.042)	(0.196)	(0.042)
Beans	0.076	0.017	0.076	0.017
	(0.319)	(0.071)	(0.319)	(0.071)
Others	0.225***	0.049***	0.225***	0.049***
	(0.019)	(0.004)	(0.019)	(0.004)
Other controls				
Cross-section	−0.283***	−0.059***	−0.283**	−0.059***
	(0.110)	(0.022)	(0.110)	(0.022)
Cobb–Douglas (CD)	0.490	0.106	0.490	0.106
	(0.373)	(0.080)	(0.373)	(0.080)
Translog	0.603	0.130	0.603	0.130
	(0.568)	(0.123)	(0.568)	(0.123)
Constant	5.135		0.342	
	(20.804)		(0.236)	
Observations	122		122	
Log-Likelihood	−1080.63		−1080.63	

Note: Robust standard errors in parentheses.
*p<0.1.
**p<0.05.
***p<0.01.

Table 3
Estimation results of the weighted fractional regressions with and without interaction terms between three groups of capitals (selected by PCA).

Variable	Model	
	Without interaction terms	With interaction terms
Nature factor	0.036	−0.004
	(0.042)	(0.071)
Human factor	0.142	0.041
	(0.150)	(0.048)
Social factor	0.042	0.179***
	(0.094)	(0.052)
Nature factor × Human factor		0.004**
		(0.022)
Nature factor × Social factor		0.220***
		(0.045)
Human factor × Social factor		0.118
		(0.095)
Climate zones		
Equatorial	−0.427***	−1.056***
	(0.113)	(0.170)
Others	0.235**	−0.150
	(0.096)	(0.146)
Types of products		
Maize	0.050	0.010
	(0.255)	(0.282)
Beans	0.146	0.005
	(0.177)	(0.100)
Others	0.055	0.033
	(0.168)	(0.243)
Other controls		
Cross-section	−0.068	−0.358*
	(0.252)	(0.209)
Cobb–Douglas (CD)	0.626	1.078***
	(0.460)	(0.301)
Translog	0.550	0.858**
	(0.530)	(0.380)
Constant	0.485	0.836**
	(0.311)	(0.327)
Observations	122	122
Log-Likelihood	−1107.35	−1094.65

Note: Robust standard errors in parentheses.
LR test of Model “Without interaction terms” vs “With interaction terms”: $\chi^2(3) = 38.722$ with p-value < 0.001, suggesting that Model “With interaction terms” is preferable.
*p<0.1.
**p<0.05.
***p<0.01.

3.3. Publication bias

Due to the dependence on data of published articles, a meta-analysis must include a publication bias test for robustness. This type of bias stems from the notion that studies with larger effect sizes are more likely to be published than those with smaller effect sizes (Davis and Rothstein, 2006). Publication bias has been proven to influence the precision and accuracy of the treatment effects. Therefore, it is essential to test for this bias in meta-analyses (Sutton et al., 2000; Hang et al., 2018; Lin and Chu, 2018).

In this paper, we adopt a method introduced by Havranek et al. (2016) to detect publication bias using funnel plots. Fig. 3 are the plots graphing the number of observations and the TE estimates of studies collected in this meta-analysis. The symmetric-inverted funnel plots imply that TE deviations decrease when estimate accuracy increases (Van Aert et al., 2019). Following Sterne and Egger (2001), we include the standard error (and variance) of TE as the vertical axis and the logarithm of odds ratio as the horizontal axis. The asymmetries of the funnel plots indicate the presence of publication bias when the TE estimation accuracy is higher as the size of studies increases. We also adopt Egger’s test, which was suggested by van Enst et al. (2014) to test funnel plot asymmetry. The result shows that small-study effects exist in our data with a p-value < 0.05.

Latruffe et al. (2004), Oh and Lee (2010) and Nandy et al. (2019) have discovered that agriculture production in different locations is subject to latent dissimilarity due to characteristics on culture, people, soil, climate, etc. Given that, we attribute the small-study effects to the difference in the study locations. To solve this, we include the variable *Regions* to control for the heterogeneity of small study effect sizes. With Egger’s test, we observe the homogeneity in different subsets with p-value $= 0.218 > 0.05$, implying a low possibility of publication bias.

Moreover, multicollinearity – a bias when one or more independent variables are correlated to other independent variables – may cause inaccurately estimated coefficients. Although Berlin and Antman (1992) claimed that multicollinearity is rarely observed in meta-analyses, we

Table A.1
Eligible studies used in the meta-regression analysis.

Authors	Year of study	Regions	Crops
Abdulai and Huffman (2000)	2000	Ghana	Rice
Abdulai et al. (2017)	2017	Ghana	Maize
Abdulai et al. (2013)	2013	Ghana	Maize
Addai and Owusu (2014)	2014	Ghana	Maize
Addai et al. (2014)	2014	Ghana	Maize
Adewuyi et al. (2013)	2013	Nigeria	Cassava
Adzawla et al. (2013)	2013	Ghana	Cotton
Ahmed and Melesse (2018)	2018	Ethiopia	Maize
Ajao et al. (2012)	2012	Nigeria	Soybean
Amaza et al. (2005)	2005	Nigeria	Grain
Amos (2007)	2007	Nigeria	Cocoa
Anang et al. (2017)	2017	Ghana	Rice
Anang et al. (2016)	2016	Ghana	Rice
Asante et al. (2013)	2013	Ghana	Tomato
Asante et al. (2014)	2014	Ghana	Rice
Asravor et al. (2016)	2016	Ghana	Pepper
Balogun et al. (2018)	2018	Nigeria	Pineapple
Bamiro and Aloro (2013)	2013	Nigeria	Rice
Bempomaa and Acquah (2014)	2014	Ghana	Maize
Binam et al. (2004)	2004	Cameroon	Groundnut, Maize
Chepng'etich et al. (2014)	2014	Kenya	Sorghum
Dlamini et al. (2012)	2012	Swaziland	Maize
Donkoh et al. (2013)	2013	Ghana	Rice
Essilfie et al. (2011)	2011	Ghana	Maize
Etwire et al. (2013)	2013	Ghana	Soybean
Fawole and Ozkan (2018)	2018	Nigeria	Cocoa
Haji (2007)	2007	Ethiopia	Vegetable
Idiong (2007)	2007	Nigeria	Wheat
Karani-Gichimu et al. (2013)	2013	Kenya	Fruit
Kitavi et al. (2015)	2015	Kenya	Rabbit
Kuwornu et al. (2013)	2013	Ghana	Maize
Liu and Myers (2009)	2009	Kenya	Maize
Mango et al. (2015)	2015	Zimbabwe	Maize
Martey et al. (2015)	2015	Ghana	Soybean
Mignouna et al. (2012)	2012	Kenya	Maize
Mohammed (2012)	2012	Nigeria	Sorghum
Ngombe (2017)	2017	Zambia	Maize
Ofori-Bah and Asafu-Adjaye (2011)	2011	Ghana	Cocoa
Ogundari and Akinbogun (2010)	2010	Nigeria	Rice
Ogundari (2013)	2013	Nigeria	Cereals
Ogundele and Okoruwa (2006)	2006	Nigeria	Rice
Oladeebo and Fajuyigbe (2007)	2007	Nigeria	Rice
Olatidote et al. (2018)	2018	Nigeria	Cotton
Ologbon et al. (2012)	2012	Nigeria	Rice
Orewa and Izekor (2012)	2012	Nigeria	Yam
Oseghale et al. (2019)	2019	Nigeria	Rice
Ouedraogo (2015)	2015	Burkina Faso	Rice
Rahman and Awerije (2015)	2015	Nigeria	Cassava
Rajendran et al. (2015)	2015	Tanzania	Vegetable
Raphael (2008)	2008	Nigeria	Cassava
Seyoum et al. (1998)	1998	Ethiopia	Maize
Shehu et al. (2007)	2007	Nigeria	Rice
Shehu et al. (2010)	2010	Nigeria	Yam
Sherlund et al. (2002)	2002	Ivory Coast	Rice
Sihlongonyane et al. (2014)	2014	Swaziland	Maize
Singbo et al. (2014)	2014	Benin	Vegetable
Taru et al. (2011)	2011	Nigeria	Cowpea
Taru et al. (2012)	2012	Nigeria	Maize
Theriault and Serra (2014)	2014	Mali	Cotton
Thirtle et al. (2003)	2003	South Africa	Cotton
Tijani (2006)	2006	Nigeria	Rice
Yami et al. (2013)	2013	Ethiopia	Wheat
Zalkuw et al. (2014)	2014	Nigeria	Tomato

still test for this bias in this study. However, the Pearson correlation test reveals no substantial correlations between our variables.

4. Results

Table 1 presents the results of fractional regressions with and without interaction terms between "Climate zones" and the explanatory variables. The full estimation results with the fractional and Tobit regressions are reported in Table A.3 (in the Appendix). The Likelihood Ratio (LR) tests of different models in Table A.3 (in the Appendix) suggest that Model "Without interaction terms" is preferable compared to other models. Moreover, we observe that the results of the fractional regressions are close to those from the Tobit estimation. In the following, our discussion is based on the results of Model "Without interaction terms".

According to Table 1, we observe that natural capital, such as elevation of food-crop farms (i.e., $Elevation$), has a positive and statistically significant impact on agricultural productivity. These results suggest that farms located in higher altitude areas are, on average, more likely to have higher farming productivity than those in other locations. Moreover, we also observe that $Temperature$ is negative and significant, indicating that higher temperatures could generally harm the TE. While $Temperature$ is negative and significant, the variable $Temperature^2$ is positive and significant, meaning temperature and TE form a decreasing concave relationship. The turning point of $Temperature$ equals to 5.958, p-value < 0.001 ($CI = [5.842, 6.073]$).[1,2] This result suggests that a temperature lower than this point could harm the farming productivity in SSA regions. This result is in line with the existing literature that high temperature in the SSA regions could create biochemical challenges for plant cells (i.e., enzymes associated with the photosynthetic pathway) (Moore et al., 2021), and thus leads to a decrease in crop yield and animal production (Kotir, 2011; Dube et al., 2013). In addition, the result of the interaction term $Temperature \times Elevation$ has a negative and significant impact on TE (see Model (2) of Table A.3 in the Appendix). Our descriptive statistics indicate that most of the collected studies as conducted in mid-altitudes (700–1,400 m), and thus according to the existing literature, increasing temperatures in mid-latitude regions could harm the productivity by reducing the soil moisture and water, thus putting the African region at the risk of increased hunger and food insecurity (Kabasa and Sage, 2009; Zhao et al., 2017).

Regarding human capital, we observe that $Education$, $Experience$ and $Extension$ are not statistically significant, implying that improving farmers' education, experience and access to extension programs do not significantly help promote agricultural productivity in Sub-Saharan regions. However, our result suggests that $CalorieIntake$ has a positive and significant impact on TE, which means that farmers in more food-secure areas have higher farming efficiency than others. One possible explanation for this result could be that $CalorieIntake$, represented by the total level of calorie intake per capita per day, was proved to be correlated with agricultural labor's quality and health (e.g., height and weight). Thus it has a positive and significant impact on agricultural productivity (Strauss, 1986; Croppenstedt and Muller, 2000). This result is also in line with the existing literature that farmers' body mass index (e.g., weight-for-height) should be improved to achieve better productivity improvement (Croppenstedt and Muller, 2000).

Besides natural and human capital, $ExtensionVisits$ and $InstitutionalTrust$, proxies of social capital, are also essential determinants of TE. The Corruption Perception Index (CPI) is used to proxy institutional trust (i.e., $InstitutionalTrust$), noting that a higher CPI implies a lower institutional trust. We observe that $InstitutionalTrust$ has a negative impact on TE, meaning that a higher level of trust in

[1] The standard error is estimated using Delta method at the 5% significant level.

[2] From Eq. (3), to calculate the turning point, we have the first order condition (i.e., necessary condition) with respect to $Temperature$ as follows:

$$\frac{dG(X_{ij}\delta)}{dtemp} = G'(X_{ij}\delta)(\beta_{temp} + 2\gamma_{temp}temp)$$
$$= \frac{e^{X_{ij}\delta}}{(1+e^{X_{ij}\delta})^2}(\beta_{temp} + 2\gamma_{temp}temp) = 0, \quad (5)$$

where $G(X_{ij}\delta) = \frac{e^{X_{ij}\delta}}{1+e^{X_{ij}\delta}}$. Thus, this condition holds if $\beta_{temp} + 2\gamma_{temp}temp = 0$ (as the preceding ratio term is positive). Therefore, the turning point of $temperature$ is given by $-\frac{\beta_{temp}}{2\gamma_{temp}temp}$. The variance of the turning point is calculated by using the delta method.

Table A.2
Definitions and descriptive statistics.

Variable	Definition	Mean	Std.Dev	Min	Max
Mean TE	Average of food-crop technical efficiency.	0.695	0.166	0.274	0.960
Human capital					
Education	Studies using variable farmer's education.	0.427	0.496	0	1
Experience	Studies using variable farmer's experience.	0.239	0.428	0	1
Extension	Studies using variable farmer's extension.	0.384	0.488	0	1
Calorie intake	Total calorie intake per capita per day in the study area.	2557.393	343.672	1684	3033
Human factor	First Principal Component of the human capital.	0	1.207	−2.733	2.589
Social capital					
Extension visits	Number of visits of extension officers.	2.827	16.410	0	163
Institutional trust	Corruption Perception index of the studied country or region.	31.937	8.961	19	48
Social factor	First Principal Component of the social capital.	0	1.029	−1.570	3.667
Natural capital					
Land size (ha)	Cultivated farmland size of food-crop farming in the study area.	25.245	12.774	1.2	209.8
Rainfall (mm)	Average precipitation in the study area.	1067.547	413.195	73.1	1854.2
Temperature (°C)	Average temperature in the study area.	24.013	4.673	12.1	35.1
Elevation (km)	Average elevation in the study area.	0.917	0.824	0.018	4.508
Natural factor	First Principal Component of the natural capital.	0	1.331	−3.614	1.785
Data type					
Panel data	Studies using panel data for data analysis.	0.119	0.325	0	1
Cross-section	Studies using cross-sectional data for data analysis.	0.880	0.325	0	1
Specification of the production function					
Cobb–Douglas (CD)	Studies using Cobb–Douglas production function.	0.541	0.500	0	1
Translog (TL)	Studies using Translog production function.	0.368	0.484	0	1
DEA	Studies using DEA (Data Envelope Analysis) method to estimate production function.	0.090	0.287	0	1
Types of products					
Rice	Studies about rice technical efficiency.	0.291	0.456	0	1
Maize	Studies about maize technical efficiency.	0.316	0.467	0	1
Beans	Studies about wheat technical efficiency.	0.085	0.281	0	1
Others	Studies about other types of food-crop efficiency.	0.308	0.463	0	1
Climate zones					
Equatorial	Studies conducted in Tropical grassland climate zone.	0.327	0.471	0	1
Tropical grassland	Studies conducted in Tropical grassland climate zone.	0.540	0.500	0	1
Others	Studies conducted in other climate zones.	0.131	0.338	0	1

institutions could result in lower farming productivity. However, the results in Tables A.2 and A.4 show that the institutional trust is low in the SSA regions (i.e., CPI score is lower than 49 points, meaning a high level of corruption). Moreover, research has suggested that low individual trust in local government in Africa could be because African people have strong cultural and indigenous beliefs (Herskovits, 1955). These strong beliefs in culture (i.e., cultural norms) and mistrust in the local government could be due to the long-lasting effects of the slave trade (Nunn and Wantchekon, 2011). Thus, they are less likely to believe in local government, neighbors, and relatives.

In addition to $InstitutionalTrust$, $ExtensionVisits$ (i.e., the number of visits from extension agencies in one agriculture year) is also statistically significant. The descriptive statistics in Table A.2 show that the number of extension visits in our collected studies varies in a wide range, with an average of 2.8 times per year. While a part of the existing literature has suggested the extension visits did not influence TE because of the low qualification of extension agents (Olurotimi et al., 2018; Dinar et al., 2007; Abdulai et al., 2013; Bäckman et al., 2011), our study suggests the opposite implication: the number of extension visits plays a vital role in promoting farming productivity. This result is therefore aligned with the other part of literature showing that inadequate extension services presented by low extension workers to farmers ratio or unhelpful extension workers may lead to lower farming TE (Haji, 2007; Enwerem and Ohajianya, 2013).

Our results indicate that three groups of capitals have different impacts on farming TE. According to the result of standardized explanatory variables and their marginal effect in Table 2, we observe that *CalorieIntake* seems to be more important than other factors in encouraging the TE, meaning that the quality of agricultural labor input should be improved to achieve high farming TE. Moreover, social capital could also be essential to promote farming productivity since all two variables *ExtensionVisits* and *InstitutionalTrust* are statistically significant. Thus, agriculture efficiency could benefit from increasing the frequency of extension visits. Additionally, natural capital seems to be less efficient than the other two capital in improving the TE. However, natural conditions, such as high temperature and low elevation, are significant barriers that need to be overcome to achieve higher productivity in the SSA regions.

Regarding different kinds of crops in collected studies, rice farms are more efficient than beans and other types of products. The descriptive statistics indicate that there are 29.1% of studies examined rice TE, 31.6% of studies examined maize TE, and only 8.5% of studies focused on bean TE (see Table A.2). Crop types also vary across regions. More specifically, Table A.4 shows that among 122 observations, studies on rice crop productivity are mainly conducted in the Equatorial climate zone, while Maize studies are distributed in the Tropical grassland climate zone. However, we found that types of food crops do not significantly impact farming TE in the SSA regions.

We observe that 54.1% of collected studies applied the Cobb–Douglas model to investigate the production function. 36.8% of collected studies applied the Translog production function. Only 9% of observations were found applying the DEA method to estimate the production function. However, our result suggests that using different production function estimation methodologies does not provide significant differences in farming TE. Moreover, we observe that data types (i.e., Cross-section) have a negative and significant impact on TE, meaning that studies using cross-section data types generally have lower mean TE estimates than those using panel data.

The role of natural, human and social capitals in different climate zones

We observe in the results of Table 1 that $Equatorial$ has no significant impact, but $Others$ (i.e., other climate zones) has a positive and significant impact on TE compared to the baseline $Equatorial$. It should be noted that we observe in the collected studies that there are disparate natural characteristics in different climate zones (see

Table A.3
Estimation results of the weighted fractional and Tobit regressions.

Variable	Fractional regression			Tobit regression		
	(0)	(1)	(2)	(3)	(4)	(5)
Natural capital						
LandSize	−0.016	0.004	0.001	−0.002	0.002	0.002
	(0.138)	(0.131)	(0.148)	(0.028)	(0.026)	(0.029)
Rainfall	0.147*	−0.263	−0.229	0.037**	−0.026	−0.006
	(0.083)	(0.638)	(0.729)	(0.018)	(0.122)	(0.131)
Temperature	−0.200	−14.491*	−6.259	−0.031	−3.208*	−1.538
	(0.279)	(7.577)	(6.787)	(0.066)	(1.531)	(1.434)
Elevation	0.563	0.502***	5.700***	0.121	0.098**	1.160**
	(0.401)	(0.150)	(1.912)	(0.089)	(0.045)	(0.483)
Rainfall^2		0.036	0.033		0.005	0.003
		(0.048)	(0.056)		(0.008)	(0.009)
Temperature^2		2.433*	1.252		0.538**	0.300
		(1.294)	(1.193)		(0.260)	(0.244)
Elevation^2		0.020	0.028		0.010	0.011
		(0.174)	(0.173)		(0.042)	(0.040)
Temperature × Elevation			−1.506***			−0.308**
			(0.497)			(0.125)
Human capital						
Education	−0.041	−0.096	−0.114	−0.005	−0.016	−0.021
	(0.085)	(0.099)	(0.151)	(0.016)	(0.020)	(0.033)
Experience	0.268	0.262	0.347	0.054	0.054	0.067
	(0.297)	(0.295)	(0.493)	(0.060)	(0.058)	(0.096)
Extension	−0.144*	−0.092	−0.161	−0.030*	−0.020	−0.039
	(0.075)	(0.094)	(0.133)	(0.015)	(0.017)	(0.028)
CalorieIntake	3.355**	2.711**	2.714**	0.719**	0.605**	0.608**
	(1.692)	(1.466)	(1.149)	(0.384)	(0.308)	(0.234)
Education × Experience			−0.181			−0.037
			(0.749)			(0.146)
Extension × Experience			−0.044			0.001
			(0.188)			(0.041)
Extension × Education			0.200			0.042*
			(0.137)			(0.025)
Social capital						
ExtensionVisits	0.272***	0.249***	0.261***	0.051***	0.048***	0.051***
	(0.077)	(0.090)	(0.066)	(0.010)	(0.012)	(0.008)
InstitutionalTrust	−1.321***	−1.387***	−1.439***	−0.295***	−0.317***	−0.328***
	(0.206)	(0.257)	(0.316)	(0.046)	(0.059)	(0.068)
Climate zone						
Equatorial	0.232	0.168	0.130	0.038	0.024	0.018
	(0.144)	(0.138)	(0.151)	(0.030)	(0.027)	(0.029)
Others	0.373***	0.428***	0.424***	0.071**	0.086***	0.085***
	(0.103)	(0.078)	(0.055)	(0.033)	(0.021)	(0.015)
Types of products						
Maize	0.235	0.249	0.281	0.053	0.058	0.061
	(0.216)	(0.196)	(0.193)	(0.048)	(0.044)	(0.038)
Beans	0.032	0.076	0.061	0.008	0.018	0.013
	(0.351)	(0.319)	(0.298)	(0.075)	(0.067)	(0.064)
Others	0.198***	0.225***	0.231***	0.045***	0.052***	0.050***
	(0.035)	(0.019)	(0.013)	(0.007)	(0.004)	(0.003)
Other controls						
Cross-section	−0.175***	−0.283***	−0.214	−0.036***	−0.058***	0.044
	(0.034)	(0.110)	(0.245)	(0.004)	(0.014)	(0.036)
Cobb–Douglas (CD)	0.530	0.490	0.467	0.109	0.098	0.096
	(0.408)	(0.373)	(0.361)	(0.096)	(0.087)	(0.083)
Translog	0.685	0.603	0.573	0.146	0.128	0.125
	(0.616)	(0.568)	(0.578)	(0.138)	(0.126)	(0.128)
Constant	−22.077*	5.135	5.322	−4.266	1.532	1.504
	(11.864)	(20.804)	(17.657)	(2.656)	(4.239)	(3.619)
Observations	122	122	122	122	122	122
Log-Likelihood	−1083.61	−1080.63	−1080.22	956.99	993.83	998.75

Note: Robust standard errors in parentheses.
LR test of Model (0) vs Model (1): $\chi^2(3) = 8.939$ with p-value $= 0.011$ (Hypothesis of Model (0) is rejected).
LR test of Model (1) vs (2): $\chi^2(3) = 1.228$ with p-value $= 0.540$ (Hypothesis of Model (2) is rejected).
Model (1) is Model "Without interaction terms" reported in Table 1.
*p<0.1.
**p<0.05.
***p<0.01.

Table A.4 in the Appendix). The Equatorial climate is a climate zone located in low altitudes with high rainfall and high temperature with a low-temperature range. The Tropical Savanna grassland is a warn climate zone with the lowest rainfall and high rainfall range compared

Table A.4
Summary statistics of natural capital, human capital, social capital and mean technical efficiency by climate zones.

	Equatorial climate	Tropical grassland climate	Others
MTE	0.746	0.656	0.757
	(0.150)	(0.173)	(0.110)
Natural capital			
Rainfall (in mm per annum)	1281.222	922.972	1129.725
	(148.570)	(498.062)	(164.430)
Temperature (in °C)	26.170	23.471	20.856
	(1.225)	(5.133)	(5.813)
Elevation (in meters)	342.725	1010.606	1920.500
	(138.473)	(767.622)	(819.705)
Human capital			
Calorie intake	2651.150	2518.106	2485.062
	(95.461)	(396.509)	(460.403)
Social capital			
Number of visits	4.100	0.752	16.696
	(23.696)	(1.814)	(42.731)
Institutional trust	24.825	35.530	36.562
	(1.998)	(8.968)	(5.999)
Types of products			
(in numbers of studies)			
Rice	23	9	2
Maize	1	32	9
Beans	4	6	0
Others	12	19	5
Numbers of observation	40	60	16

Notes: Standard deviation of the mean in parenthesis.

to other climate zones. Other climate zones, including Temperate, Arid and Semi-Arid, represent climate zones receiving moderate rainfall, located on high latitudes and have low temperatures.

To enrich the results about the crucial role of natural capital in the sense that they could drive the farming TE, we perform the fractional regressions with interaction terms between "Climate zones" and explanatory variables in Model "With interaction terms" in Table 1 and subgroups of three climate zones (i.e., Equatorial, Tropical grassland and Others) in Table A.5 (in the Appendix). However, we should be cautious when interpreting some of these results because of the small number of observations in these regressions. For instance, the regression presented in Model "With interaction terms" (i.e., other climate regions) corresponds to only 16 observations. Thus, the discussion about the impact of natural, human and social capital in different climate zones will be based on the result in Model "With interaction terms" in Table 1.

Because of the natural characteristics in different climate zones, we observe differences in sign and significant levels of the interaction between natural capital variables and climate zones (see Model "With interaction terms" in Table 1). Particularly, farms located in Equatorial climate are not more efficient than those in Tropical grassland climate, but their productivity benefits from larger land size. Moreover, farms' productivity in other climate zones (i.e., high altitude and low temperature) could benefit from higher rainfall. However, a too high level of precipitation could also harm the farming productivity at high elevations since the interaction term $Rainfall^2 \times Others$ are negative and significant. On the other hand, $Temperature$ does not significantly influence farming productivity in different climatic zones.

Since the calorie intake has no significant difference in different climate zones, we observe no significant impact of the interaction between "Climate zones" and $CalorieIntake$ on TE. Moreover, results of Model "With interaction terms" in Table 1 suggest that promoting farmers' farming experience and extension could improve the TE. However, it is more efficient to enhance farmers' farming experience in Tropical grassland than in Equatorial and other climate regions. Our result also suggests that farms in high altitudes (i.e., other climate regions) could benefit more from improving farmers' education than in other climate zones. Results of Table 1 also suggest that providing more extension visits (i.e., higher the number of visits from extension agents) could benefit the farming productivity in the Equatorial climate region. Additionally, strengthening the institutional trust is essential to improve farming efficiency in SSA regions.

The composite effects of natural, human and social capital

Table 3 presents our results on the impact of nature, human, and social capital factors selected by Principal Component Analysis (PCA) and their composite effects according to the interaction between them on farming TE. The first model represents a model without interaction terms, including three different factors representing three groups of capitals, while the second model introduces additional interaction terms between these three factors to assess the composite effects of these capitals on TE.

Results of Model "With interaction terms" in Table 3 indicate that natural capital and human capital do not significantly impact TE, whereas social capital could help improve TE at a 1% significance level. This result is in line with our previous findings in Table 1 that social capital, consisting of $ExtensionVisits$ and $InstitutionalTrust$, is more important than the other two capitals in encouraging farming productivity. The interaction terms between the "Nature factor" and the other two capitals suggest a positive composite effect of natural and other capitals on TE. These results provide empirical evidence raised by previous studies about the co-effect of human and social capital regarding a comprehensive ecosystem contributing to agriculture production (Ostrom, 1990; Johansson, 1994; Ghali et al., 2016; Dasgupta, 2021; Hoang-Khac et al., 2021). Activities nurturing and accumulating these three capitals in a sustainable manner that involves simultaneous improvement would benefit agriculture productivity in the Sub-Saharan Africa (SSA) regions.

5. Policy implications

With given results and discussions, we propose several critical points to policymakers in Sub-Saharan Africa (SSA) for further development of agriculture in this area.

Firstly, considering human capital factors, since education and extension training does not significantly affect farming TE, we recommend authorities in SSA regions to reassess the effectiveness of their extension training programs and reduce unnecessarily inefficient expenses. Moreover, our results also indicate that farmers' calorie intake, representing their health and labor quality, is essential to promoting TE. Thus, SSA governments should put efforts into eradicating malnutrition to help their citizens break the vicious circle of food insecurity and become self-sufficient.

Table A.5
Estimation results of the weighted fractional meta regressions with subgroups of climate zones.

Variable	Sub-groups of climate zones		
	Equatorial	Tropical grassland	Others
Natural capital			
LandSize	0.222	−0.183	0.210
	(0.202)	(0.136)	(7.469)
Rainfall	139.852**	−2.106	279.572
	(75.181)	(2.147)	(140.321)
Temperature	−384.741**	−4.041	446.584
	(176.235)	(11.903)	(419.539)
Elevation	−9.501***	−0.0001	−3.867
	(3.558)	(1.388)	(14.599)
Rainfall^2	−9.781*	0.185	−198.488***
	(5.291)	(0.180)	(8.982)
Temperature^2	−58.152**	0.590	70.096
	(26.857)	(1.995)	(68.244)
Elevation^2	21.717***	0.437	0.590
	(6.636)	(0.774)	(6.710)
Human capital			
Education	−0.013	−0.389	1.959**
	(0.182)	(0.247)	(0.894)
Experience	−0.186	0.831**	0.284***
	(0.153)	(0.322)	(0.012)
Extension	0.573**	−0.119	−2.824
	(0.269)	(0.235)	(1.722)
CalorieIntake	−9.153*	5.189***	24.028
	(4.907)	(1.817)	(16.389)
Social capital			
ExtensionVisits	0.704***	−0.011	0.270
	(0.251)	(0.153)	(0.606)
InstitutionalTrust	−2.987	−1.893***	1.389
	(1.921)	(0.677)	(9.870)
Types of products			
Maize	−0.486	0.043	
	(0.418)	(0.415)	
Beans	−0.919**	−1.009**	
	(0.398)	(0.432)	
Others	−0.312	−0.415	−3.374
	(0.426)	(0.485)	(20.327)
Other controls			
Cross-section	−0.573	1.398	6.658
	(0.357)	(0.968)	(4.680)
Cobb–Douglas (CD)	1.237***	−0.273	−2.716
	(0.378)	(0.350)	(22.464)
Translog	3.178***	−0.586*	−2.480
	(0.675)	(0.351)	(32.325)
Constant	−1054.158**	−21.585	
	(508.929)	(26.464)	
Observations	40	66	16
Log-Likelihood	−287.66	−670.911	−92.59

Note: Robust standard errors in parentheses.
*p<0.1.
**p<0.05.
***p<0.01.

Secondly, our results indicate that the number of extension visits is a substantial social factor that helps promote farming TE. This result suggests that SSA governments have thorough reassessments of this system. Our results and discussions have pointed out that a low impact of extension service on TE might stem from a lack of consulting ability of extension officers or low extension workers to farmers ratio. Suppose this situation is true in SSA countries. In that case, the governments should redesign more effective extension service programs, including enhancing extension workers' capacity via official training, improving farming technology and increasing the number of extension workers.

Thirdly, apart from extension services, institutional trust is a factor that governments should highly focus on because trust in institutions is vital for development since a high level of institutional trust could promote citizens' willingness to follow and take advantage of agricultural supporting policies, including subsidies or extension schemes (Bjornskov and Meon, 2013; Dearmon and Grier, 2011). However, we observe that institutional trust in the SSA countries is sufficiently low, and thus it results in a significant and negative impact on TE. Therefore, we suggest that governments should improve their citizens' institutional trust through increased transparency, communication strategy, interaction with populations, etc.

Finally, natural capital, e.g., temperature and elevation, is an important driver that helps maintain high farming TE in different SSA climate regions. In particular, farms in higher altitude regions are endowed with favorable natural conditions (e.g., lower temperature) and thus have higher average TE. However, higher altitude and cooler temperature regions rely more heavily on rainfall to achieve high TE than other climate zones. Therefore, besides human and social capital, governments should also pay more attention to natural capital and issue proper guidelines for farmers to optimize agricultural efficiency with given conditions. In other words, agricultural development orientation must base on regional and climate characteristics.

6. Conclusions

This study analyzed the spontaneous impact of human, social and natural capital on food crop technical efficiency (TE) of 64 collected studies and 122 observations in Sub-Saharan Africa (SSA) via meta-regression analysis. We hypothesized a conceptual framework that three factors, including natural, human and social capitals, are individually and interactively impacted on farming TE.

By adopting Egger's test, we observe the homogeneity in our data that implies a low possibility of publication bias after controlling for the regional difference. Moreover, a Pearson correlation test verifies that multicollinearity bias does not exist in our dataset. To correct the heterogeneity of TE estimates, the weighted fractional and Tobit regressions are employed to estimate the nexus proposed in our conceptual framework. In our results, the composite effects of the three capitals validate the interactive relationship between the three capitals in terms of stimulating farming TE. Calories intake has a positive and significant impact on farming TE. Farmers in the Equatorial zone retrieve lower farming productivity than farmers in a tropical grassland.

Several policy implications have been drawn from the results. We recommend that SSA governments invest in human capital by taking care of farmers' health and improving their calorie intake to enhance human capacity. Governments should also invest in improving the frequency of extension visits and strengthen people's trust in institutions via increasing transparency and reducing corruption. Lastly, agricultural policies must also consider the different climate characteristics (e.g., temperature and elevation) in different climate zones to efficiently achieve the targeted agricultural productivity.

CRediT authorship contribution statement

Tuan Nguyen-Anh: Conceptualization, Methodology, Data curation, Software, Investigation, Writing – original draft. **Chinh Hoang-Duc:** Visualization, Data curation, Investigation, Writing – original draft. **Tuyen Tiet:** Methodology, Software, Investigation, Writing – reviewing and editing, Validation. **Phu Nguyen-Van:** Methodology, Supervision, Validation. **Nguyen To-The:** Conceptualization, Data curation, Writing – original draft, Validation.

Appendix

See Tables A.1–A.5

References

Abdul-Rahaman, A., Abdulai, A., 2018. Do farmer groups impact on farm yield and efficiency of smallholder farmers? Evidence from rice farmers in northern Ghana. Food Policy 81, 95–105.

Abdulai, A., Hazell, P.B., 1996. The role of agriculture in sustainable economic development in Africa. J. Sustain. Agric. 7, 101–119.

Abdulai, A., Huffman, W., 2000. Structural adjustment and economic efficiency of rice farmers in Northern Ghana. Econom. Dev. Cult. Chang. 48, 503–520.

Abdulai, S., Nkegbe, P.K., Donkoh, S.A., 2013. Technical efficiency of maize production in Northern Ghana. Afr. J. Agric. Res. 8, 5251–5259.

Abdulai, S., Nkegbe, P.K., Donkor, S.A., 2017. Assessing the economic efficiency of maize production in Northern Ghana. Ghana J. Dev. Stud. 14, 123–145.

Addai, K.N., Owusu, V., 2014. Technical efficiency of maize farmers across various agro ecological Zones of Ghana. J. Agric. Environ. Sci. 3, 149–172.

Addai, K.N., Owusu, V., Danso-Abbeam, G., 2014. Effects of farmer–based-organization on the technical efficiency of maize farmers across various agro-ecological zones of Ghana. J. Econ. Dev. Stud. 2, 141–161.

Adekalu, K., Balogun, J., Aluko, O., Okunade, D., Gowing, J., Faborode, M., 2009. Runoff water harvesting for dry spell mitigation for cowpea in the savannah belt of Nigeria. Agricult. Water Manag. 96, 1502–1508.

Adewuyi, S.A., Agbonlahor, M.U., Oke, A.T., 2013. Technical efficiency analysis of Cassava farmers in Ogun state, Nigeria. Int. J. Agric. Food Sci. 4, 515–522.

Adzawla, W., Fuseini, J., Donkoh, S.A., 2013. Estimating technical efficiency of cotton production in Yendi municipality, Northern Ghana. J. Agric. Sustain. 4, 58–65.

Ahmed, M.H., Melesse, K.A., 2018. Impact of off-farm activities on technical efficiency: Evidence from maize producers of eastern Ethiopia. Agric. Food Econ. 6, 1–15.

Ajao, A.O., Ogunniyi, L.T., Adepoju, A.A., 2012. Economic efficiency of soybean production in Ogo-Oluwa local government area of Oyo state, Nigeria. Am. J. Exp. Agric. 2, 667–679.

Alem, H., 2021. The role of technical efficiency achieving sustainable development: A dynamic analysis of Norwegian dairy farms. Sustainability 13 (1841).

Amaza, P.S., Kamara, A.Y., Helsen, J., 2005. Determinants of food crop production and technical efficiency in the Guinea savannas of Borno state, Nigeria. In: African Crop Science Conference Proceedings, Vol. 76. pp. 1–765.

Amos, T.T., 2007. An analysis of productivity and technical efficiency of smallholder cocoa farmers in Nigeria. J. Soc. Sci. 15, 127–133.

Anang, B.T., Bäckman, S., Rezitis, A., 2017. Production technology and technical efficiency: Irrigated and rain-fed rice farms in northern Ghana. Eurasian Econ. Rev. 7, 95–113.

Anang, B.T., Bäckman, S., Sipiläinen, T., 2016. Technical efficiency and its determinants in smallholder rice production in northern Ghana. J. Dev. Areas 50, 311–328.

Anderson, J.R., Feder, G., 2004. Agricultural extension: Good intentions and hard realities. World Bank Res. Observer 19, 41–60.

Asadullah, M.N., Rahman, S., 2009. Farm productivity and efficiency in rural Bangladesh: The role of education revisited. Appl. Econ. 41, 17–33.

Asante, B.O., Osei, M.K., Dankyi, A.A., Berchie, J.N., Mochiah, M.B., Lamptey, J.N.L., Haleegoah, J., Osei, K., Bolfrey-Arku, G., 2013. Producer characteristics and determinants of technical efficiency of tomato based production systems in Ghana. J. Dev. Agric. Econ. 5, 92–103.

Asante, B.O., Wiredu, A.N., Martey, E., Sarpong, D.B., Mensah-Bonsu, A., 2014. NERICA adoption and impacts on technical efficiency of rice producing households in Ghana: Implications for research and development. Am. J. Exp. Agric. 4, 244–262.

Asravor, J., Onumah, E.E., Osei-Asare, Y.B., 2016. Efficiency of chili pepper production in the volta region of Ghana. J. Agric. Extension Rural Dev. 8, 99–110.

Bäckman, S., Islam, K.Z., Sumelius, J., 2011. Determinants of technical efficiency of rice farms in north-central and north-western regions in Bangladesh. J. Dev. Areas 73–94.

Balogun, O.L., Adewuyi, S.A., Disu, O.R., Afodu, J.O., Ayo-Bello, T.A., 2018. Profitability and technical efficiency of pineapple production in Ogun state, Nigeria. Int. J. Fruit Sci. 18, 436–444.

Bamiro, O.M., Aloro, J.O., 2013. Technical efficiency in swamp and upland rice production in Osun state. Scholarly J. Agric. Sci. 3, 31–37.

Barro, R.J., McCleary, R.M., 2003. Religion and economic growth across countries. Am. Sociol. Rev. 68, 760–781.

Baten, M.A., Kamil, A.A., Fatama, K., 2009. Technical efficiency in stochastic frontier production model: An application to the manufacturing industry in Bangladesh. Aust. J. Basic Appl. Sci. 3, 1160–1169.

Becker, G.S., 1962. Investment in human capital: A theoretical analysis. J. Polit. Econ. 70, 9–49.

Bempomaa, B., Acquah, H.d.-G., 2014. Technical efficiency analysis of maize production: Evidence from Ghana. Appl. Stud. Agribus. Commerce 8, 73–79.

Berlin, J.A., Antman, E.M., 1992. Advantages and limitations of meta-analytic regressions of clinical trials data. Control. Clin. Trials 13, 422.

Binam, J.N., Tonye, J., Nyambi, G., Akoa, M., et al., 2004. Factors affecting the technical efficiency among smallholder farmers in the slash and burn agriculture zone of Cameroon. Food Policy 29, 531–545.

Bjornskov, C., 2006. The multiple facets of social capital. Eur. J. Political Econ. 22, 22–40.

Bjornskov, C., 2012. How does social trust affect economic growth? Southern Econ. J. 78, 1346–1368.

Bjornskov, C., Meon, P.-G., 2013. Is trust the missing root of institutions, education, and development? Public Choice 157, 641–669.

Bjornskov, Meon, 2015. The productivity of trust. World Dev. 70, 317–331.

Bojnec, Š., Fertő, I., 2013. Farm income sources, farm size and farm technical efficiency in Slovenia. Post-Communist Econ. 25, 343–356.

Bravo-Ureta, B.E., Pinheiro, A.E., 1993. Efficiency analysis of developing country agriculture: A review of the frontier function literature. Agric. Resour. Econ. Rev. 22, 88–101.

Bravo-Ureta, B.E., Solís, D., López, V.H.M., Maripani, J.F., Thiam, A., Rivas, T., 2007. Technical efficiency in farming: A meta-regression analysis. J. Prod. Anal. 27, 57–72.

Caballé, J., Santos, M.S., 1993. On endogenous growth with physical and human capital. J. Polit. Econ. 101, 1042–1067.

Chepng'etich, E., Bett, E.K., Nyamwaro, S.O., Kizito, K., 2014. Analysis of technical efficiency of sorghum production in lower Eastern Kenya: A data envelopment analysis approach. J. Econ. Sustain. Dev. 5, 58–65.

Chiona, S., Kalinda, T., Tembo, G., 2014. Stochastic frontier analysis of the technical efficiency of smallholder maize farmers in central province, Zambia. J. Agric. Sci. 6, 108.

Chuzu, P.M., 2002. Social Capital Effects on Poverty and Technical Efficiency in Rural Kwazulu-Natal. University of Illinois at Urbana-Champaign, South Africa.

Coff, R.W., 2002. Human capital, shared expertise, and the likelihood of impasse in corporate acquisitions. J. Manag. 28, 107–128.

Coleman, J.S., 1988. Social capital in the creation of human capital. Am. J. Sociol. 94, S95–S120.

Croppenstedt, A., Muller, C., 2000. The impact of farmers' health and nutritional status on their productivity and efficiency: Evidence from ethiopia. Econom. Dev. Cult. Chang. 48, 475–502.

Cui, W., 2017. Social trust, institution, and economic growth: Evidence from China. Emerg. Mark. Finance Trade 53, 1243–1261.

Dalei, N.N., Joshi, J.M., 2020. Estimating technical efficiency of petroleum refineries using DEA and tobit model: An India perspective. Comput. Chem. Eng. 142, 107047.

Dasgupta, P., 2021. The Economics of Biodiversity: The Dasgupta Review. HM Treasury.

Davis, A.L., Rothstein, H.R., 2006. The effects of the perceived behavioral integrity of managers on employee attitudes: A meta-analysis. J. Bus. Ethics 67, 407–419.

Dearmon, J., Grier, R., 2011. Trust and the accumulation of physical and human capital. Eur. J. Political Econ. 27, 507–519.

Dimelis, S.P., Papaioannou, S.K., 2014. Human capital effects on technical inefficiency: A stochastic frontier analysis across industries of the Greek economy. Int. Rev. Appl. Econ. 28, 797–812.

Dinar, A., Karagiannis, G., Tzouvelekas, V., 2007. Evaluating the impact of agricultural extension on farms' performance in Crete: A nonneutral stochastic frontier approach. Agric. Econ. 36, 135–146.

Djomo, J.M.N., Sikod, F., 2012. The effects of human capital on agricultural productivity and farmer's income in Cameroon. Int. Bus. Res. 5, 134.

Dlamini, S.I., Masuku, M.B., Rugambisa, J., 2012. Technical efficiency of maize production in Swaziland: A stochastic frontier approach. Afr. J. Agric. Res. 7, 5628–5636.

Donkoh, S.A., Ayambila, S., Abdulai, S., 2013. Technical efficiency of rice production at the Tono irrigation scheme in Northern Ghana. Am. J. Exp. Agric. 3, 25–42.

Dube, S., Scholes, R.J., Nelson, G.C., Mason-D'Croz, D., Palazzo, A., 2013. South AfricaN food security and climate change: Agriculture futures. Economics 7, 1–54.

Ehui, S., Pender, J., 2005. Resource degradation, low agricultural productivity, and poverty in Sub-Saharan Africa: Pathways out of the spiral. Agric. Econ. 32, 225–242.

Enwerem, V., Ohajianya, D., 2013. Farm size and technical efficiency of rice farmers in Imo state, Nigeria. Greener J. Agric. Sci. 3, 128–136.

Essilfie, F.L., Asiamah, M.T., Nimoh, F., 2011. Estimation of farm level technical efficiency in small scale maize production in the Mfantseman Municipality in the Central Region of Ghana: A stochastic frontier approach. J. Dev. Agric. Econ. 3, 645–654.

Etwire, P.M., Martey, E., Dogbe, W., 2013. Technical efficiency of soybean farms and its determinants in Saboba and Chereponi districts of northern Ghana: A stochastic frontier approach. Sustain. Agric. Res. 2, 106–116.

FAO, 2012. Statistical Yearbook 2011: World Food and Agriculture. Food and Agriculture Organziation of the United Nations, Rome, Italy.

Färe, R., Lovell, C.K., 1978. Measuring the technical efficiency of production. J. Econom. Theory 19, 150–162.

Fawole, W.O., Ozkan, B., 2018. Revisiting the profitability and technical efficiency of cocoa production amidst economic diversification program of the Nigerian government: A case study of Ondo state. J. Agribus. Dev. Emerg. Econ. 8, 186–200.

Fedderke, J., Klitgaard, R., 1998. Economic growth and social indicators: An exploratory analysis. Econom. Dev. Cult. Chang. 46, 455–489.

Ferreira, M.D.P., Féres, J.G., 2020. Farm size and land use efficiency in the Brazilian Amazon. Land Use Policy 99, 104901.

Food and A. O. E. C. on Agriculture; African Union Commission, 2020. 2019 Africa Regional Overview of Food Security and Nutrition. Food and Agriculture Organization.

Funke, M., Strulik, H., 2000. On endogenous growth with physical capital, human capital and product variety. European Econ. Rev. 44, 491–515.
Gadanakis, Y., Areal, F.J., 2020. Accounting for rainfall and the length of growing season in technical efficiency analysis. Oper. Res. 20, 2583–2608.
Ghali, M., Latruffe, L., Daniel, K., 2016. Efficient use of energy resources on french farms: An analysis through technical efficiency. Energies 9, 601.
Ghosh, B.N., Sharma, N.K., Alam, N.M., Singh, R.J., Juyal, G.P., 2014. Elevation, slope aspect and integrated nutrient management effects on crop productivity and soil quality in North-West Himalayas, India. J. Mountain Sci. 11, 1208–1217.
Glass, G.V., 1977. Integrating findings: The meta-analysis of research. Rev. Res. Educ. 5, 351–379.
Gollin, D., Parente, S., Rogerson, R., 2002. The role of agriculture in development. Amer. Econ. Rev. 92, 160–164.
Gori Maia, A., Silveira, R.L.F.d., Veneo Campos Fonseca, C., Burney, J., Cesano, D., 2021. Climate resilience programmes and technical efficiency: Evidence from the smallholder dairy farmers in the Brazilian semi-arid region. Clim. Dev. 1–11.
Grabowski, R., 1985. Technical efficiency in nepalese agriculture. J. Dev. Areas 19, 515–526.
Gundersen, C., Ziliak, J.P., 2015. Food insecurity and health outcomes. Health Affairs 34, 1830–1839.
Guzzo, R.A., Jackson, S.E., Katzell, R.A., et al., 1987. Meta-analysis analysis. Res. Org. Behav. 9, 407–442.
Haji, J., 2007. Production efficiency of smallholders' vegetable-dominated mixed farming system in eastern Ethiopia: A non-parametric approach. J. Afr. Econ. 16, 1–27.
Hakim, R., Haryanto, T., Sari, D.W., 2021. Technical efficiency among agricultural households and determinants of food security in East Java, Indonesia. Sci. Rep. 11, 1–9.
Hang, M., Geyer-Klingeberg, J., Rathgeber, A.W., Stöckl, S., 2018. Measurement matters: A meta-study of the determinants of corporate capital structure. Q. Rev. Econ. Finance 68, 211–225.
Haq, S.U., Boz, I., 2019. Estimating the Efficiency Level of Different Tea Farming Systems in Rize Province Turkey. Ciencia Rural, p. 49.
Havranek, T., Horvath, R., Zeynalov, A., 2016. Natural resources and economic growth: A meta-analysis. World Dev. 88, 134–151.
Hedges, L.V., 1992. Meta-analysis. J. Educ. Stat. 17, 279–296.
Helfand, S.M., Taylor, M.P., 2021. The inverse relationship between farm size and productivity: Refocusing the debate. Food Policy 99, 101977.
Henderson, H., 2015. Considering technical and allocative efficiency in the inverse farm size–productivity relationship. J. Agric. Econ. 66, 442–469.
Herdt, R.W., Mandac, A.M., 1981. Modern technology and economic efficiency of Philippine rice farmers. Econom. Dev. Cult. Chang. 29, 375–399.
Herskovits, M.J., 1955. Peoples and cultures of Sub-Saharan Africa. Ann. Am. Acad. Political Soc. Sci. 298, 11–20.
Ho, T.T., Shimada, K., 2019. The effects of climate smart agriculture and climate change adaptation on the technical efficiency of rice farming—an empirical study in the Mekong Delta of Vietnam. Agriculture 9 (99).
Hoang-Khac, L., Tiet, T., To-The, N., Nguyen-Anh, T., 2021. Impact of human capital on technical efficiency in sustainable food crop production: A meta-analysis. Int. J. Agric. Sustain. 1–22.
Hopkins, N., 2011. Religion and social capital: Identity matters. J. Commun. Appl. Soc. Psychol. 21, 528–540.
Huffman, W.E., 2001. Human capital: Education and agriculture. In: Handbook of Agricultural Economics, Vol. 1. pp. 333–381.
Huy, H.-T., Nguyen, T.-T., 2019. Cropland rental market and farm technical efficiency in rural Vietnam. Land Use Policy 81, 408–423.
Ibrahim, K., Shamsudin, M.N., Yacob, R., Radam, A.B., 2014. Technical efficiency in maize production and its determinants: A survey of farms across agro ecological zones in Northern Nigeria. Trends Agric. Econ. 7, 57–68.
Idiong, I.C., 2007. Estimation of farm level technical efficiency in smallscale swamp rice production in cross river state of Nigeria: A stochastic frontier approach. World J. Agric. Sci. 3, 653–658.
Johansson, O., 1994. Investing in Natural Capital: The Ecological Economics Approach to Sustainability. Island Press.
Johnson, D.G., 1993. Role of agriculture in economic development revisited. Agric. Econ. 8, 421–434.
Johnston, B.F., Mellor, J.W., 1961. The role of agriculture in economic development. Am. Econ. Rev. 51, 566–593.
Kabasa, J.D., Sage, I., 2009. Climate change and food security in Africa. Clima. Change Africa 21, 1–49.
Kalirajan, K., 1984. Farm-specific technical efficiencies and development policies. J. Econ. Stud. 11, 3–13.
Kalirajan, K., Shand, R., 1988. Firm and product-specific technical efficiencies in a multiproduct cycle system. J. Dev. Stud. 25, 83–96.
Karani-Gichimu, C., Mwangi, M., Macharia, I., 2013. Assessment of passion fruit orchard management and farmers' technical efficiency in central-eastern and north-rift highlands, Kenya. J. Econ. Sustain. Dev. 4, 183–190.
Kitavi, S.M., Kibet, L.K., Lagat, J.K., Koech, W., 2015. Evaluation of technical efficiency of rabbit production in Buuri sub-county, Meru county, Kenya. Asian J. Agric. Sci. 7, 24–35.
Knack, S., Keefer, P., 1997. Does social capital have an economic payoff? A cross-country investigation. Q. J. Econ. 112, 1251–1288.
Kotir, J.H., 2011. Climate change and variability in Sub-Saharan Africa: A review of current and future trends and impacts on agriculture and food security. Environ., Dev. Sustain. 13, 587–605.
Kuwornu, J.K.M., Amoah, E., Seini, W., 2013. Technical efficiency analysis of maize farmers in the eastern region of Ghana. J. Soc. Dev. Sci. 4, 84.
Latruffe, L., Balcombe, K., Davidova, S., Zawalinska, K., 2004. Determinants of technical efficiency of crop and livestock farms in Poland. Appl. Econ. 36, 1255–1263.
Le Van, C., Nguyen, A.N., Nguyen, N.-M., Simioni, M., 2018. Growth strategy with social capital, human capital and physical capital—Theory and evidence: The case of Vietnam. J. Public Econ. Theory 20, 768–787.
Lema, T.Z., Tessema, S.A., Abebe, F.A., 2017. Analysis of the technical efficiency of rice production in Fogera district of Ethiopia: A stochastic frontier approach. Ethiop. J. Econ. 26, 88–108.
Lemoalle, J., de Condappa, D., 2010. Farming systems and food production in the Volta Basin. Water Int. 35, 655–680.
Lin, L., Chu, H., 2018. Quantifying publication bias in meta analysis. Biometrics 74, 785–794.
Little, R.J.A., Rubin, D.B., 2019. Statistical Analysis with Missing Data. John Wiley & Sons.
Liu, Y., Myers, R., 2009. Model selection in stochastic frontier analysis with an application to maize production in Kenya. J. Prod. Anal. 31, 33–46.
Lockheed, M.E., Jamison, T., Lau, L.J., 1980. Farmer education and farm efficiency: A survey. Econom. Dev. Cult. Chang. 29, 37–76.
Looga, J., Jürgenson, E., Sikk, K., Matveev, E., Maasikamäe, S., 2018. Land fragmentation and other determinants of agricultural farm productivity: The case of Estonia. Land Use Policy 79, 285–292.
Makki, M.F., Ferrianta, Y., Suslinawati, R., 2012. Impacts of climate change on productivity and efficiency paddy farms: Empirical evidence on tidal swamp land South Kalimantan Province–Indonesia. J. Econ. Sustain. Dev. 3, 66–72.
Mandal, D., Sharda, V., 2011. Land classification employing integrated bio-physical approach for sustainable land use. J. Indian Soc. Soil Sci. 59, 218–223.
Mango, N., Makate, C., Hanyani-Mlambo, B., Siziba, S., Lundy, M., 2015. A stochastic frontier analysis of technical efficiency in smallholder maize production in Zimbabwe: The post-fast-track land reform outlook. Cogent Econ. Finance 3, 117–189.
Martey, E., Dogbe, W., Etwire, P.M., Wiredu, A.N., 2015. Impact of farmer mentorship project on farm efficiency and income in rural Ghana. J. Agric. Sci. 7, 79–93.
Maudos, J., Pastor, J.M., Serrano, L., 2003. Human capital in OECD countries: Technical change, efficiency and productivity. Int. Rev. Appl. Econ. 17, 419–435.
McCullagh, P., 1989. Generalized Linear Models. Routledge.
Mignouna, D.B., Manyong, V.M., Mutabazi, K.D.S., Senkondo, E.M., Oleke, J.M., 2012. Assessing the technical efficiency of maize producers with Imazapyr-resistant maize for striga control in western Kenya. J. Dev. Agric. Econ. 4, 245–251.
Minviel, J.J., Latruffe, L., 2017. Effect of public subsidies on farm technical efficiency: A meta-analysis of empirical results. Appl. Econ. 49, 213–226.
Mohammed, W.A., 2012. Technical efficiency of sorghum production in hong local government area of Adamawa state, Nigeria. Russian J. Agric. Soc.-Econ. Sci. 6, 10–15.
Moore, C.E., Meacham-Hensold, K., Lemonnier, P., Slattery, R.A., Benjamin, C., Bernacchi, C.J., Lawson, T., Cavanagh, A.P., 2021. The effect of increasing temperature on crop photosynthesis: From enzymes to ecosystems. J. Exp. Bot. 72, 2822–2844.
Moreira Lopez, V.H., Bravo-Ureta, B.E., 2009. A study of dairy farm technical efficiency using meta-regression: An international perspective. Chilean J. Agric. Res. 69, 214–223.
Mukherjee, P., Ray, B., Bhattacharya, R.N., 2017. Status differences in collective action and forest benefits: Evidence from joint forest management in India. Environ., Dev. Sustain. 19, 1831–1854.
Nandy, A., Singh, P.K., Singh, A.K., 2019. Systematic review and meta-regression analysis of technical efficiency of agricultural production systems. Global Bus. Rev. 21, 1–26.
Nations, U., 1997. Glossary of Environment Statistics, Studies in Methods. United Nations New York, NY.
Nauges, C., O'Donnell, C.J., Quiggin, J., 2011. Uncertainty and technical efficiency in finnish agriculture: A state-contingent approach. Euro. Rev. Agric. Econ. 38, 449–467.
Ndour, C.T., 2017. Effects of human capital on agricultural productivity in Senegal. World Sci. News 64, 34–43.
Ngombe, J.N., 2017. Technical efficiency of smallholder maize production in Zambia: A stochastic meta-frontier approach. Agrekon 56, 347–365.
Nunn, N., Wantchekon, L., 2011. The slave trade and the origins of mistrust in Africa. Amer. Econ. Rev. 101, 3221–3252.
Nyagaka, D.O., Obare, G.A., Omiti, J.M., Nguyo, W., 2010. Technical efficiency in resource use: Evidence from smallholder irish potato farmers in Nyandarua north district, Kenya. Afr. J. Agric. Res. 5, 1179–1186.
O'Connor, M., 2000. Natural capital. Cambridge Research for the Environment.
Ofori-Bah, A., Asafu-Adjaye, J., 2011. Scope economies and technical efficiency of cocoa agroforesty systems in ghana. Ecol. Econom. 70, 1508–1518.

Ogada, M.J., Muchai, D., Mwabu, G., Mathenge, M., 2014. Technical efficiency of Kenya's smallholder food crop farmers: Do environmental factors matter?. Environ. Dev. Sustain. 16, 1065–1076.
Ogundari, K., 2013. Crop diversification and technical efficiency in food crop production: A study of peasant farmers in Nigeria. Int. J. Soc. Econ. 40, 267–287.
Ogundari, K., Akinbogun, O.O., 2010. Modeling technical efficiency with production risk: A study of fish farms in Nigeria. Mar. Resour. Econ.s 25, 295–308.
Ogundele, O.O., Okoruwa, V.O., 2006. Technical Efficiency Differentials in Rice Production Technologies in Nigeria. Tech. Rep, African Economic Research Consortium (AERC).
Oh, D.-h., Lee, J.-d., 2010. A metafrontier approach for measuring malmquist productivity index. Empir. Econ. 38, 47–64.
Oladeebo, J.O., Fajuyigbe, A.A., 2007. Technical efficiency of men and women upland rice farmers in Osun state, Nigeria. J. Hum. Ecol. 22, 93–100.
Olatidote, M.S., Alimi, T., Akinola, A.A., 2018. Determinants of technical efficiency in cotton production in the southern cotton growing zone of Nigeria: A stochastic production frontier approach. Asian J. Agric. 2, 58–63.
Ologbon, O., Ikheloa, E., Akerele, E., et al., 2012. Adoption of 'ofada' rice variety and technical efficiency of rice-based production systems in Ogun state, Nigeria. World J. Agric. Sci. 8, 624–631.
Olurotimi, P.O., Bamire, A., Ogunleye, A.S., 2018. Effects of social capital on technical efficiency of cassava production in Oyo state, Nigeria. Afr. J. Rural Dev. 3, 695–704.
Onyenweaku, C., Nwaru, J., 2005. Application of a stockastic frontier production function to the measurement of technical efficiency in food crop production in Imo state, Nigeria. Nigeria Agric. J. 36, 1–12.
Orewa, S., Izekor, O., 2012. Technical efficiency analysis of yam production in Edo state: A stochastic frontier approach. Int. J. Dev. Sustain. 1, 516–526.
Oseghale, A.I., Ayinde, I.A., Shittu, A.M., Adeofun, C.O., 2019. Effect of agrochemical related illness on technical efficiency of lowland rice farmers in Niger and Ogun states Nigeria. J. Trop. Agric., Food, Environ. Extension 18, 1–6.
Ostrom, E., 1990. Governing the Commons: The Evolution of Institutions for Collective Action. Cambridge University Press.
Ouedraogo, S., 2015. Technical and economic efficiency of rice production in the KOU valley-Burkina Faso: Stochastic frontier approach. Asian J. Agric. Rural Dev. 5, 53–63.
Owens, T., Hoddinott, J., Kinsey, B., 2003. The impact of agricultural extension on farm production in resettlement areas of Zimbabwe. Econom. Dev. Cult. Chang. 51, 337–357.
Oyekale, A.S., 2012. Impact of climate change on cocoa agriculture and technical efficiency of cocoa farmers in South-West Nigeria. J. Hum. Ecol. 40, 143–148.
Papke, L.E., Wooldridge, J.M., 1996. Econometric methods for fractional response variables with an application to 401 (k) plan participation rates. J. Appl. Econometrics 11, 619–632.
Peiro-Palomino, J., 2016. Social capital and economic growth in Europe: Nonlinear trends and heterogeneous regional effects. Oxford Bull. Econ. Stat. 78, 717–751.
Piazza-Georgi, B., 2002. The role of human and social capital in growth: Extending our understanding. Cambridge J. Econ. 26, 461–479.
Pindiriri, C., Mumbengegwi, C., Zhou, H., 2016. The impact of drought on technical efficiency of smallholder farmers in Hurungwe, Zimbabwe. Botswana J. Econ. 14, 71–92.
Poudel, K.L., Mishra, B., Johnson, T.G., 2017. Farm efficiency and its determinants in different farm size and altitude categories: A case of organic coffee. J. Econ. Insight 43, 1–18.
Rahman, S., Awerije, B.O., 2015. Technical and scale efficiency of cassava production system in Delta State, Nigeria: An application of two-stage DEA approach. J. Agric. Rural Dev. Tropics Subtropics 116, 59–69.
Rajendran, S., Afari-Sefa, V., Karanja, D.K., Musebe, R., Romney, D., Makaranga, M.A., Samali, S., Kessy, R.F., 2015. Technical efficiency of traditional African vegetable production: A case study of smallholders in Tanzania. J. Dev. Agric. Econ. 7, 92–99.
Ramalho, E.A., Ramalho, J.J., Murteira, J.M., 2011. Alternative estimating and testing empirical strategies for fractional regression models. J. Econ. Surv. 25, 19–68.
Raphael, I.O., 2008. Technical efficiency of cassava farmers in south eastern Nigeria: Stochastic frontier approach. Agric. J. 3, 152–156.
Rasul, G., Thapa, G.B., Karki, M.B., 2011. Comparative analysis of evolution of participatory forest management institutions in south Asia. Soc. Nat. Resour. 24, 1322–1334.
Rezitis, A.N., Kalantzi, M.A., 2016. Investigating technical efficiency and its determinants by data envelopment analysis: An application in the Greek food and beverages manufacturing industry. Agribusiness 32, 254–271.
Sampaio Morais, G.A., Silva, F.F., de Freitas, C.O., Braga, M.J., 2021. Irrigation, technical efficiency, and farm size: The case of Brazil. Sustainability 13, 1–21.
Santarelli, E., Tran, H.T., 2013. The interplay of human and social capital in shaping entrepreneurial performance: The case of Vietnam. Small Bus. Econ. 40, 435–458.
Sasson, A., 2012. Food security for Africa: An urgent global challenge. Agric. Food Secur. 1, 1–16.
Schuller, T., 2001. The complementary roles of human and social capital. Canad. J. Policy Res. 2, 18–24.
Schultz, T.W., 1961. Investment in human capital. Am. Econ. Rev. 51, 1–17.
Seyoum, E.T., Battese, G.E., Fleming, E.M., 1998. Technical efficiency and productivity of maize producers in eastern ethiopia: A study of farmers within and outside the Sasakawa-global 2000 project. Agric. Econ. 19, 341–348.
Shehu, J., Iyortyer, J., Mshelia, S., Jongur, A., 2010. Determinants of yam production and technical efficiency among yam farmers in Benue state, Nigeria. J. Soc. Sci. 24, 143–148.
Shehu, J.F., Mshelia, S.I., Tashikalma, A.K., 2007. Analysis of technical efficiency of small-scale rain-fed upland rice farmers in north-west agricultural zone of Adamawa state, Nigeria. J. Agric. Soc. Sci. 3, 133–136.
Sherlund, S.M., Barrett, C.B., Adesina, A.A., 2002. Smallholder technical efficiency controlling for environmental production conditions. J. Dev. Econ. 69, 85–101.
Sihlongonyane, M., Masuku, M., Belete, A., 2014. Economic efficiency of maize production in swaziland: The case of Hhohho, Manzini and Shiselweni regions. Res. Appl. Econ. 6, 179–195.
Singbo, A.G., Lansink, A.O., Emvalomatis, G., 2014. Estimating farmers' productive and marketing inefficiency: An application to vegetable producers in Benin. J. Prod. Anal. 42, 157–169.
Singh, K., Dey, M.M., Rabbani, A.G., Sudhakaran, P.O., Thapa, G., 2009. Technical efficiency of freshwater aquaculture and its determinants in Tripura, India. Agric. Econ. Res. Rev. 22, 185–195.
Smidt, C.E., Smidt, S.F.C.E., 2003. Religion As Social Capital: Producing the Common Good. Baylor University Press.
Solís, D., Bravo-Ureta, B.E., Quiroga, R.E., 2009. Technical efficiency among peasant farmers participating in natural resource management programmes in Central America. J. Agric. Econ. 60, 202–219.
Southavilay, B., Teruaki, N., Shigeyoshi, T., 2012. Analysis on technical efficiency of maize farmers in the northern province of Laos. Afr. J. Agric. Res. 7, 6579–6587.
Stanley, T.D., 2008. Meta-regression methods for detecting and estimating empirical effects in the presence of publication selection. Oxford Bull. Econ. Stat. 70, 103–127.
Stanley, T.D., Doucouliagos, H., Giles, M., Heckemeyer, J.H., Johnston, R.J., Laroche, P., Nelson, J.P., Paldam, M., Jacques, P., Geoff, P., Rosenberger, R.S., Katja, R., 2013. Meta-analysis of economics research reporting guidelines. J. Econ. Surv. 27, 390–394.
Sterne, J.A., Egger, M., 2001. Funnel plots for detecting bias in meta-analysis: Guidelines on choice of axis. J. Clin. Epidemiol. 54, 1046–1055.
Strauss, J., 1986. Does better nutrition raise farm productivity? J. Political Econ. 94, 297–320.
Sutton, A.J., Duval, S., Tweedie, R., Abrams, K.R., Jones, D.R., 2000. Empirical assessment of effect of publication bias on meta analyses. Br. Med. J. 320, 1574–1577.
Takemura, K., Uchida, Y., Yoshikawa, S., 2014. Roles of extension officers to promote social capital in Japanese agricultural communities. PLoS One 9, e91975.
Taru, V.B., Lamba, C., Jare, N., 2012. Economic efficiency of maize production in Yola North Local Government area of Adamawa State, Nigeria. J. Tropical Agric., Food, Environ. Extension 11, 1–8.
Taru, V., Lawal, H., Tizhe, I., 2011. Technical efficiency of sole cowpea production in Adamawa State, Nigeria: A Cobb–Douglas stochastic frontier function. J. Econ. Int. Finance 3, 504–507.
Tasnim, Z., Hafeez, A.G., Majumder, S., 2015. Climate change and wheat production in drought prone areas of Bangladesh-A technical efficiency analysis. J. Agric. Sci. 7 (43).
Theriault, V., Serra, R., 2014. Institutional environment and technical efficiency: A stochastic frontier analysis of cotton producers in West Africa. J. Agric. Econ. 65, 383–405.
Thiam, A., Bravo-Ureta, B.E., Rivas, T.E., 2001. Technical efficiency in developing country agriculture: A meta-analysis. Agric. Econ. 25, 235–243.
Thirtle, C., Beyers, L., Ismael, Y., Piesse, J., 2003. Can GM-technologies help the poor? The impact of Bt cotton in Makhathini flats, KwaZulu-natal. World Dev. 31, 717–732.
Tijani, A.A., 2006. Analysis of the technical efficiency of rice farms in Ijesha land of Osun state, Nigeria. Agrekon 45, 126–135.
Timmer, C.P., 2002. Agriculture and economic development. In: Handbook of Agricultural Economics, Vol. 2. pp. 1487–1546.
To-The, N., Nguyen-Anh, T., 2021. Impact of government intervention to maize efficiency at farmer's level across time: A robust evidence in northern Vietnam. Environ, Dev. Sustain. 23, 2038–2061.
Tsui, C.-C., Chen, Z.-S., Hsieh, C.-F., 2004. Relationships between soil properties and slope position in a lowland rain forest of southern Taiwan. Geoderma 123, 131–142.
Twumasi, M.A., Jiang, Y., 2021. The impact of climate change coping and adaptation strategies on livestock farmers' technical efficiency: The case of rural Ghana. Environ. Sci. Pollut. Res. 28, 14386–14400.
Van Aert, R.C., Wicherts, J.M., Van Assen, M.A., 2019. Publication bias examined in meta-analyses from psychology and medicine: A meta-meta-analysis. PLoS One 14.
van Enst, W.A., Ochodo, E., Scholten, R.J., Hooft, L., Leeflang, M.M., 2014. Investigation of publication bias in meta-analyses of diagnostic test accuracy: A meta-epidemiological study. BMC Med. Res. Methodol. 14 (70).
Verbeke, G., Molenberghs, G., 2009. Linear Mixed Models for Longitudinal Data. Springer Science & Business Media.
Vigh, E., Ferto, I., Fogarasi, J., 2018. Impacts of climate on technical efficiency in the Hungarian arable sector. Stud. Agric. Econ. 120, 41–46.
Wang, X., Taniguchi, K., et al., 2002. Does Better Nutrition Cause Economic Growth? the Efficiency Cost of Hunger Revisited. Tech. Rep., Food and Agriculture Organization of the United Nations, Agricultural.

Wooldridge, J.M., 2009. Introductory Econometrics: A Modern Approach, fourth ed. CENGAGE Learning, Canada.

Yami, M., Solomon, T., Begna, B., Fufa, F., Alemu, T., Alemu, D., 2013. Source of technical inefficiency of smallholder wheat farmers in selected waterlogged areas of Ethiopia: A translog production function approach. Afr. J. Agric. Res. 8, 3930–3940.

Yang, D.T., An, M.Y., 2002. Human capital, entrepeneurship, and farm household earnings. J. Dev. Econ. 68, 65–88.

Zalkuw, J., Singh, R., Pardhi, R., Gangwar, A., 2014. Analysis of technical efficiency of tomato production in Adamawa State, Nigeria. Int. J. Agric., Environ. Biotechnol. 7, 645.

Zhao, C., Liu, B., Piao, S., Wang, X., Lobell, D.B., Huang, Y., Huang, M., Yao, Y., Bassu, S., Ciais, P., et al., 2017. Temperature increase reduces global yields of major crops in four independent estimates. Proc. Natl. Acad. Sci. 114, 9326–9331.

Zheng, H., Ma, W., Wang, F., Li, G., 2021. Does internet use improve technical efficiency of banana production in China? Evidence from a selectivity-corrected analysis. Food Policy 102044.