UNIVERSITY OF EDUCATION, WINNEBA

TECHNICAL EFFICIENCY OF SALT PRODUCTION IN GHANA: THE CASE OF SMALL-SCALE SALT PRODUCERS IN ELMINA

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DECLARATION

STUDENT'S DECLARATION

I, MAWUSI DAKE, do hereby declare that except for the references cited which are duly acknowledged, this thesis titled "TECHNICAL EFFICIENCY OF SALT PRODUCTION IN GHANA: THE CASE OF SMALL-SCALE SALT PRODUCERS IN ELMINA" is the product of my own research work undertaken in the Department of Economics Education, University of Education, Winneba. This research work has never been presented in whole or in part for any other degree of this university or elsewhere.

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SUPERVISORS' DECLARATION

We hereby declare that the preparation and presentation of this work was supervised in accordance with the guidelines for supervision of thesis as laid down by the University of Education, Winneba.

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DEDICATION

This work is dedicated to my lovely parents Dr. G.Y. Dake and Mrs. Bertha Dake for their help and support in diverse ways to make my studies successful.

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LIST OF ABBREVIATIONS

ECOWAS	Economic Community of West African States
ESPA	Elmina Salt Producers Association
GEPA	Ghana Export Promotion Authority
GSS	Ghana Statistical Service
GDP	Gross Domestic Product

ABSTRACT

Technical efficiency of resource-use, particularly in salt production is a major concern for the level of productivity and profitability of salt miners depend on it. Thus, the study was conducted to estimate the level of technical efficiency among small scale salt producers in Elmina. The study used the entire population of 96 salt producers in Elmina. The study reveals that, Cobb-Douglas stochastic production frontier best fits small scale salt producers in Elmina. The results of the mean technical efficiency reveal that, small scale salt producers were not fully technically efficient as the mean technical efficiency is 37.8%. Among the five (5) salt socio-economic variables employed, the technical efficiency model indicates that the number of ponds is statistically significant at 1%, but inversely correlated with technical efficiency. However, the coefficient of interest paid on loans is negative but significant at 5%. Moreover, level of education and distance from the campsite to homestead are significant at 10% levels and positive. The results of the study suggest that, number of ponds and interest paid on loans play an integral role in increasing the level of technical efficiency among small-scale salt producers in Elmina. The major recommendations of the study include Government, Minerals Commission and District Assembly should liaise with various financial institutions to provide interest free loans or loans at affordable interest rate to small-scale salt producers to undertake capital and labour investment as a panacea for increasing efficiency. Also, the Minerals Commission, District Assembly and chiefs should educate the small-scale salt producers on the need to develop and mine few walls (ponds) since they are under resourced. This will help improve on the technical efficiency among the small-scale salt miners in Elmina.

CHAPTER ONE

INTRODUCTION

1.1 Background to the Study

Salt production is an integral part of modern civilization and to achieve rapid economic growth, many countries have resorted to salt mining across the globe. About 100 countries are engaged in salt production in the world and they produce to the tune of 181.5 million tons annually (Venkatesh and Rizwan, 2013). However, out of the total salt produced in the world, America alone produces about 22 percent of the total world capacity (Venkatesh and Rizwan, 2013).

According to Venkatesh and Rizwan (2013), out of 181.5 million tons of salt produced globally, Sub-Saharan Africa (SSA) produces only 5 million tons (Venkatesh and Rizwan, 2013). The countries engaged in commercial salt production in Sub-Sahara Africa (SSA) include Angola, Botswana, Ethiopia, Ghana, Mozambique, Namibia, Senegal, South Africa, Sudan, and Tanzania (Venkatesh and Rizwan, 2013). The technique for salt production in Sub-Saharan Africa (SSA) is said to be conventional and primitive (Livingston, 2005). However, the salts produced in the sub-region have the potential to make the greatest impact on iodized salt coverage in the region. In the Economic Community of West African States (ECOWAS) sub-region, Ghana and Senegal are the biggest regional players producing 350,000 tons annually between 2005 and 2010 (Affam and Asamoah, 2011).

According to Livingston (2005), sodium chloride (salt) plays a critical role in the chloro-alkali industry and it is used by humans and animals in their diets. In Ghana, salt mining dates back to the trans-Saharan trade many centuries ago when the Shongai Empire, Ghana Empire and Mali Empire were engaged in barter trade across

North Africa and the Middle East. Although Ghana continues to trade in salt with North African countries, the volume of salt trade has decreased over the years and is now limited to West African countries such as Mali, Burkina Faso, Togo and Benin (Venkatesh and Rizwan, 2013).

Salt mining in Ghana stretches about 500km along the coastline of the country and the areas noted for commercial salt production in the country include Keta lagoon, the Songhor lagoon, Nyanya lagoon, Oyibi lagoon, Amisa lagoon, and Benyah lagoon among others (Affam and Asamoah, 2011).

Four methods of salt recovery exist in Ghana and these include solution mining, rock salt, solar salt production and processing of rock salt (Mawuena and Andy, 2013). The solar salt production method is the traditional method which is widely used in the country because of the high rate of evaporation and low precipitations in the salt mining areas in the country. Additionally, Ghana's geographical location, climatic and meteorological conditions are suitable for solar salt production in the country.

According to Ghana Export Promotion Authority (2009), Ghana has a production potential capacity of more than two (2) million tons annually, but only produces 250,000 metric tons, representing 10 per cent of the production potential capacity of the country. Despite this, salt production contributes about GHC5 billion to the revenue base of the government annually and estimated to employ about 1,000 workers, a figure which increases substantially during harvest (GEPA, 2009). According to Quarshie and Aggey (2013), the chemical industry is the largest consumer of salt in Ghana. The industry consumes about 60% of the total salt produced in the country. On the other hand, the food industry consumes about 30% and the rest, 10% goes to other sectors. The following industries are major users of salt; Water softening, Textile Dyeing, Dyes manufacturing, Soap, detergent and glycerin, Chlor-Alkali and Tanning.

In Ghana, studies conducted indicate that, salt mining is concentrated predominantly in Greater Accra, Volta and Central Region where climatic conditions are most favorable. However, areas such as the Keta lagoon, the Songor lagoon, the Densu Delta area, Nyanya lagoon, Oyibi lagoon and Amisa lagoon are the dominant mining zones (Affam and Asamoah, 2011). In the Central Region, Elmina is one of the dominant communities engaged in salt mining. According to the Ghana Statistical Service (2010), Elmina is the district capital of Komenda, Edina, Eguafo and Abirem (KEEA) with a district population of about 144,705. Elmina is situated on a bay on the Atlantic Ocean about 12km west of Cape Coast. Salt mining is the second most important occupation among the people of Elmina. In view of this, Elmina is strategically positioned for the study.

1.2 Statement of the Problem

Even though, the salt industry contributes immensely to the economy of Ghana, the country is gradually losing-out on its production potential capacity of over 2 million tons per annum (GEPA, 2009).

According to GEPA (2009), Ghana can only manage a maximum of 250,000 metric tons per annum. This represents about 10 percent of the production potential capacity of the country. The irony is that, whilst the demand for industrial salt is estimated at over 3 million tons per annum, record shows that, some small scale salt producers in the country have either folded-up or minimized their production levels (GEPA, 2009).

If, however, there is an increase in salt output, it will lead to increase export earnings and eventual increase in the GDP of the country. Understanding technical efficiency among small-scale salt producers in Ghana can help improve on the performance of the salt industry. Based on this, the study only considered small scale salt producers in the efficiency analysis. Although much work has been done on technical efficiency in Ghana, most of them are in agricultural production (Edward et al., 2008; Amaechi et al., 2014 and Rahman et al., 2012). However, the few studies conducted on salt mining only made references to other countries such as Guinea (Boubacar et al., 2014). Based on this, there remains a gap in literature on the technical efficiency of small-scale salt production in the country. It is against this backdrop that the study seeks to estimate the level of technical efficiency among small-scale salt producers in Elmina. If salt production is inefficient, how can it be made more efficient and if efficient, how can the industry be improved?

1.3 The Objectives of the Study

The overall objective of the study is to investigate and analyze the level of technical efficiency among small-scale salt producers in Elmina.

The specific objectives are to:

1. estimate the level of technical efficiency among small-scale salt producers in Elmina.
2. examine the determinants of technical efficiency among small-scale salt miners in Elmina.

1.4 Research Questions

The research study shall seek to answer the following questions:

1. What is the level of technical efficiency of small-scale salt producers in Elmina?

2. What are the determinants of technical efficiency among small-scale salt producers in Elmina?

1.5 Significance of the Study

This study is relevant in view of the significant contributions of salt mining to the socio-economic development of Ghana.

1. The study serves as a valuable source of information for artisans, salt mining companies, policy makers, development agencies and other stakeholders in the industry.
2. The study gives an insight into the level of technical efficiency and necessary recommendations made on how to improve the salt industry.
3. The research serves as a valuable contribution to literature and a pointer towards the need for further study in the area.
4. The study would be used to advise government and stakeholders on policy direction that may lead to improvement in the industry.

1.6 Scope of the Study

The research work is a case study involving salt production in Elmina. The study focused on the level of technical efficiency among small scale salt producers in Elmina.

1.7 Organization of the Study

The study was organized into five chapters: Chapter one (1) is the introductory chapter, which deals with the background to the study, the statement of the problem, objectives of the study, research questions, significance of the study, the scope of the study and organization of the study.

In chapter two, literature is reviewed on the various theoretical and empirical research works underpinning the study. It highlights the various types of production function with emphasis on Cobb-Douglas production function and Translog production function. This chapter also identified and discussed the determinants of technical efficiency among salt producers. In view of this, the researcher came out with a framework using the various theoretical and empirical studies.

Chapter three discussed the methods employed in undertaking the study. It gave a detailed description about the study design, the study area and information on the respondents based on the target population and sampling techniques adopted by the researcher. Additionally, it provided an outline of the research instruments for data collection. The methods adopted by the administration of the research instrument, data collection procedure and data analysis and the method of estimation used were justified in this section of the work.

Chapter four focused on data analyses and discussion of the empirical results. It also presented the major findings of the study and discussed the key results of the study in relation to the literature.

The final chapter outlined the major findings of the study and concluded with recommendations.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter reviewed relevant literature on the topic under study. It took into consideration views of authorities on the topic and identifies empirical and theoretical framework that underpins the study. The theoretical review highlights the theories that served as a guide to the choice of appropriate method and variables employed. Furthermore, the literature review identified various studies on the determinants of technical efficiency among small-scale salt producers. This formed the basis of the model used in the study.

2.2 Review of the Theoretical Literature

The theoretical review highlights the four main types of production function with emphasis on Cobb-Douglas production function and Translog production function. The four main types of production function discussed in this section include Cobb-Douglas Production Function, Translog Production Function, Leontief Production Function and Constant Elasticity of Substitution (CES) Production Function.

2.3 Production Function

The performance of the supply side of an economy is often identified with the growth rate of potential output. The use of the production function for measuring output takes into consideration labor, capital and total factor productivity and hence the supply-side functioning. The production function is a mathematical expression that describes the way in which quantity of a particular produce depends upon the quantities of inputs used (Bishop and Toussaint, 1972).

According to David (2017), it is believed that Philip Wicksteed (1984) was the first economist to algebraically formulate the relationship between inputs and outputs in the production function known as:

$p = f(x_1, x_2, x_3, \dots \dots \dots .., x_m)$.

Literature suggests that Johann Von Thunen first postulated the relationship between input and output in the 1840's (Humphrey, 1997). Research has shown that, from 1950's to the late 1970's, many economists were interested in the production function. During this period, various specifications relating inputs to output were proposed, well analyzed and used to draw various conclusions (Davis, 2017).

Production functions were initially postulated with the individual firms in mind. However, the literature reveals that almost all economic theories currently presumed a production function, either on the firm level or the aggregate level (Daly, 1997; Cohen and Harcourt, 2003). This is because macro-economists came to realize the importance of the production function in estimating certain key parameters that cannot be directly estimated from national account data. These parameters include partial elasticity of the individual inputs (capital and labor inputs) and the elasticity of substitution between capital and labor (Banaeian and Zangeneh, 2011).

Banaeian and Zangeneh (2011) contended that the production function is one that specifies the output of a firm, an industry, or an entire economy. Lipsey (1973) on her part stated that, the relation between factor services used as inputs in the production process and the quantity of output obtained could be expressed in functional form called production function. The production function is written mathematically as: $Q = f(L, K)$, where Q is the quantity of output, L is the quantity of labor employed and K is the amount of capital used.

2.3.1 Cobb-Douglas Production Function

The Cobb-Douglas Production Function is widely used in economics and productivity studies across many sectors. The Cobb-Douglas production function represents the functional relationship between inputs and outputs of goods and services produced in an economy (Tan, 2008). Literature revealed that, Cobb-Douglas production function was originally developed by Knut Wicksell (1851-1926) and tested against statistical evidence by Charles Cobb and Paul Douglas in 1928 (Tan, 2008). With this, Charles Cobb and Paul Douglas in 1928 conducted a study where they modeled the growth of the American economy during the period (1899-1922). Charles Cobb and Paul Douglas in their study, employed two-factor production function (labor and capital) to determine the output of goods and services produced, of which the model proved to be accurate (Tan, 2008).

The literature reveals that, the test results conducted by Charles Cobb and Paul Douglas indicates that production is determined by the amount of labor involved and the amount of capital invested. However, the concept is known as the Cobb-Douglas function. Bhanumurthy (2002) stressed that the two-factor Cobb-Douglas production function is given by:

$$Y = AK^{\alpha}L^{\beta}$$

Where; Y is the total production (the monetary value of all goods produced in a year), L is labor input (total number of person-hours worked in a year), K is capital input (the monetary worth of all machinery, equipment and buildings), and A is total factor productivity. The Greek letter α and β are the output elasticity of capital and labor respectively. When the Greek exponential characters sum up to one (α+β=1), it portrays that the production function is first-order homogeneous, which implies constant returns to scale.

The Cobb-Douglas production function has several properties which have made it widely used and accepted in the analysis of economic theories. One of such properties is that the degree of homogeneity of the function is the summation of the output elasticity of $\propto$ and β. It could be less than, greater than or equal to one depending on the values of the output elasticities. The literature reveals that, where the input elasticity sum is greater than one (α+β>1), it indicates increasing returns to scale. On the other hand, where the sum of inputs elasticity is less than one (α+β<1), it represents decreasing returns to scale. Finally, when the sum of all inputs elasticity is equal to one (α+β=1), then it implies constant returns to scale (Bhanumurthy, 2002). If we introduce a constant factor as "t" to the production function, we arrive at:

$$Y = A(tK)^{\alpha}(tL)^{\beta} = t^{\alpha+\beta}(AK^{\alpha}L^{\beta} = t^{\alpha+\beta}(Y).$$

From the result, if we increase capital and labor by a constant factor "t", Output (Y) would increase by the factor $t^{\alpha+\beta}$. With this, the Cobb-Douglas production function is said to be homogeneous of degree one (α+β=1). In this case, output increases by the introduced constant factor "t". On the other hand, if the sum of the output elasticities of the inputs is different from one, then we have a generalized version of the Cobb-Douglas function.

The second property of Cobb-Douglas production function is that the average and marginal products of labor and capital would all be functions of capital-labor ratio. Assume given a linear homogenous production function of the form $Y = AK^{\alpha}L^{\beta}$. The average product of, say labour becomes

$$AP_L = \frac{Y}{L} = \frac{AK^{\alpha}L^{\beta}}{L} = AK^{\alpha}L^{\beta-1} = AK^{1-\beta}L^{\beta-1} = A(\frac{K}{L})^{1-\beta} \ldots\ldots\ldots\ldots\ (1)$$

Based on this, the marginal product of input says labour becomes:

$$MP_L = \frac{dy}{dL} = \beta AK^{\alpha}L^{\beta-1} = \beta AK^{1-\beta}L^{\beta-1} = \beta A(\frac{K}{L})^{1-\beta} \ldots\ldots\ldots\ldots\ldots\ (2)$$

From the two equations (1) and (2), it can be observed that the average and marginal products of labor are functions of capital-labor ratio. The same is true for capital. The economic implication of this is that, if a firm changes the quantities of its inputs keeping their ratios the same as before the change, the marginal and average products of such a firm would remain the same. In view of this, the marginal and average products of the firm can only change if the firm changes the inputs in different proportions.

The third property is that, the marginal rate of technical substitution is the ratio of the marginal products of the inputs. This is shown as:

$$MRTS_{L,K} = \frac{MP_L}{MP_K} = \beta A \left(\frac{K}{L}\right)^{1-\beta} / \alpha A (\frac{L}{K})^{1-\alpha}$$

With Cobb-Douglas production function, the average and marginal product curves are downward sloping. This indicates that, as one of the inputs is increased with the other remaining constant, the average and marginal product of the former input (i.e. the input that is increased) would reduce. It is therefore advisable for firms to alter both inputs simultaneously. On the other hand, inputs employed are paid the rate of their respective marginal products. This implies that total output would be exhausted.

The literature reveals that Cobb-Douglas production function has several advantages that makes it unique and widely suitable in its usage. One major advantage of Cobb-Douglas production function is that, technology is well represented compared to other production functions (Bhanumurphy, 2002). However, one major limitation of the Cobb-Douglas production function is the application to both macro and micro-economic analyzes, which is the two-factor input in this production function. Bhanumurphy (2002) on his part wrote an article where he argued a case for Cobb-

Douglas production function. The paper argued that, Cobb-Douglas (CD) production function merits its use for analyzing production process, not because it is regarded as simple tool which can be handled easily but because it can handle multiple inputs in its generalized form.

Klump and Herald (2000) cited by Gerald and Venoo (2017) came out that, in a situation where there is biasedness in the technical progress, the factor shares may not be constant or the capital to output ratio can be non-stationary. In view of this, if the technical progress becomes more labor or capital-augmenting, then the Cobb-Douglas production function is not an appropriate specification anymore.

When it comes to Cobb-Douglas production function, various econometric estimation problems such as serial correlation, heteroscedasticity and multicolinearity can be handled adequately and easily by it (Bhanumurphy, 2002). Studies indicate that, most of the criticism against Cobb-Douglas production function is the inflexibility in its functional form (Lau, 1986). The paper argues that, technology is well represented by a Cobb-Douglas production function compared to other production functions (Lau, 1986).

2.3.2 Translog Production Function

Research has shown that, Translog production function was pioneered by J. Kmenta in 1967 for the approximation of constant elasticity of substitution (CES) production function with a second order Taylor series, when the elasticity of substitution is very close to the unitary value, which is the case of Cobb-Douglas production function. According to Florin (2011), the above mentioned production function is represented in the form: $InY = InA_3 + \alpha_3 . InK + \beta_3 . InL + X_3 In^2 (\frac{K}{L})$…………………(1)

Where: In is the natural logarithm, Y is the output (Gross domestic product), K is fixed capital, L is employed population and A3, α3, β3, γ3 represent the parameters to be estimated. However, in 1971, Grilichs and Ringstad proposed a new form of production function called labour productivity function which was one of a second order polynomial in the logarithms of the single input considered. The form of the above mentioned production function is:

$$InY/L = InA_2 + \alpha_2.InK + \beta_2.InL + X_2In^2(\tfrac{K}{L}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

The second form of Translog production function was defined in conditions of relaxing the constraints imposed to the parameters in the Kmenta function, in order to test the homotheticity assumptions written as:

$$InY = InA_{KL} + a_K\,.InK + a_L\,.InL + \beta_{K^2}In^2K + \beta_{L^2}.In^2K + \beta_{KL}\,.InK.InL \ldots..(3)$$

The main characteristics of Translog production function is that the elasticity of substitutions varies between factors of production including: capital-labor, capital-land, land-labor ratios. The Translog production function provides a more flexible kind of the functional forms for the production functions (Allen and Hall, 1997). Additionally, Klacek et al. (2007) argued that, Translog production function is not rigid, causing a perfect substitution between factors of production as compared to Cobb-Douglas production function. The generalized form of Translog production function is expressed as:

$$InY = \emptyset + \sum_{i=1}^{n} a_i\, InX_i + \; 1/2^n \sum_{i=1}^{n} \sum_{j=1} \beta_{ij}\, InX_i\, InX_j \ldots\ldots\ldots\ldots\ldots\ldots (4)$$

Where; $\emptyset = InA$

2.3.3 Leontief Production Function

Another functional form of the production function is the Leontief production function named after Wassily Leontief, a Nobel Prize winner who pioneered input-output analysis. The Leontief production function involves the minimum combination of factor inputs to produce a certain amount of output. Based on this, the Leontief production function will only occur when the material inputs used are in strict proportion to the value added (Basu, 1996). This means that, even if a firm increases one of the inputs while the other input remains unchanged, the output will not increase.

The central assumption of this model is that production requires a fixed proportion of inputs. The general formula for the Leontief production function is as follows:

$$Q_t = Y_1 + Y_2K_t + Y_3L_t + Y_4K_t^{0.5}L_t^{0.5} + \varepsilon_t$$

Where Q_t is output or value added at a time (t), K_t is capital at time t, L_t is labor at time t, ε_t is disturbance termY_S'Parameters to be statistically estimated.

The main drawback of the Leontief production function is that it does not permit substitution among the factors of production even if the price ratios among these factors of production change (Nicholson and Christopher, 2011).

2.3.4 Constant Elasticity of Substitution (CES) Production Function

Elasticity of substitution between capital and labor is defined as the percentage change in the capital-labor ratio over the percentage change in the marginal rate of technical substitution (MRTS). However, MRTS is the rate at which labor can be substituted for capital along an isoquant line. The literature reveals that, Robert Solow first introduced Constant Elasticity of Substitution (CES) production function and later made popular by Chenery, Arrow, Minhas and Solow in 1961.

According to Miller (2008), the elasticity of substitution shows how easy it is to shift between capital and labor. It is mathematically expressed as:

$$Y = b[(aK^r + (1 - a)L^r]$$

Where "Y" is the output, "b" represents the factor productivity or the efficiency parameter that indicates the state of technology and organizational aspects of production, "a" the share parameter, "L" and "K" the primary production factors, $r=(s-1)/s$, and $s=1/(1-r)$ are the elasticity of substitution of the function which is the reason behind the name constant elasticity of substitution (CES) production function. In this CES function, the elasticity of substitution is constant and not necessarily equated to one.

There are two main types of Constant Elasticity of Substitution (CES) production functions (Klump and Herald, 2000). The first type of CES production function was pioneered by Pitchford (1960) and Arrow et al (1961) and modified by other scholars in their work (Klump and Herald, 2000). The Constant Elasticity of Substitution (CES) function exhibits the following properties:

1. The value of the elasticity of substitution depends on the value of substitution parameter.
2. The marginal product of any input will increase when other factor inputs increase.
3. The marginal products of labor and capital are always positive whenever the assumption of constant returns to scale is assumed and also slopes downward.

Some of the advantages of Constant Elasticity of Substitution (CES) function include: its coverage on all types of returns, generality, accounting for several parameters, also considers the raw materials among its inputs, easy to estimate and devoid of unrealistic assumptions. Nevertheless, there are some drawbacks. With the constant elasticity of substitution, the researcher is restricted to only two variables to be estimated at once. This makes it unsuitable for the study. Moreover, one may encounter problems such as a large number of choices of exogenous variables, estimation procedure and the problem of multicollinearities in estimating the CES function. Also in attempting to remove the problem of multicollinearities there is a possibility of magnifying the errors in measurement of variables.

Overall, the Cobb-Douglas production function has been used by several authors to examine the relationship between input costs and yield (Rafiee et al., 2010; Hatirli et al., 2006) showing better estimates in terms of statistical significance and expected signs of parameters.

2.4 Concepts of Efficiency

Literature on production efficiency began in 1950s and by 197, Farrell proposed that the efficiency of a firm can be calculated empirically and hence, propounded an innovation method of efficiency frontier estimation from real situations of production observations. The efficiency of a firm is defined as the relative ratio of the actual product that a firm obtained to its maximum potential productivity (Farrell, 1957). A firm is efficient if it is able to obtain maximum output from a set of inputs (Rogers, 1998). This suggests that, in improving on the growth of a firm, more commodities must be produced with fewer resources or the same amount of resources. Therefore, a firm is said to be more efficient if the growth of the firm is higher than its competitors within the industry.

According to Coelli et al. (1998), efficiency of labour can be categorized into two main components, namely, technical efficiency and allocative efficiency. Technical efficiency (TE) measures the ability of a decision making unit (DMU) to produce the maximum feasible output from a given bundle of inputs (output oriented technical efficiency) or produce a given level of output using the minimum feasible amounts of inputs (input-oriented technical efficiency) (Farrell, 1957). This indicates that, a firm is technically efficient if is able to obtain maximum output with a given set of inputs.

Allocative efficiency occurs when a firm chooses the optimal combination of inputs, given the level of prices and production technology (Rogers, 1998). However, in a situation when a firm fails to choose the optimum input combinations at a given price level, the firm is said to be allocatively inefficient despite the firm may be technically efficient. Coelli et al. (1998) emphasized that the combination of technical efficiency and allocative efficiency result in economic efficiency (overall efficiency). Overall efficiency occurs when a firm is able to achieve maximum output with limited resources at a minimum cost. With regard to production possibility curve, Coelli et al. (1998) argue that firms that produce on the production frontier are operating at maximum productivity and therefore are recognized as technically efficient. Conversely, firms that produce below the production possibility curve are considered technically inefficient.

The study adopted technical efficiency (output-oriented) approach since salt mining plays an integral part in the economy of Ghana in terms of export. Moreover, the high demand for salt in the sub-region requires constant adjustment to the volume of salt export particularly in the study area. Based on this, the study considers the output-oriented approach the most appropriate in measuring technical efficiency among the salt producers in Elmina.

Efficiency can be expressed in mathematical equation as: $H = \frac{Q}{N}$, where Q denotes the value of the economic effect being obtained, and N denotes the value of expenditure incurred in obtaining the intended effect and H represents the efficiency of production (Justyna, 2017). According to Justyna (2017), two methods of estimating technical efficiency can be identified, namely; parametric (economic) and non-parametric approach.

2.4.1 Non-Parametric Approach of Efficiency Measurement

The literature reveals that non-parametric frontier used in estimating technical efficiency was pioneered by Farrell (1957) and later extended by Charnes et al. (1978) to include multiple output-input technologies. Moreover, the parametric frontier approach incorporated into stochastic frontier approach (SFA) is mathematically demanding, compared to non-parametric approach. In view of this, non-parametric methods lie in linear programming methods, of which the DEA method is very important. When it comes to efficiency measurement, the Data Envelopment Analysis (DEA) is able to build a linear function from empirical observation of inputs and outputs without assuming any priori functional relationship between them.

Schmidt (1986) argue that one major deficiency of non-parametric approach is that the results of technical efficiency obtained may be less accurate since non-parametric approach makes use of less information (observations) compared to the parametric approach in analyzing technical efficiency results. This makes Farrell's model sensitive to extreme observations and measurement error (Forsund et al. 1980).

Another limitation is that, Data Envelopment Analysis (DEA) does not permit tests of hypothesis in relation to differences in technical efficiency to be performed statistically as required in scientific study (Schmidt, 1986). Moreover, it is conceptually difficult to separate measurement errors resulting from farm management differences and uncontrollable environmental variables (Jaforullah and Whiteman, 1999).

Some of the authors that applied Data Envelopment Analysis (DEA) in their study include Prochazka et al. (2017). They applied Data Envelopment Analysis (DEA) in analyzing technical efficiency of potato farmers in Syria. Moreover, Ahmed et al. (2016) used bootstrap Data Envelopment Analysis (DEA) to analyze the efficiency of major mining companies in Australia and Hosaena and Stein (2015) carried out quasi-experimental evidence on the technical efficiency and productivity differential effects on land right certification in Ethiopia using Data Envelopment Analysis (DEA).

2.4.2 Parametric Approach of Efficiency Measurement

The parametric frontier approach is the functional form of efficient frontier that uses either panel data or cross sectional data in analyzing technical efficiency (Aigner et al., 1977). The literature reveals that, parametric frontier approach imposes restriction on production function, but allows for a test of statistical inferences as well as different hypotheses on the estimated parameters of the production frontier.

According to Kibirige (2008), the parametric frontier approach can be sub-divided into two, namely; deterministic production frontier and stochastic production frontier approach. The deterministic production frontier assumes that any deviation resulting from unfavorable climatic conditions, socio-economic and demographic factors and uncertainties from the efficiency frontier are under the control of the farmer and not considered inefficient (Constantin et al., 2009). One major drawback of this approach is that, any approximation or measurement errors, specification problems and other output variation are attributed to inefficiency. The deterministic frontier model is represented as;

$$Y_i = f(X_i; \beta_i)\exp(u_i)$$

Where Y_i (kg/ha) represents the productivity of the i^{th} farm, with the deterministic part$f(X_i; \beta_i)$ common for all producers, $X_i$denote vector of inputs for the i^{th} farm, $\beta_i$is unknown parameters to be estimated. The $u_i$is a non-negative random variable representing inefficiency with the following distributional assumption for different specifications such as Half-normal, Truncated, Exponential and Gamma distribution (Songsrirote and Singhapreecha, 2007). For deterministic frontier, the technical efficiency (*TEi*) of individual farmers is defined as the ratio of observed output $Y_i = f(X_i; \beta_i)\exp(u_i)$ to the corresponding potential output $Y_i^* = f(X_i; \beta_i)$ where there is no inefficiency. Therefore, technical efficiency of deterministic frontier is presented as:

$$TE_i = f(X_i; \beta).\frac{\exp(-u_i)}{f(X_i; \beta)} = \exp(-u_i)$$

The emergence of stochastic frontier analysis (SFA) was fuelled primarily by the presence of inefficiencies in production. According to Subal et. al. (2004), by 1977, Aigner, Lovell and Schmidt (1977), and Meeusen and van den Broeck (1977) propounded the Stochastic Frontier Model. The stochastic frontier model is specified as:

$$Y_i = F(x_i\,;\ \beta)\exp(v_i - u_i)\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ (1)$$

Where $Y_i$is the output of the firm i; x_i is (n+1) row vector where the first element "1" represents the intercept and the remaining elements represent quantities of inputs employed to produce Y; β is an (n+1) column vector of technology parameters to be estimated. Moreover, v_i is the random error term (statistical noise) and u_i is the one side representing technical efficiency of the farm (Boubascar and Abner, 2000).

The study adopted stochastic frontier approach primarily because it captures random error term (v_i) and inefficiency term (u_i). According to Coelli et al. (1998), the random error terms are factors outside the control of the production unit whilst inefficiency term takes care of the factors within the control of the farmer. The two error terms account for the difference between actual output and the potential output known as stochastic element in production or disturbance term (Coelli et al., 1998).

Technical efficiency (TE) can be calculated using the output orientation method as a ratio of actual (observed) output relative to potential (maximum feasible) output as:

$$TE_i = \frac{Y_i}{F(X_i;\beta)\exp(v_i} = E(Y_i|u_I, x_I)/E(Y|u_i = 0, x_i) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

The technical efficiency (TE) measure takes values between 0 and 1 with smaller ratios reflecting greater inefficiency of firms (Boubascar and Abner, 2000). Additionally, with regard to fully efficient firms (u_i= 0), with value of 1 indicates that actual output equals frontier output. The frontier output is obtained by estimating technology using linear programming (Boubascar and Abner, 2000). Some of the authors that applied stochastic frontier analysis (SFA) in their study include: Koop and Tole (2008). They applied stochastic frontier analysis (SFA) to examine the environmental performance of global gold mining firms and found that, most firms are inefficient. Additionally, Tsolas (2001) also applied both DEA and SFA to examine the level of efficiency of Greek bauxite mining firms. It was discovered that, both methods suggested that most firms were inefficient and that the major source of inefficiency was deviations from the optimal scale of production.

The use of stochastic frontier analysis (SFA) demands that, we choose a production function model (Bezat, 2009). This includes: Cobb-Douglas production function, constant elasticity of substitution (CES), Translog production function, generalized Leontief model, normalized quadratic and its variants. Since the same technology is adopted by salt producers in Elmina, the study adopted Cobb-Douglas production function which exhibit constant technology.

2.5 Methods of Salt Mining

The literature revealed that, there are four different types of salt recovery methods globally (Mawuena and Andy, 2013; Affam and Asamoah, 2011). This include rock salt mining, solution mining, vacuum evaporation and solar evaporation method.

1. Rock salt mining is also known as underground mining (Abu-Khader, 2006). According to Dennis (2006), rock salt is mined by the room-and-pillar method, which is similar to that used in coal and Trona mining. The pillar widths are controlled by the percentage of extraction permissible at the various depths and room widths. With this, most room-and-pillar operations recover about 45% to 65% of the resource, with the remainder left behind as pillar supports for structural integrity of the mine (Dennis, 2006). This process involves conventional mining of the underground deposits through drilling and blasting, whereby solid rock salt is removed. The mining is carried out at depths between 100 m to more than 1500 m below the surface (Abu-Khader, 2006).
2. Salt in brine (solution mining): With this, water is injected into a salt layer through cased wells, and the saline brine is pumped to the surface where water is evaporated using mechanical means such as steam-powered multiple effect or electric powered vapor compression evaporators. In the process, thick slurries of

brine and salt crystals is formed. Solution mining fields start off as single well systems and transition to multi-well systems as the connectivity of the cavities increases (Briggs, 1996). A number of technologies commonly found in the oil industry also apply to solution mines (Sanford, 1996). Wells are cased to protect aquifers, hydro fracturing is employed to increase cavern connectivity, and horizontal drilling has been used in some solution fields.

3. Vacuum evaporation: According to Dennis (2006), vacuum pan salt is not mined, but is a type of salt produced using mechanical evaporation technology. Although rock salt, solar salt, and salt brine may be used to make vacuum pan salt, virtually all domestic vacuum pan salt is obtained from solution mining underground salt formations. Vacuum pan salt is obtained by dehydrating brine using heat alone or in combination with a vacuum. The vacuum pan process conserves energy by utilizing multiple-effect evaporators connected to vacuum pumps. A saturated salt solution will boil at a higher temperature than pure water. When a vacuum is applied, the brine boils at a lower temperature, enabling the superheated vapor that is generated to act as the heating medium for the next evaporator.

4. Solar evaporation method: This method uses the wind and the sun to evaporate the water and is an effective method of producing solar salt in areas of high evaporation and low precipitation (Dennis, 2006). According to Abu-Khader (2006), solar evaporation involves extraction of salt from the oceans and saline water bodies by evaporation of water in solar ponds leaving salt crystals, which are then, harvested using mechanical means. Solar and wind energy is used in the evaporation process. The method is used in regions where the evaporation rate exceeds the precipitation rate.

Research has shown that, more than one third of the salt production worldwide is produced by solar evaporation of sea water or inland brines (Sedivy, 2009). According to Affam and Asamoah (2011), the solar salt method is the most widely used in Ghana because of high evaporation rates and low precipitation that exist along the coast. In addition, Ghana's geographical location, climate and meteorological conditions are suitable for solar salt production (Mawuena and Andy, 2013). Literature revealed that there are three systems of evaporating the sea water and or brine in solar salt evaporation namely; single-pond system, double-pond system and multi-pond system.

1. Single-pond System: With single-pond evaporating technique, despite production cost will be lower, quality of salt is very much reduced and the production rate is also limited. Impounding of sea water in all the ponds and after evaporation scrapping of salt from all the ponds-a batch wise process – reduced the production cost. However, complete evaporation in the same pond results in the crystallization of all the salts present in sea water or brine which makes NaCl impure.
2. Double-pond System: The second system, in the process of salt recovery from sea water is made by the division of the evaporation basin into two: the first basin, usually called nurse pond, is used for the production of NaCl-saturated brine, which is fed into the second basin, usually called crystallizer. Thus, it is made possible to achieve continuous salt production (crystallization) and to eliminate those sea water, salts, with less solubility than NaCl (i.e. CaCO3 and CaSO4), since these crystallize in the first basin and remain there.
3. Multi-pond System: The third and most decisive system concerned was the division of the nurse pond into several interconnected basins. With this design, sea

water enters the first basin and, as it flows through successive ponds and evaporates in the sun, its concentration increases. This production method ensures greater control over the concentrations and quantities of the brines fed through the system, thus resulting in the unobstructed production of much better quality and quantity of the salt. Nursing ponds cover around 90% of the total area of the saltern and create a complete, living ecosystem. In view of this, the multi - pond system of salt evaporation method is still used nowadays for the recovery of salt from sea water, although there have been improvements and variations, allowing for the production of some hundred to a few million tons of salt, depending on the size of the area in use. These three stages (reservoirs, condensers and crystals) constitute the basic steps towards improving the salt manufacturing technology.

Modern Methods of Salt Mining in Ghana

In the modern salt mining method, sea water is pumped into ponds with dykes to prevent the water from escaping (Fig. 2.1). It is continuously evaporated by solar heating and wind flow. As the water evaporates, its concentration rises and the constituent salt crystallizes out. The crystallized salt is then washed to remove the insoluble matter like sand and as well as other impurities. It is then allowed to drain and dry in the sun. The range of salinity of the water in each of the ponds is regulated and is graded with the lower salinities in the evaporators and concentrators.

MODERN SALT MINING IN GHANA

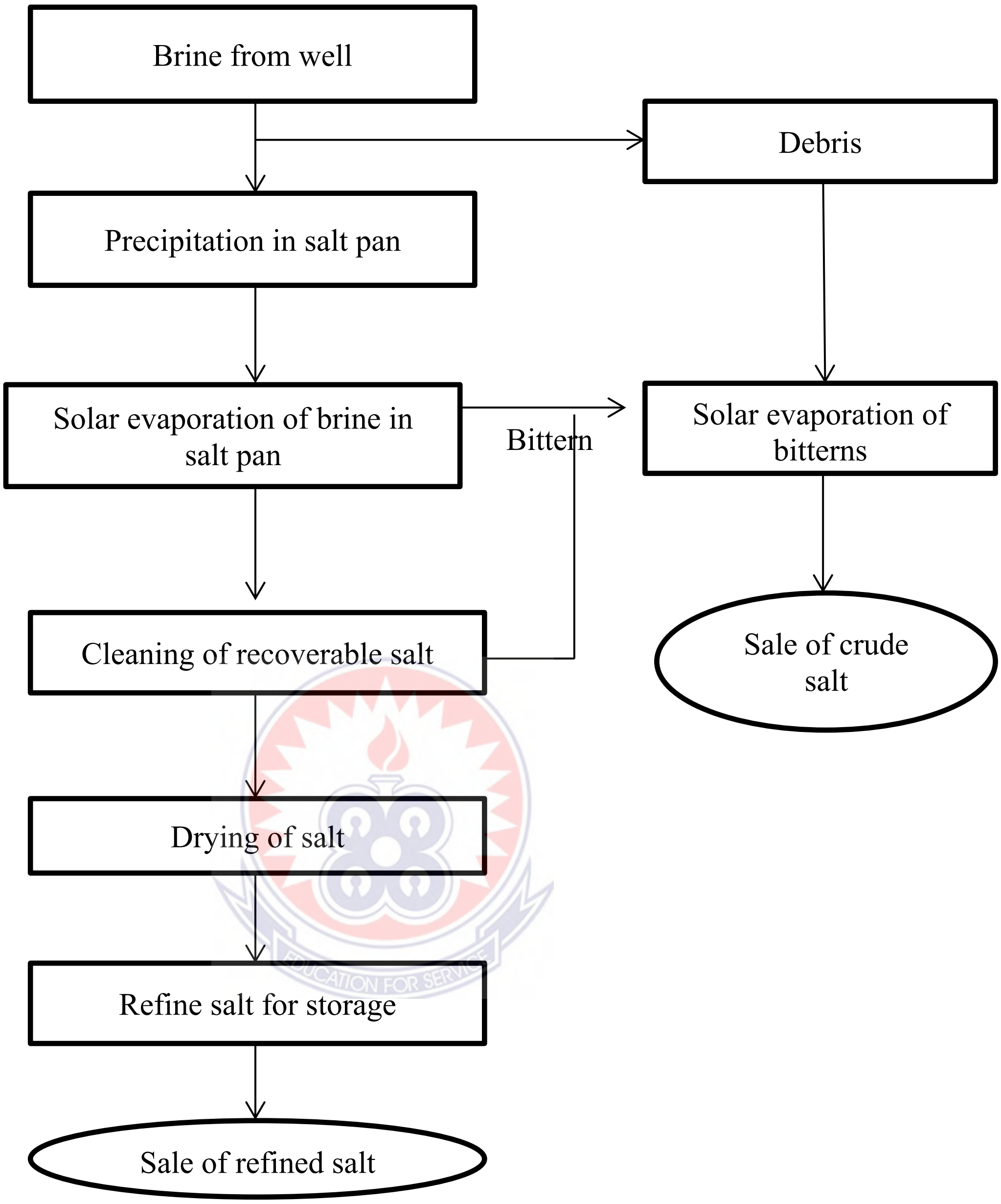


Figure 2.1: Flow chart of modern salt production in Ghana (Affam and Asamoah, 2011)

TRADITIONAL SALT MINING METHOD IN GHANA

The traditional salt mining method involves fractional crystallization of various dissolved salts in lagoon or seawater in various ponds as the water is moved from evaporators through concentrators to crystallizers where sodium chloride is crystallized out as indicated below.

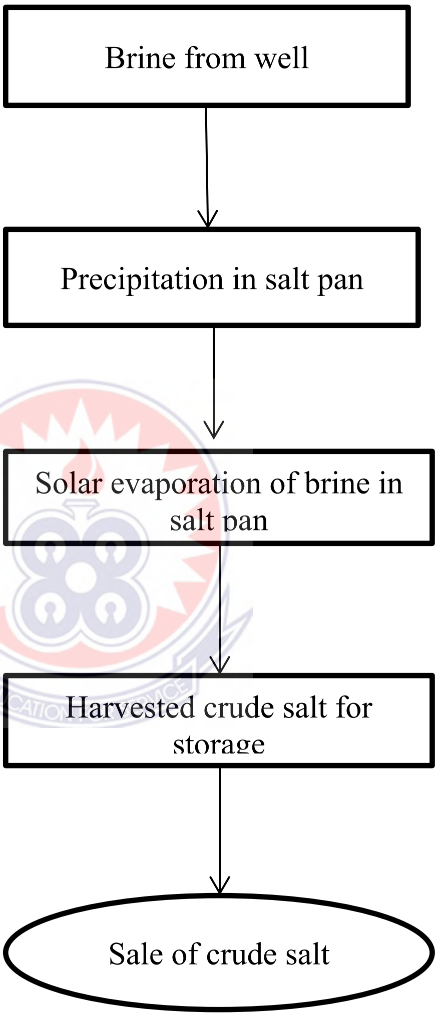


Figure 2.2: Flow chart of traditional salt production in Ghana (Affam and Asamoah, 2011).

2.6 Review of the Empirical Literature

A lot of literature was reviewed on the level of technical efficiency among the small-scale producers in the agricultural industry. However, those that relate closely to salt mining were reviewed and discussed in this section.

Determinants of Technical Efficiency among Small-Scale Salt Producers

Boubascar et al. (2014) undertook a study on measuring technical efficiency of small-scale salt production using a stochastic frontier approach in Guinea. Primary data was collected through a structured questionnaire and a sample size of 100 respondents was used for the study. However, the study only took into consideration 65 salt producers engaged in improved salt production techniques. The study undertook empirical analysis using stochastic frontier production (SFP) and efficiency measurement. The study adopted Cobb-Douglas production function based on Coelli et al. (1998). The study also conducted inefficiency test using two stage estimation techniques in FRONTIER 4.1. The result of the study reveals that, labour cost and dimension of basins contribute tremendously to improvement in the performance of salt production in terms of revenue earned. Furthermore, the results of the inefficiency model revealed that, membership in salt producer organizations, producers' participation in activities organized by local and or international institutions; family size and land rent significantly influenced technical inefficiency of small scale salt producers. The result also indicates that, the best salt miners were also inefficient. The mean level of their technical efficiencies was estimated at 27%, while the efficiency ranged from 0.0 to 92%. In addition, the estimation of the loss due to the inefficiency occurring seasonally was significant and valued at 601,024 Guinean francs per basin. For improved production, the study recommended coating basins for minimizing the loss of salt during extraction, encouraging producers' participation in activities organized by the government and its partners and strengthening producers' organizations to enhance producer participation in salt production.

Even though, the results of the study conducted by Boubacar et al. (2014) reveal that, small scale salt miners in Guinea were 73% technically inefficient, the individual efficiency scores indicate that, some of the small scale salt producers were 92% technically efficient. The study failed to interrogate factors that might have accounted for a high level of technical efficiency among some small-scale salt producers in Guinea. Moreover, the study could have compared the Cobb-Douglas production function and Translog production function to find out which production function best fits small scale salt miners in Guinea. Instead, the Cobb-Douglas production function was probably used without any justification. Although a lot of researches have been conducted in technical efficiency Ghana, most of them are in to the agricultural sector. In fact, the few researches conducted on salt mining only made references to other countries such as Guinea creating a gap.

Edward et al. (2008) undertook an investigation on the Cobb-Douglas, Translog Stochastic production function and Data Envelopment Analysis in total productivity of main Brazilian grain crops. The objective of the paper was to apply a Cobb-Douglas, Translog Stochastic Production Function and Data Envelopment Analysis (DEA), particularly the Malmquist index, to estimate the increases or decreases of inefficiencies over time as well as the sources of TFP changes for the main Brazilian grain crops, namely, rice, beans, maize, soybeans and wheat using available data from 2001-2006. The results of the study revealed that for the Cobb-Douglas model, elasticity was greatest in the harvest area followed by agricultural credit and limestone. However, the Translog production function (TPF) presents an amelioration of aggregate productivity over time and in a decreasing order. In view of this, the regions that presented the greatest degree of efficiency include Northeast, North, South, and Southeast and Center-West regions. The results of the study indicate that, although there have been positive changes in TFP for the sample analyzed, a decline in the use of technology prevalent in all the principal Brazilian grain crops between 2005/2007 when the observation took place. In fact, the study revealed that, there was a remarkable downfall in the use of inputs in the agricultural sector.

Though the study conducted by Edward et al. (2008) adopted SFA model and DEA model, it could be difficult comparing the rate of increase and decreases in inefficiencies. This is because the SFA is mathematically demanding compared to the DEA. Moreover, the SFA model is able to separate the statistical noise from the error term whilst the DEA lumps both the statistical noise and the error term together. In view of this, the study could not have effectively compared the inefficiencies in these models. However, Cobb-Douglas stochastic frontier model and Translog stochastic frontier model could have presented better estimates than the DEA model. Whilst the study identified a considerable downfall in the use of agricultural inputs, a similar study conducted by Rahman et al. (2012) reveals that, farm inputs such as fertilizer, manure, irrigation cost, insecticide cost, and land are instrumental in rice production in Bangladesh.

Rahman et al. (2012) conducted a study on a stochastic frontier approach (SFA) to model technical efficiency of rice farmers in Bangladesh. The purpose of the study was to estimate the farm size and technical efficiency of all rice crops in Bangladesh. The farm-size specific technical efficiency scores were estimated using stochastic production frontiers. The results of the study revealed a variation of productivity among farms, where large farms exhibited the highest productivity. From the study, the gross return was the highest for small farms and net return was the highest for marginal farms. In addition, the marginal farms experienced the highest benefit-cost ratio (BCR) followed by small and medium farms. Average technical efficiency for large, medium, small, marginal and all farms were respectively 0.88, 0.92, 0.94, 0.75 and 0.88. Furthermore, there was a significant technical inefficiency in the production of rice for marginal farms only. In view of this, production cannot be increased by increasing efficiency with the existing technology except in marginal farms. This implies that, farmers could increase 12 percent output with existing inputs and production technology. The study also revealed that, fertilizer, manure, irrigation cost, insecticide cost, area under production and experience were important factors necessary to increase productivity. Finally, with regard to the effect of technical inefficiency, age, education and family size had a positive impact on efficiency effect, whereas land under household had a negative impact on efficiency effect.

Amaechi et al. (2014) conducted a study on the technical efficiency of the small semi-mechanized oil palm produce millers in Nigeria using the Translog stochastic frontier (TSF) production function model. The study employed multi-stage sampling technique to sample 30 respondents-mills in the study area. A cost route approach was employed in data collection. The results of the study indicate that, mills showed a higher level of technical efficiency with a mean of 70.62 and the range of 37.48% to 93.46%. This wide variation in oil palm production from the frontier output was due to differences in management practices rather than random variation. This also means that, under the existing technology, there is potential for improvement in production efficiency with proper utilization of available resources. The study also revealed that, education, processing experience, membership of cooperative society, credit, capital, petroleum energy and water were significant and positive determinants of technical efficiency while age, household size and interest on loans were negatively related to technical efficiency. It was recommended that, policies and programs should be geared towards improving education, cooperativeness, and access to credit/capital, oil palms plantation rehabilitation, sustainable petroleum energy and supply of other necessary facilities to ensure increased productivity.

Even though, the study undertaken by Amaechi et al. (2014) employed Translog production function probably because of its flexibility over other production functions, Cobb-Douglas production function could have presented a better estimate considering that, technology is constant among semi mechanized oil palm producers in Nigeria. Moreover, the study failed to compare the Cobb-Douglas production function and Translog production function to find out which production function is employed by small semi-mechanized oil palm producers in Nigeria. The study identified education, processing experience, membership of cooperative society, credit, capital, petroleum energy and water as the major determinants of technical efficiency. In contrast, a similar study conducted by Aliudin et al. (2014) on block palm sugar agro-industry in Indonesia identified partially tapped labor, labor process, labor fuel, and experience as having a significant effect palm sugar production in Indonesia.

Aliudin et al. (2014) conducted a survey on applied Cobb-Douglas production function on home industry of palm sugars in Cimenga District, Lebak Region, Indonesia. The primary objective of the study was to determine eight effects of production factors on the block palm sugar agro-industry. The factors of production include: labour tap, labour process, labour fuel and tapping experience. However, the productive age of trees, number of tapping trees, mileage, and ratio of crop represents the yield to total plant. The stratified random sampling method was used to sample 54 producers. The result of the study revealed that, labour input taps, labour input processing, input fuel wood, tree age, number of tapped trees, tapped experience, workshop distance to garden, and ratio of productive crop with non-productive plants simultaneously have an effect on the production. Moreover, partially tapped labour, labour process, labour, fuel, and tapped experiences have a significant effect on block palm sugar production. While the productive age of trees, number of tapping trees, mileage, the ratio of crop yield to total plant does not have any significant effect on production of block palm sugar.

Triyani et al. (2017) carried out a study on the technical efficiency of catfish and Nile tilapia farming in Bangka Tengah Regency, Indonesia. The objective of the paper was to analyze factors affecting catfish and Nile tilapia production and to measure the level of technical efficiency. The paper adopted stratified random sampling and systematic sampling to sampled 71 catfish farmers and Nile tilapia farmers in the study. Moreover, the stochastic frontier production approach was used to determine the effect of inputs on catfish and Nile tilapia production. However, this was followed by the analysis of technical efficiency (TE). The study revealed that, the stochastic frontier Cobb-Douglas production function on input variables such as pond size, fingerlings, feed, labour, salt, lime and fuel pump have a significant impacts on the catfish production, where the output elasticity associated with fingerlings is the highest (0.715). Additionally, the analysis of the study revealed that, pond size, labour, salt, and fuel pump have significant impacts on the Nile tilapia production, where the output elasticity associated with labor is the highest (1.005). Furthermore, the technical efficiency (TE) of catfish farming ranges between 0.130 and 0.999 with a mean of 0.678, and the technical efficiency (TE) of Nile tilapia farming ranges between 0.047 and 0.999 with a mean of 0.221. The analysis of technical inefficiency suggested that, formal education and membership of association are significant to technical efficiency of catfish farms. On the part of Nile tilapia farming, a variable such as membership of fish farmers was significant and positive to technical efficiency. The study recommended that, government should intensify training of fish farmers, particularly fish farmers who have never participated in training workshops to enhanced productivity.

Although the study conducted by Triyani et al. (2017) reveals that, catfish farmers and Nile tilapia farmers in Indonesia were not fully technically efficient, the study failed to interrogate what could have accounted for the large differences in the mean technical efficiencies between catfish farmers and nile tilapia farmers in Indonesia. Moreover, the study only identified the factors influencing tilapia farming and catfish farming, the study could have gone further to interrogate what accounted for the differences in these factors. Moreover, the study could have compared the various production functions, particularly Cobb-Douglas production function and Translog production function and identified the production function that best fits the catfish farmers and tilapia farmers in Indonesia.

Srinivas et al. (2012) conducted a survey on the technical efficiency of seed potato farmers of Badakshan Province, Afghanistan. The primary objective of the study was to find out if the high yielding potato variety introduced and its production technology has actually helped reduce the level of poverty and increased food production in the Bahrak district of Badakhshan province of Afghanistan. The study adopted purposive and multistage sampling technique to sample seed potato farmers in the study. The stochastic production function of Cobb-Douglas form was specified, and used for the study. Primary data was obtained from the participating and non-participating farmers in the intervention. The results of the study revealed a high level of inefficiency up to (76%) on the part of potato farmers. This means that, farmers have the opportunity to improve their farming practices by 76% just by way of realizing technical efficiency. The study recommended the use of improved technology and cost effective practices through more trainings and field days to improve potato production.

What the study conducted by Srinivas et al. (2012) sought to do is to find out the extent to which high yielding potato variety introduced into its system and associated technology has actually helped to reduce the level of poverty and increased food sufficiency in Afghanistan. However, the study failed to interrogate the extent to which high yield potato seeds actually helped to minimize the poverty levels among potato farmers in Afghanistan. Despite the study adopted Cobb-Douglas stochastic production frontier, a similar study conducted by Prochazka et al. (2017) employed DEA to estimate the determinants of technical efficiency among potato farmers in Syria. Despite the study adopted DEA model, the study could have employed the SFA since the SFA is able to separate the errors which are outside the domain of the producer from the inefficiencies which are within the control of the producer. The results of the studies indicate that, potato farmers in Afghanistan were 34% technically efficient as against 53% efficiency in Syria. The study conducted by Srinivas et al. (2012) identified technology as one key determinant of technical efficiency whilst Prochazka et al. (2017) revealed that, farm size is a major determinant of increased productivity among potato farmers in Syria. However, the study identified household size, occupation, farm Size, experience, seed type and membership as major parameters that determine technical inefficiency among potato farmers in Syria.

Prochazka et al. (2017) conducted an investigation on factors affecting potato production in Syria. The study adopted a non-parametric DEA in analyzing the technical efficiency of farmers. Two–limit Tobit regression model was used for the analysis. The results of the study indicate that, technical efficiency amounted to about 53% and most of the farms are operating below technical efficiency level. The study revealed that, farm size is positively correlated with productivity. This suggests that, large farms have the highest net farm income per thousand square meters and are the most efficient technically compared to small and medium farm sizes. However, household size, occupation, farm Size, experience in farming, seed type and membership are socioeconomic factors that influence the level of technical inefficiency among potato farmers. The study recommended more investment in farm research and extension programmers to improve efficiency.

Ahmad et al. (2016) undertook a study on analyzing the efficiency of the performance of major Australian mining companies using bootstrap data envelopment analysis (DEA). The purpose of the study was to ascertain which companies climbed the efficiency ladder and which companies slipped back in efficiency over a period. The study revealed that, mining companies involved in metal processing or mining services have been more efficient than those involved in exploration and extraction activities. Furthermore, the variable returns to scale (VRS) adopted for the study revealed that, on average, the mining companies could improve their performance between a minimum of 17% in 2010 and a maximum of 34% in 2008, relative to the best practice performers. The results also indicate that, most mining companies became more efficient over time, with the top performers generally maintaining a ranking in the top third of companies in terms of efficiency throughout the period.

What the study conducted by Ahmad et al. (2016) sought to do is to ascertain which companies climbed the efficiency ladder and those that slipped back. What the study failed to achieve is to ascertained factors that may have accounted for the differences in technical efficiency among these companies. A similar study conducted by Oleg et al. (2006) on the determinants of technical efficiency of firms reveals that, industry effect, size of firms and location of headquarters is the major parameters that influence technical efficiency of firms. However, ownership structure, legal form, age of the firm and outsourcing activities negatively influences the efficiency of firms in Germany.

Oleg et al. (2006) carried out a study on what determines the technical efficiency of a firm using industry, location and size. The purpose of the study was to investigate the factors that explain the level of technical efficiency of a firm in Germany. A sample of 35,000 firms in 256 industries was obtained for the study. Data was obtained from the German Cost Structure Census over the years 1992-2004. The study estimated the technical efficiency of the firms and relates it to firm- and industry specific characteristics. The results of the study revealed that, one third of the explanatory power is due to industry effects. However, the size of firm accounts for another 25 percent and the headquarters location explains ten percent of the variation in efficiency. Most other firm characteristics such as ownership structure, legal form, age of the firm and outsourcing activities have an extremely small explanatory power.

Boubaker and Abner (2000) carried out a study on measurement and explanation of technical efficiency in Missouri Hog production. The objective of the study was to use stochastic production frontier and farm level data to measure and explain technical efficiency in Missouri hog production. Moreover, the study adopted a Cobb-Douglas production function. The study estimated the mean technical efficiency for farms which were sampled at 82 percent. The result of the study reveals that the mean technical efficiency is 82 percent. This indicates that, with regard to hog production, firms were 18 percent technically inefficient. The technical efficiency model proved the effects of technology and managerial competence on the level of productive efficiency. Also, the study discovered economics of scale in hog production, thus explaining the consolidation in the industry.

Abdul and Benjamin (2010) undertook an investigation into farm efficiency in Bangladesh. The primary objective of the study was to determine the level of efficiency among rice farmers in the High Barind region of Bangladesh. The study adopted the Stochastic Frontier Approach (SFA) and Data Envelopment Analysis (DEA) to measure the factors associated with technical, allocative and economic inefficiency of rice farmers in High Barind Region. The Translog stochastic frontier was used to compute the technical efficiency by modeling socioeconomic, infrastructure and environmental degradation factors in a single stage estimation technique using maximum likelihood method. Additionally, technical and scale efficiency was calculated using output- and input-oriented, constant returns to scale (CRS) and variable returns to scale (VRS) DEA frontiers. A Tobit model was used to evaluate factors associated with technical and scale inefficiency from both input-oriented and output-oriented CRS and VRS frontiers. Same factors were analyzed as in the Translog stochastic frontier. The results of Translog stochastic frontier indicate that on average, farm households were 79 percent technically efficient. However, the output-oriented DEA frontier results show that on average, technical efficiency was estimated between 79 and 86 per cent under CRS and VRS assumptions. Based on this, the average scale efficiency was 92 per cent. Moreover, the average values for technical efficiency measures and scale efficiency of the input-oriented CRS and VRS frontiers were 79, 85and 93 per cent respectively. The Translog stochastic frontier exhibits decreasing returns to scale, whereas the DEA frontier exhibits decreasing, constant and increasing returns to scale. Additionally, the Translog stochastic frontier and Tobit analysis for DEA frontier revealed that, irrigation infrastructure and environmental degradation were significant factors in determining technical inefficiency. The study revealed a considerable amount of inefficiency existed among farm households and to minimize the inefficiency, there is the need for improvement in technique, allocative and economic efficiency. The study recommended rural electrification program by the government as a key measure to convert diesel pumps into electricity-operated pumps for irrigation in rural areas and adopt policies which lead to reduced environmental degradation, thereby increasing rice production and the welfare of farm households.

Although the study conducted by Abdul and Benjamin (2010) adopted Translog stochastic frontier approach (TSFA) and Data Envelopment Analysis (DEA) to determine the level of technical efficiency among rice farmers in Bangladesh, the study should not have employed the SFA and DEA to estimate the technical efficiency levels. This is because whilst the SFA is able to separate the statistical noise from the error term, the DEA model lumps both the statistical noise and the error term together. In view of this, comparing efficiency levels may be misleading. Additionally, the DEA is not mathematically demanding as compared to SFA. The study could have adopted Cobb-Douglas stochastic frontier and Translog stochastic frontier and compared the efficiency levels among the rice producers in Bangladesh.

A similar study undertaken by Adam et al. (2003) employed Cobb-Douglas stochastic production frontier to estimate the technical efficiency of Chinese grain. The results of the study conducted by Abdul and Benjamine (2010) identified irrigation infrastructure and environmental degradation as the major parameters that contribute to inefficiencies whilst the study conducted by Adam et al. (2003) reveals that, human capital and farm-level specialization significantly contributed to technical efficiency.

Adam et al. (2003) carried out a study on the technical efficiency of Chinese Grain Production using a Cobb-Douglas stochastic production frontier approach. It was discovered that, the marginal products of labor and fertilizer are much smaller than that of land. Moreover, human capital and farm-level specialization have a positive effect on efficiency. However, land fragmentation was detrimental to efficiency, but older farmers were more efficient than younger farmers. They also examined the effects of size, mechanization and geographic location. The simulation results also show that significant output gains can be obtained by eliminating land fragmentation, improving rural education and promoting specialization and mechanization.

Abani et al. (2005) undertook a study on the analysis of technical efficiency in the coal mining sector in Illionois, USA. The paper employed the data envelopment analysis and stochastic frontier in the study. The study used the stochastic frontier to analyze the efficiency. The model is given as: $[(Y_i) = X_i\beta - u_i]$. Furthermore, the Cobb-Douglas form of the production function proposed by Aigner and Chu (1968) was also used in the study. Data was obtained from the Key Stone Coal Manual and some data generated based on discussions with the mine owners. The results of the study revealed that, irrespective of the amount of coal produced, a mine can operate technically efficiently if the production is maximized with optimal use of inputs with no quantitative increase.

The study conducted by Abani et al. (2005) sought to analyze the extent to which coal miners were technical efficient in Illionois, USA. This could have been done by adopting SFA or DEA. However, the paper employed both the Cobb-Douglas production frontier and DEA in analyzing technical efficiency of coal miners in the USA. What is not clear is whether the study seeks to compare the determinants of technical efficiency of SFA and DEA. Moreover, the study failed to clearly interrogate whether it is adopting allocative efficiency or technical efficiency and what informs the decision. Despite the study talks about allocative efficiency, the result of the study indicates otherwise. However, a similar study conducted by Tsolas (2001) employed the DEA model to measure the technical efficiency and occupational safety among the Greek lignite miners. The study could not have compared the level of technical efficiency of both the SFA and DEA because the SFA is more demanding mathematically. Also, the SFA is able to separate the statistical noise from the error term whilst the DEA model lumps both the statistical noise and the error term together.

Tsolas (2001) conducted a research on technical efficiency measurement and occupational safety level. The purpose of the study was to measure technical efficiency in Greek lignite mining taking into consideration input-output data and mine accidental data. The study adopted data envelopment analysis (DEA) model which takes into account conventional data (i.e., real output, labor and fixed capital) and the number of disabling injuries. The DEA was used to measure the technical efficiency of the firm. The results of the study revealed that, the Greek light mining firm is technically efficient. Despite the limitations, the study recommended that, more detailed and comprehensive data (e.g., waste volume processed, another 'negative' output imposed by geological factors, intermediary inputs, etc.) are needed and the assumption of constant returns to scale is relaxed, the results of newly formulated DEA models could be more reliable.

Budeba et al. (2014), conducted a research on determining the technical efficiency of surface coal mine supply chain through modeling. The study used the Data Envelopment Analysis (DEA) to evaluate the efficiency of a surface coal mine for export as:

$$EFFICIENCY = \frac{Weighted\ sum\ output}{Weighted\ sum\ of\ inputs}$$

Also, the paper used the DEA to model a multistage sampling used for data analysis. The paper identified a lot of challenges associated with coal mining such as: diminishing reserves of high-quality coal, remote location of new coal deposits, infrastructure problems, environmental legislation, and the effects of climate. The results of the study indicate that, the surface coal mine is technically efficient with a score of one (1). This study suggests that future research should be focused on creating models to predict the efficiency of new surface mines, taking into account both the discretionary and non-discretionary variables from the results of the efficiency score. This would help new mines to evaluate their operational variables before spending more capital, making them competitive in any given business environment.

Arindam (2004) conducted a survey on technical efficiency in agricultural production and access to credit using stochastic frontier approach. The purpose of the study was to examine the role of credit in ensuring efficiency in agricultural production in West Bengal, India. The study attempted to desegregate the analysis of two mutually exclusive groups: bank customers and non-bank customers. The analysis of the study was based on stochastic frontier. The results of the study revealed that, farming households having access to formal credit produced more efficiently by channeling credit in the utilization of agricultural inputs. Moreover, contractual arrangements and operated farm size were found to be significant determinants of observed variation of technical efficiency estimates in case of bank customers. The paper also revealed that, farmers who had access to credit facilities achieved higher efficiency by adopting improved levels. The study recommended that, credit facilities should be made available to farmers to enable them to produce more efficiently and effectively.

Awunyo-Victor et al. (2013) conducted a study on estimation of farm level technical efficiency of small-scale cowpea production. The objective of the study was to investigate the determinants of small-scale cowpea production in the Ejura/ Sekyedumase Municipality in the Ashanti Region, Ghana. Simple random sampling was used to sample 200 cowpea farmers in the district. The study employed Cobb-Douglas stochastic production frontier to estimate the production function of small-scale cowpea farmers. Data was analyzed using maximum likelihood techniques. The Cobb-Douglas stochastic frontier model was used for analyzing technical efficiency. The results of the study indicate that, small-scale cowpea farmers were not fully technically efficient as the mean efficiency score was 66%. Additionally, farm size, seed, pesticides and labour were the major input factors that influenced changes in cowpea output. The study also reveals that, membership of farmer based organizations, educational level and access to extension services significantly influenced their technical efficiency. However, household size and off-farm income contributed immensely to inefficiency. The study recommends that, policies that would encourage cowpea farmers to join farmer based organizations and provide them with easy access to extension services should be promoted.

Even though the study conducted by Awunyo-Victor et al. (2013) employed SFA, a similar study conducted by Babakholov et al. (2018) used the DEA to estimate the determinants of technical efficiency of wheat cultivation in Uzbekistan. The Cobb-Douglas stochastic production frontier was adopted because it is able to separate the inefficiencies from the statistical noise, but the study failed to compare the various production functions and draw the conclusion of the production function best employed by cowpea producers in Ashanti Region. Moreover, the results of the study conducted by Awunyo-Victor et al. (2013) reveals that, membership of farmer based organizations, educational level and access to extension services are the parameters that significantly influenced technical efficiency. Conversely, Babakholov et al. (2018) identified the age of farmers, farmers' education on agriculture, soil fertility, and the quality of seed as a major determinants of technical efficiency among wheat farmers in Uzbekistan.

Babakholov et al. (2018) carried out a survey on agricultural transition and technical Efficiency using an empirical analysis of wheat-cultivating Farms in Samarkand Region, Uzbekistan. The objective of the study was to determine the technical efficiency of wheat-cultivating farms in the Samarkand region. Data was analyzed in two steps. In the first instance, technical efficiency of wheat farms was estimated using data envelopment analyses (DEA) and determinants of inefficiencies were analyzed using the Tobit model in the second step. Data for this study were collected from 124 randomly sampled private farms engaged in wheat production in the

Samarkand region. The mean value of technical efficiency scores of wheat-growing farmers were found to be 0.79 and 0.82 under the constant return to scale (CRS) and variable return to scale (VRS) assumptions. Empirical results suggest that there is a considerable scope for increasing production through reallocation of existing resources can reduce their input costs by 21 and 18 percent while holding the same production levels. The age of farmers, farmers' education on agriculture, soil fertility, and the quality of seeds were found as the main determinants of technical efficiency in the study area.

2.7 Summary of the Literature Review

The review of relevant literature in the study presents a complete picture about how various authors used the parametric and non-parametric methods to estimate the technical efficiency of both agricultural sector and the extractive industry. Ahmed et al. (2016) stated that, in estimating technical efficiency of a firm, two methods can be employed, namely stochastic frontier analysis (SFA) and data envelopment analysis (DEA). One major advantage of stochastic frontier analysis is that, it takes into consideration statistical noise resulting from measurement errors compared to the DEA (Ahmed et al., 2016). Some of the authors who used the SFA in their study include Boubascar et al. (2014), Srinivas et al. (2012), and Rahman et al. (2012).

From the empirical literature, most of the authors who used the stochastic frontier analysis also adopted and adapted Cobb-Douglas production function. In view of this, Bezat (2009) reiterated that, to use SFA, we choose one production function. This includes Cobb-Douglas production function, Constant Elasticity of Substitution (CES), Translog production function, Generalized Leontief model, normalized quadratic and its variants. Most of the studies adopted Cobb-Douglas production function because it shows better estimates in terms of statistical significance. Moreover, it assumes that technology is constant (Banaeian and Zangensh, 2011).

Some of the explanatory variables identified in estimating technical efficiency among salt producers in the empirical literature include dimension of the basin, credit accessibility, education, years in salt mining and household size. Additionally, most of the models used in estimated technical efficiency adopted a model postulated by Battese and Coelli (1995) and Coelli et al. (1998). Although much work has been done on technical efficiency in Ghana, most of them are in agricultural production (Edward et al., 2008; Amaechi et al., 2014 and Rahman et al., 2012). However, the few studies conducted on salt mining only made references to other countries such as Guinea (Boubacar et al., 2014). Based on this, there remains a gap in literature on the technical efficiency of small scale salt production in the country. It is against this backdrop that the study seeks to estimate the level of technical efficiency among small-scale salt producers in Elmina.

CHAPTER THREE

METHODOLOGY

3.1 Introduction

This section discusses the procedures employed in undertaking the study. It gives a detailed description of the study design, the study area and information on the respondents based on the target population and sampling techniques adopted in the study. Additionally, it provides an outline of the research design and instruments for data collection. The methods adopted by the administration of the research instrument, data collection procedure and data, analyzes and the methods of estimation used are justified in this section of the work.

3.2 Theoretical Framework

Production frontier can be estimated using parametric or non-parametric approach. The parametric approach uses production function whilst the non-parametric approach deals in linear programming which requires the DEA method (Justyna, 2017). The choice between parametric and non-parametric approach depends on the underlying reasons for estimating productive efficiency (Padilla-Fernandez and Nuthall, 2009).

According to Ahmed et al. (2016), the stochastic frontier approach (SFA) takes into consideration statistical noise resulting from measurement errors or random noise as compared to data envelopment analysis (DEA). The literature reveals that the stochastic frontier approach (SFA) has been used in a study conducted by Rahman et al. (2012) and Constantin and Martin (2009) based on its comparative advantage. The study adopted a stochastic frontier approach (SFA) due to its corrective ability to account for random error. According to Boubakar and Abner (2000), the stochastic frontier model is specified as:

$$Y_i = F(x_i\,;\,\beta)\exp(v_i - u_i) \text{ ....(1)}$$

Where Y_i is the output of the firm i; x_i is (n+1) row vector where the first element "1" represents the intercept and the remaining elements represent quantities of inputs employed to produce Y; β is an (n+1) column vector of technology parameters to be estimated. Moreover, v_i is the random error term and u_i is the one side representing technical efficiency of salt producers.

To determine which production function is more suitable for the study, the Cobb-Douglas production function and Translog production function were adopted in the study. However, the technical efficiency of salt producers was estimated using Cobb-Douglas stochastic frontier below:

Technical Efficiency $(TE) = InY_i/InY_i^*$

$$TE = f(X_i;\,\beta)\,expV_i - U_i/f(X_i;\,\beta)\exp(V_i)$$

$$TE = \exp(U_i) \text{...(4)}$$

Where: Y_i =Observed output, Y_i^* =Frontier output and In =Natural logarithm

The variance ratio y, explains the total variation in output from the frontier level of output attributed to technical efficiencies which will be computed as; $y = \delta^2 u/\delta^2$.

3.3 Model Specification

1. Identification of the Production Function Employed by Small Scale Salt Miners in Elmina.

(a) Estimating stochastic frontier Cobb-Douglas production function

$$Y = AK^{\alpha}L^{\beta} \text{...(1)}$$

Log-linearizing of Cobb-Douglas production function and addition of stochastic error term

$$\log Y = logA + \alpha logK + \beta logL + v_i - u_i$$

log Y= log A + αlog K + βlog L + $v_i - u_i$.............................(2)

The study adopted and adapted Cobb-Douglas stochastic production frontier model involving three (3) variables as:

$$logY = logA + \beta_1 logK + \beta_2 logL + \beta_3 logSB + v_i - u_i$$

log Y= log A + $\beta_1$log K + $\beta_2$log L +β_3SB+$v_i - u_i$ ....(3)

Where:

Y= Output/revenue

A= Technology which is constant

K= Capital cost (Willington boot, shovel, head pan and brush)

L= Cost of labour

SB=Size of Basin

The v_i and u_i are the components of the error term (ε_i)

(a) Estimating stochastic frontier Translog production function

$$InYi = a_0 + \sum_{i=1}^{n} ai\ InXi + \ 1/2^n \sum_{i=1}^{n} \sum_{j=1} bij\ InXi\ InXj + Vi - Ui \ldots. (4)$$

Where;

In=The natural logarithm

i = ith respondent of salt producers

Yi =Output/revenue obtained from salt mining

X =Variable inputs

X_j =Fixed inputs

a_0, a_i, b_i and b_{ij} are parameters to be estimated

$V_i s$ = Assumed to be independently and identically distributed normal errors, having zero means and unknown variance (δ_v^2)

$U_i s$=Technical efficiency, which are assumed to be independent of V_is

For the purpose of this study, the stochastic Translog production function was adopted and adapted as follows:

$$InY_i = \beta_0 + \beta_1 InK_1 + \beta_2 InL_2 + \beta_3 InSB_3 + 1/2\beta_4 InK_1^2 + 1/2\beta_5 InL_2^2 + 1/2\beta_6 InSB_3^2 + \beta_7 InK_1 InL_2 + \beta_8 InK_1 InSB_3 + \beta_9 InL_2 InSB_3 + \varepsilon_i \ldots\ldots\ldots(5)$$

Where:

$In = Natural\ logarithm$

Y_i = Output/revenue

K_1 = Cost of capital (Willington boot, head pan, shovel, brush and land cost)

L_2 = Cost of labour (family labour and hired labour)

SB_3 = Size of basin (m^2)

δs = Coefficients to be estimated

ε_i = Error term $V_i - U_i$

2. Examination of Determinants of Technical Efficiency in Small-Scale Mining.

   The technical efficiency model is specified as follows:

$$TE_i = \delta_0 + \delta_1 NOP_{1i} + \delta_2 IPL_{2i} + \delta_3 EDU_{3i} + \delta_4 DTX_{4i} + \delta_5 LNX_{5i} + v \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

Where:

TE_i=Technical efficiency

δ_0=Constant term

δ_1= Coefficients

NOP_{1i}=Number of ponds

IPL_{2i}=Interest paid on loans

EDU_{3i}=Education

DTX_{4i}= Distance from the mining site to homestead

LNX_{5i}=Loans

v= Error term

Table 3.1: Definition of Variables and their Expected Signs

VARIABLES	UNIT	EXPECTED SIGN
SALT SPECIFIC VARIABLES ON TECHNICAL EFFICIENCY (TE_i)		
NUMBER OF PONDS (NOP_{1i})	COUNTING	-
INTEREST PAID ON LOANS (IPL_{2i})	GHS	-
EDUCATION (EDU_{3i})	YEARS	+
DISTANCE (DTX_{4i})	km	+/-
LOAN ACCESSIBILITY (LX_{5i})	GHS	+

3.4 The Definition of Variables and Expected Signs

Table 3.1 summarizes the variables used in the technical efficiency model and their expected signs. A description of the variables used in the efficiency model was as follows:

NOP_{1i}=Number of ponds is expected to have a negative sign because a decrease in the number of ponds increases the level of technical efficiency among small-scale salt producers in Elmina. Since the small-scale salt producers are under resourced, it would be prudent to reduce the number of walls so as to produce efficiently.

IPL_{2i}= Interest paid on loans is expected to have a negative sign because increasing interest rate on loans increases technical inefficiency among small-scale salt producer.

EDU_{3i}=Level of education (years of schooling) used as a proxy for decision-making for proper application of production inputs is expected to have a positive effect on technical efficiency. Hence, educated salt producers may be able to take up improved technologies faster and also understand the need for proper input combinations to increase technical efficiency among small scale salt miners.

DTX_{4i}= Distance from the mining site (km) to the homestead is expected to have either positive or negative influence on small-scale salt producers. This is because the further away a person is from the mining site the less efficient he becomes and the closer, the more efficient the person would be.

LNX_{5i}= Loan accessibility (GHS) is expected to have a positive effect on technical efficiency because increase in credit accessibilities to salt miners would lead to increased investment in capital-labour input combinations hence increasing technical efficiency.

3.5 Research Design

Research design is the arrangement of conditions for the collection and analysis of data in order to meet the research objectives through empirical evidence. According to Bryman (2004), research design is the master plan of specifying the methods and procedures for collecting and analyzing the needed information. The process of designing a research involves a lot of interrelated decisions (Minocha, 2008). The most important is the choice of approach employed in the study. This is because it determines how the information will be obtained. According to Blumberg and Schindler (2008), tactical research decisions are made once the research approach has been chosen. In view of this, the study focused on specific measurement or relevant questions to be asked, the structure and length of the interview guide and the procedure for choosing a sample.

The research design adopted by the study is census survey. According to Brynman (2004), census survey is defined as the statistical method of enumeration where all the units or members of the population are studied. The study employed census survey because the population under study is small. In all, 96 small scale salt producers which constitute the total population of small scale salt producers in Elmina were used for the study. These small scale salt producers were classified into four (4) zones. Notably, zone one (1) consists of Bronyibima, zone two (2), Tetegu, zone three (3), Bantama and zone four (4), Kuntu.

3.6 Data Collection

3.6.1 Types of Data Collected

Data collection plays a very essential role in gathering the required information about respondents for statistical analyzes. Data is defined as the raw material for information (Zins, 2007). Hence data is a set of values of qualitative or quantitative variables. Before one can present and interpret information, there has to be a process of gathering and sorting data. With the help of data, the objectives of the study were achieved. In order to undertake a detailed study on the technical efficiency of small scale salt producers in Elmina, the study employed both primary and secondary data collection methods.

Data is classified into two, namely; primary data and secondary data (Douglas, 2007). As the name suggests, primary data are data originated for the first time by the researcher through direct efforts and experience, specifically for the purpose of addressing his or her research problem. Joop and Hennie (2005) defined primary data, as data that are collected for the specific research problem at hand, using procedures that fit the research problem best. In view of this, the study adopted both the primary data and the secondary data to obtain in-depth information on small scale salt producers in Elmina.

The primary data sources include: surveys, observations, experiments, questionnaire and personal interview. Whilst the secondary data implies second-hand information which has been already collected and recorded by any person other than the user for a purpose, not relating to the current research problem. In view of this, secondary data are data which have already been collected by someone, may be sorted, tabulated and have undergone a statistical treatment (Muhammad, 2014). Secondary data sources include censuses, government publications, reports, books, journal articles and websites.

3.6.2 Data Collection Instruments

Data collection instruments refer to devices used to collect data such as questionnaires, tests, structured interview schedules and checklists (Polit and Hungler, 1999). Data collection instrument used in the study is the interview. The interview guide was adopted because the salt miners are uneducated. The interview guide was translated into the local language (Twi) to respondents and their responses written down. Furthermore, the study took into consideration the validity of the data collected. Instrument's validity can be regarded as the extent to which the instrument actually reflects the abstract construct being examined (Burns and Grove, 2001). Both the internal and external validity were improved in the study considering the fact that explanations were provided to the participants and by not pressurizing them into giving any responses. In view of this, respondents were requested to be as honest as possible.

On data collection, two (2) research assistants were employed to assist in collecting cross sectional data. To ensure validity and reliability of data collected, the research assistants were trained on how to conduct the interview. The study adopted interview guide in collecting cross sectional data. The interview questions were translated in the local language for the respondents and their response indicated. After data collection, data cleansing was carried out to ensure that the data obtained is correct. This was achieved by identifying incomplete, incorrect, inaccurate or irrelevant part of the data and then modifying or completing them. Data entry was done using SPSS and data was presented using statistical tables and diagrams.

3.6.3 Data Analysis

Data analyses play an integral role when it comes to undertaking research study. According to Saunders et al. (2009), data analyses have to do with gathering, summing, and collating data with the results reflecting important aspects relating to the problem under study. In view of this, after a successful data collection exercise, the obtained data was verified and edited for completeness and consistency. The data collected was analyzed using descriptive statistics to provide simple summaries about the observations that had been made. Data was entered in SPSS first, and then exported to STATA (Version 14). STATA performs most general statistical analyses (regression, logistic regression, survival analysis, analysis of variance, factor analysis and some multivariate analysis). According to Mugenda and Mugenda (1999), descriptive statistics enable a meaningful description of a distribution of scores or measurements using a few indices or statistics. In view of this, the study employed statistical analysis involving tables, charts and statistical diagrams. However, on data estimation, the study used STATA (Version 14) to estimate the Cobb-Douglas production function and Translog production function. This was followed by estimating the Cobb-Douglas stochastic frontier and Translog stochastic frontier using normal/half normal model. However, the level of technical efficiency among small scale salt producers in Elmina was estimated using the two-way estimation technique.

3.7 Total Population

Total population sampling is a purposive sampling technique (non-probability sampling) where the whole population of interest is studied. According to Gay (1987), total population is the totality of all subjects that conform to a set of specifications, comprising the entire group of persons that is of interest to the researcher and to whom the research results can be generalized. Based on this, total population sampling becomes relevant when the respondent has good knowledge of what is wanted. In practice, total population sampling is done when the target population is small and set apart by unusual and well defined characteristics. From the study, total population sampling was adopted to sample small scale salt producers in Elmina due to the small nature of the population size. The study adopted total population sampling, which consists of 96 small scale salt producers in Elmina. The small scale salt miners were classified into four (4) zones, namely; zone one (1) which consists of Bronyibima with 17 members, zone two (2) -Tetegu with 14 members, zone three (3) -Bantama with 27 members and zone four (4) -Kuntu with 38 salt miners.

3.8 Ethical Consideration

Ethical consideration is essential in every research. According to Nomazulu (2018), the researcher is ethically responsible to seek consent, ensure confidentiality and anonymity of the subjects who participate in the study. With this in mind, introductory letter was obtained from the University prior to data collection. Moreover, ethical guidelines for informed consent, confidentiality and anonymity were adhered to. The participants in the study were informed of the purpose of the study before inviting them to participate in the research. The participants were assured of strict confidentiality and anonymity of the information provided.

3.9 Pilot Study

A pilot study was conducted with twenty (20) respondents engaged in salt mining in Apam. This was to ensure validity and reliability of the instrument used in data collection and to find out whether it is suitable for the study. A pilot study is defined as data collected for a small-scale exploratory research project that uses sampling, but does not apply rigorous standards (Zikmund, 2003). This is confirmed by Cooper and Schindler (1998) who posited that the purpose of a pilot study is to detect the weaknesses in the design and instrumentation of a research instrument and also to provide proxy data for sections of a probability sample. In order to ensure suitability of the research instruments, a pilot study was conducted prior to the survey.

CHAPTER FOUR

DATA ANALYSIS AND DISCUSSIONS

4.1 Introduction

This chapter focuses on data analysis and discussions of the results to address the specific objectives of the study. The chapter begins with a detailed descriptive statistics of the variables used in the stochastic frontier and the technical efficiency model. The Ordinary Least Square (OLS) approach was used in the linear estimation of Cobb-Douglas production function and Translog production to determine which production function is suitable and most appropriate in estimating technical efficiency among small scale salt producers in Elmina. Estimation of parameters in the stochastic frontier functions was obtained using normal/half-normal distribution. This is followed by estimating the parameters of technical efficiency using Cobb-Douglas stochastic frontier production function.

4.2 Socioeconomic Characteristics of the Respondents

This section presents the key parameters of socio-economic characteristics of small scale salt producers in Elmina. The specific parameters include: Age distribution, sex distribution, level of education and marital status of respondents.

Table 4.1: Age Distribution of Salt Producers in Elmina

AGE GROUPS (YEARS)	FREQUENCY	PERCENTAGE (%)
25-30	5	5.21
31-35	3	3.13
36-40	15	15.63
41-45	14	14.58
46-50	11	11.46
51-55	15	15.63
56-60	7	7.29
61+	26	27.08
TOTAL	**96**	**100.00**

Source: Field survey (2019).

Table 4.1 above represents the age distributions of salt producers in the study area. The results of the study indicate that, 3.13% of the salt producers were aged between 31 and 35 years. This age group recorded the minimum population of three (3) miners out of the total population of 96 salt producers in Elmina.

The age group between 25 to 30 years and 56 to 60 years represents the second and third lowest population of 5.21% and 7.29% respectively. The highest percentage of 27.08%, which represents 61 years and above group indicate that, much older salt producers are fully engaged in salt mining in Elmina. The second highest age group is between 51 to 55 years and 36 to 40 years representing 15.63%. The results point out that the age group 51-55 years, 56-60 years and 61 years and above constitute about 50% of the entire salt producers whilst the youthful population constitutes about 8.33%. This suggests that, 50% of the salt producers are from 51 years and above and represents an ageing population. The reason for this higher number may be attributed to the unattractive nature of salt mining to the youth of the area.

The majority of the salt producers interviewed argued that despite the salt mining is not lucrative, they have no alternative. Also, the result indicates that the economically active population constitutes about 43.56%. This points out that, most of the youth are not engaged in salt mining probably because it is capital intensive and less lucrative. Although age of respondents was not used in estimating technical efficiency among salt producers, analyzing the effects of age is necessary based on the fact that the age of salt producers largely affects their level of efficiency.

Table 4.2: Sex Distribution of Salt Producers in Elmina

SEX	FREQUENCY	PERCENTAGE (%)
FEMALE	18	18.75
MALE	78	81.25
TOTAL	**96**	**100.00**

Source: Field survey (2019)

Table 4.2 above shows the sex distribution of salt producers in Elmina. From the study, the total number of salt producers in Elmina is ninety-six (96). Out of this, males constitute seventy-eight (78) representing 81.25% of the total salt producers in Elmina. The remaining eighteen (18) representing 18.75% of salt producers represents female population. The insight this provides is that salt mining is a male oriented activity because of the physical strength required.

Table 4.3: Educational Level of Salt Producers in Elmina

CATEGORY	FREQUENCY	PERCENTAGE (%)
NONE	27	28.13
BASIC	33	34.38
SECONDARY	24	25.00
TERTIARY	12	12.50
TOTAL	**96**	**100.00**

Source: Field survey (2019)

Table 4.3 above shows the educational level of salt producers in Elmina. The study indicates that out of the total population of salt miners in Elmina, twenty-seven (27) of them representing 28.13% had no formal education. However, thirty-three (33) respondents representing 34.38% had basic education up to the Junior High School (JHS) level. This indicates that about 62.51% of salt producers in Elmina had only formal education up to Junior High School (JHS). Furthermore, the study reveals that 24 respondents representing 25% of the small scale miners had Senior High School (SHS) education whilst 12.5%, representing twelve (12) salt producers attained tertiary level of education. This signifies that, only 37.5% of the salt producers obtained higher education whilst more than 62% had not gone beyond the basic educational level. Since education is used as a proxy for decision making for optimum application of production inputs, the inference is that most of the small-scale salt miners may not be able to engage in optimum input combinations to increase the level of technical efficiency because of the high illiteracy rate.

Table 4.4: Marital Status of Salt Producers in Elmina

CATEGORY	**FREQUENCY**	**PERCENTAGE (%)**
SINGLE	10	10.42
MARRIED	52	54.17
SEPARATED	10	10.42
WIDOW/WIDOWER	11	11.46
DIVORCE	13	13.54
TOTAL	**96**	**100.00**

Source: Field survey (2019)

Table 4.4 above represents the marital status of salt producers in Elmina. Out of ninety-six (96) salt producers in Elmina, fifty-two (52) respondents representing 54.17% are married. This indicates that more than fifty (50%) of the salt producers are married. On the other hand, 10.42%, representing (10) respondents are either single or separated. The widows/widowers constitute about 11.46%. From the study, divorce cases constitute the second highest representing 13.54%. Despite the study failed to explore the extent to which marital status influences salt production, this parameter is necessary to enable us have a fair idea about the marital status of salt miners in Elmina.

Table 4.5: Age and Household Size of Salt Producers in Elmina

		HOUSEHOLD SIZE				TOTAL
		1-2	3-4	5-6	7-8	
AGE (YEARS)	25-30	0	5	0	0	5
	31-35	1	2	0	0	3
	36-40	1	12	2	0	15
	41-45	1	5	6	0	12
	46-50	0	4	5	2	11
	51-55	0	3	9	3	15
	56-60	0	1	3	5	9
	61+	0	1	9	16	26
	TOTAL	**3**	**35**	**32**	**26**	**96**

Source: Field survey (2019)

Table 4.5 above shows the cross tabulation of age group and household size of salt producers in Elmina. The table indicates that out of ninety-six (96) salt producers in Elmina, thirty-five (35) respondents have the highest household size of 3 to 4 dependency group. This represents about 36.5% of the total salt miners in the study area. This indicates that, thirty-five (35) salt producers have family size ranging between 3 and 4 dependents. This constitutes the highest family size or a dependency group among salt producers in Elmina. Conversely, three (3) salt producers representing 3.1% have a minimum dependency population ranging between 1 and 2. The results of the study reveal that, twenty-six (26) respondents which constitute the third (3^{rd}) lowest number of salt producers in Elmina have the highest household size between 7 and 8 respectively. From the study, salt producers who are 61 years and above have the highest household size between 7 and 8. This constitutes about27.1% of the total population of small scale salt miners in Elmina. However, the salt producers age between 25 and 35 years altogether have the least household size of eight (8) representing 8.3%. This indicates that among salt producers in Elmina, the aged have the highest dependency ratio compared to the youth age. Though the study does not explore the extent to which household size influences technical efficiency, it contributions significantly to labour.

Table 4.6: Loan Information of Salt Producers in 2018

CREDIT SOURCE	**LOAN AMOUNT (GHS)**				**TOTAL**
	0-5000	5001-10000	10001-15000	15001-20000	
FAMILY	10	0	0	0	**10**
FRIENDS	7	4	2	0	**13**
BANKS	25	10	8	5	**48**
OTHERS	8	4	1	0	**13**
TOTAL	**50**	**18**	**11**	**5**	**84**

Source: Field survey (2019)

Table 4.6 above shows the cross tabulation of sources of credit and credit (loan) received by small scale salt producers in 2018. The study indicates that, out of ninety-six (96) salt producers in Elmina, 12.5%, representing eight (12) respondents did not receive any credit facilities in 2018. The salt producers who did not take any loan cited high interest rate charged by financial institutions as a major constraint in accessing loan. On the other hand, eighty-four (84) respondents which constitute 87.5% received financial assistance from various sources in 2018 to mine salt. This indicates that, credit accessibility is an essential factor that contributes positively to expansion in salt mining. Out of the 84 respondents who received credit facilities, 57.1% of them representing 48 salt miners accessed loan from banks. The study indicates that among the four main sources of accessing credit facilities, banks constitute the highest with 57.1%. This suggests that, more than 50% of the salt producers in Elmina access credit facilities from financial institutions. The study also reveals that, 13 respondents representing about 15.5% obtained loans from friends and other sources respectively. This shows that apart from financial institutions, friends and other sources are the second most important source of obtaining credit facilities by salt producers in Elmina. Apart from banks, the other sources of obtaining loan constitute about 42.9% which is significant. The implication is that, salt producers are beginning to explore other sources of obtaining credit facilities probably because of high interest rate charged by banks. On loan amount, the study indicates that, about 60% of the respondents who received credit in 2018 took a loan below GHS5, 000.00. However, only 6% of small scale salt producers received credit facilities above GHS15, 000.00. Though the study did not compare the extent to which various sources of credit accessibility influences output, it is a key parameter in determining technical efficiency of salt miners in Elmina.

4.3 Summary Statistics of Study Variables for Salt Production in Elmina

Table 4.7 below provides descriptive statistics of variables used in the stochastic production frontier and the technical efficiency model. The table shows that the average value of output or revenue (Y_i) generated from salt mining in 2018 is GHS12, 026.147 (343.6042*GHS35.00) with a minimum output of thirty (30) bags of salt and a maximum output of 2000 bags of salt. This indicates that, whilst some producers barely make GHS450.00 (30*GHS35.00) others recorded GHS70, 000.00 (2000*GHS35.00) from selling salt in 2018. The inputs represent the capital cost (KA_1), labour cost (LA_2) and size of the basin (SB_3). The capital cost includes; Willington boot cost, head pan cost, shovel cost, working gear cost, brush cost and cost of land acquisition. However, the labour cost (L_2) consists of family labour and hired labour categorized into male and female. Labour has a mean value of 2372.438

with a minimum cost of GHS310.00 and maximum cost of GHS6,000.00 incurred in engaging labour at different stages of production. The capital cost average 2032.813 with a minimum cost of GHS383.00 and maximum cost of GHS3, 460.00. The capital cost and labour cost are valued per unit basis.

The size of the basin (SB_3) used as a proxy for land size has a mean value of 3.332083m and ranges between one (1) and six (6). This signifies that, the minimum dimension of the basin is 40m*100m whilst the maximum dimension is 100m*100m. The size of the basin is measured in meters square (m^2). Specific variables of salt production on technical efficiency include number of ponds (NOP_{1i}) average about 3.34375 basins with a minimum of one (1) pond and a maximum of six (6) ponds. The number of ponds is expected to be inversely correlated with efficiency.

Interest paid on loans (IPL_{2i}) has a mean value of 1.895833 and a standard deviation of 1.156029 with a minimum value of zero (0) and maximum value of three (4). This indicates that, some of the small-scale salt producers did not take any loan whilst other small-scale salt miners took a loan and paid interest of GHS10,000.00. The loan interest is expected to be inversely correlated with technical efficiency.

Level of education (EDU_{3i}) measured in terms of years of schooling is an important indicator for measuring the level of technical efficiency. It forms the basis for motivating producers to adopt more proactive ways of salt mining. The average level of education among salt producers is basic education (1.21875) and standard deviation of.9968701 with a minimum value of zero (0) and maximum value of three (3). This shows that, some of the salt producers have not obtained any formal education whilst some attended up to the tertiary level. The level of education is expected to be significant and positively correlated with technical efficiency.

The mean distance from homestead to the campsite (DTX_{4i}) of salt mining activity in Elmina is 1.8km (1.791667km) with a minimum distance of 1km and maximum of 4km.

Loan (LX_{5i}) average about GHS8941.667.00 ranges between zero (0) and GHS20, 000.00. This signifies that, the minimum amount of loan obtained by salt producers in 2018 is GHS 900 whilst the maximum loan amount is GHS20,000.00. Loan is essential, particularly in pond preparation, purchase of working tools and hiring labor to facilitate salt mining.

Table 4.7: Summary Statistics of the Study Variables for Salt Production in Elmina

VARIABLES	MEAN	ST. DEV	MIN	MAX
SPECIFIC VARIABLES ON SALT PRODUCTION				
OUTPUT/REVENUE (Y_i)	343.6042	333.4316	30	2000
KAPITAL (K_1)	2032.813	976.3394	383	3460
LABOUR (L_2)	2372.438	1284.392	310	6000
SIZE OF BASIN (SB_3)	3.332083	1.492929	1	6
SALT SPECIFIC VARIABLES ON TECHNICAL EFFICIENCY				
NUMBER OF PONDS (NP_{1i})	3.34375	1.212463	1	6
INTEREST PAID ON LOAN (IPL_{2i})	1.895833	1.156029	0	4
EDUCATION (EDU_{3i})	1.21875	.9968701	0	3
DISTANCE (DTX_{4i})	1.791667	.843006	1	4
LOAN ACCESSIBILITY (LNX_{5i})	8941.667	7614.324	900	20000

Source: Field Survey (2019)

4.4 The Production Function Employed by Small Scale Miners

The first objective of the study is to identify which production function is employed by small scale miners. In view of this, the study adopted Cobb-Douglas production function and Translog production function purposely because Cobb-Douglas production function can handle multiple inputs in its generalized form (Bhanumurphy, 2002). Additionally, the technology employed by the miners is traditional method which is constant. According to Lau (1986), the technology is well represented by a Cobb-Douglas production function compared to other production functions. Furthermore, the Translog production function is an extension of Cobb-Douglas production used in most of the literature. STATA (Version 14) was used to run the linear regression for Cobb-Douglas production function and Translog production function.

Table 4.8: Regression for Cobb-Douglas Production Function

Output (Y)	**Coefficient**	**Std. Error**	**t**	**P>| t |**
K	.0443829	.0302118	1.47	0.145
L	.154425	.0228661	6.75	0.000
SB	-1.759135	17.6385	-0.10	0.921

Source: Computation using STATA

Legend: K=Capital, L=Labour and SB=Size of basin

Table 4.8 above represents the linear regression for Cobb-Douglas production function using OLS. The result indicates that, with Cobb-Douglas production function, labour (L) is statistically significant at 1% and positively correlated with output. This signifies that, 1% increase in labor would lead to 15% increase in output. However, capital (K) and size of the basin (SB) are insignificant, but capital has a positive outlook. This suggests that, increase in capital investment could enhance productivity.

Table 4.9: Regression for Translog Production Function

Output (Y)	Coefficient	Std. Error	t	P>| t |
K	-.0768731	.1129475	-0.68	0.498
L	.1664601	.0922078	1.81	0.075
SB	-6.427918	96.47258	-0.07	0.947
KAP	.0000504	.0000565	0.89	0.374
LAB	.0000531	.0000282	1.89	0.063
BAX	-10.21868	23.21253	-0.44	0.661
KL	-.0000506	.0000324	-1.56	0.122
KSB	.0505435	.0216638	2.33	0.022
LSB	-.025074	.0175845	-1.43	0.158

Source: Computation using STATA

Legend:

K=Capital, L=Labour, SB=Size of basin

KL=Capital-Labour input combinations

KSB=Capital-Size of basin input combinations

LSB=Labour-Size of basin input combinations

Table 4.9 above shows the linear regression of Translog production functions using OLS. The result of the study reveals that, labour (L) is significant at 10% and positively correlated with output. Capital (K) and size of the basin (SB) are insignificant and have a negative relationship with the output. Among the input combinations, only the capital-size of the basin (KSB) input combination has a positive coefficient and is significant at 10% level. However, capital-labor (KL) and labor-size of the basin (LSB) are insignificant and inversely correlated with output.

Table 4.10: Akaike's Information Criterion and Bayesian Information Criterion for Cobb-Douglas Production Function

Model	Obs	11 (null)	11 (model)	df	AIC	BIC
.	96	-693.4215	-665.4815	4	1338.963	1349.22

Table 4.11: Akaike's Information Criterion and Bayesian Information Criterion for Translog Production Function

Model	Obs	11 (null)	11 (model)	df	AIC	BIC
.	96	-693.4215	-656.7801	10	1333.56	1359.204

Table 4.10 and 4.11 above compares the Akaike's information criterion (AIC) and the Bayesian information criterion (BIC) for linear regression of Cobb-Douglas production function and Translog production function using OLS. The AIC is adopted to identify the best fitting model for analyzing the technical efficiency of salt producers. According to Yoshio and Hamparsum (1987), the model with a minimum value of AIC is chosen as the best fitting model among several competing models.

The results of the study in Table 4.10 and 4.11 above indicate that the AIC of Cobb-Douglas production function is 1338.963 and AIC of Translog production function is AIC of 1333.56. Based on this, the Translog production function has the minimum AIC of 1333.56 (1338.963>1333.56). This reveals that the Translog production function is the best fitting model employed by small scale salt producers in Elmina. Despite the AIC is used to determine the best fitting model, one cannot conclude that it is the true model. Rather, it means that the model is more suitable among competing models because it gives the closest approximation to the true model or reality (Yoshio and Hamparsum, 1987).

According to Yoshio and Hamparsum (1987), the true model is the actual model employed by producers. In view of this, the true model is obtained by comparing the Bayesian information criterion (BIC) of both Cobb-Douglas production function and Translog production function and choosing the model with the minimum BIC. The results of the BIC of both the Cobb-Douglas production function and the translog production function shows that the Cobb-Douglas production function has a minimum BIC of 1349.22 compared (1349.22<1359.204). Based on this, the true model employed by the small scale salt miners in Elmina is Cobb-Douglas production function. In view of this, Cobb-Douglas fits the production of salt better than the Translog. Therefore, the Cobb-Douglas will better tell about salt production in Elmina. Hence, Cobb-Douglas is used in the estimation of technical efficiency (TE) of salt production among small scale salt miners using the stochastic frontier.

4.5 Parameter Estimates of Stochastic Production Frontier

The stochastic frontier is used to affirm which production function is suitable for estimating technical efficiency of salt producers in the study area. In frontier studies, the estimated parameters indicate best practice performance that is technically efficient in the application of the variable inputs.

Table 4.12: Parameter Estimates of Cobb-Douglas Stochastic Production Frontier

In_output (Y)		COEFF.	STD. ERR.	Z	P>|Z|
Intercept	β_0	-3.720437	.9624075	-3.87	0.000
In_K	β_1	.4123508	.1363939	3.02	0.003
In_L	β_2	.8754688	.1167969	7.50	0.000
In_SB	β_3	-.1416169	.1200236	-1.18	0.238

95% Confidence Interval

Prob>chi2=0.0000

Wald chi2 (3)=117.09

Source: Computation using STATA

Legend:

K=Capital, L=Labour and SB=Size of basin

Table 4.12 above specifies the parameter estimates of Cobb-Douglas stochastic frontier using normal/half-normal distribution. The model entirely is statistically significant at 1% because Chi-square is significant at the 1% level (Prob>chi2=0.0000). The results of the parameter estimates indicate that, capital is significant at the 5% level and positively correlated with output. This indicates that, a 1% increase in capital (K) investment would lead to about 41% increase in salt production. The implication of this finding suggests that, capital (K) is a key parameter in determining salt output. Hence, increasing capital investment by adopting modern mining method could enhance the level of salt production among small scale miners in the study area. The result of the study confirms an earlier study conducted by Akanbi et al. (2011) who identified capital investment as an important contributor to improving the level of output.

The study also reveals that, labour (L) is statistically significant at 1% and has a positive relationship with the output. This suggests that, a unit increase in labor (L) would lead to about a 88 % increase in salt productivity. In view of this, increasing labour (L) investment would lead to increase output. This implies that, investment in labour (L) remains an important contributor to salt output in Elmina. This finding confirmed the results of an earlier study conducted by Boubascar et al. (2014) on stochastic frontier approach for measuring technical efficiency of small-scale salt production in Guinea. The study indicates that, investment in labour (L) could bring about a significant improvement in salt production. However, the coefficient of "size of basin" (SB) used as a proxy for land size is negative and insignificant. This shows that, pond dimension has nothing to do with output. Hence, the increasing pond dimension may not necessarily lead to increased productivity among small scale salt miners in Elmina.

The parameter estimates of Translog stochastic production frontier reveal that the overall model is significant at 1% (Prob>chi2=0.0000). However, among the input variables (capital, labor and size of the basin) employed in the study, only the size of the basin (SB) is significant at the 10% level but inversely correlated with output. Capital (K) and labour (L) are insignificant, but labor (L) has a positive outlook. On input combinations, capital-labor (KL) and capital-size of the basin (KSB) are significant at 10% and 10% respectively. However, the coefficient of capital-labour (KL) input combination is negative. Despite that the Translog stochastic production frontier model is statistically significant at 1% (Prob>chi2=0.0000), the Cobb-Douglas stochastic production frontier model is the most appropriate production function employed by small scale salt producers in Elmina. With Cobb-Douglas stochastic frontier model, capital and labour are statistically significant at 1% and positively correlated with output whilst with Translog stochastic production frontier, capital and labour are insignificant. Moreover, the whole model is significant at 1%

(Prob>chi2=0.0000). Hence, Cobb-Douglas stochastic frontier model is most appropriate and best fitting model in estimating technical inefficiency among small scale salt producers in Elmina.

4.6 Technical Efficiency Scores

Table 4.13 below presents the technical efficiency scores of individual salt miners in Elmina. The study reveals that, out of 96 small scale salt miners in Elmina, only one (1) producer representing 1.04% obtained efficiency score ranging between 91%-100% (0.9001-1.0000). This constitutes the highest efficiency score recorded among the salt producers. Also, the results of the study indicate that, two (2) producers constituting 2.08% obtained efficiency scores ranging between 81%-90% (0.8001-0.9000) the second highest. For the study, only 15 producers representing 15.63% were able to obtain efficiency scores above 50%. The inference is that, more that 82% of the salt miners were inefficient since their level of efficiency was below 50%. Hence, the mean technical efficiency of 37.8% (. 3779774) is clearly explained by the high level of inefficiency recorded by the individual salt miners.

Table 4.13 Technical Efficiency Scores

RANGE	FREQUENCY	PERCENTAGE (%)
0.1001 - 0.2000	7	7.29
0.2001 - 0.3000	26	27.08
0.3001 - 0.4000	31	32.29
0.4001 - 0.5000	17	17.71
0.5001 - 0.6000	6	6.25
0.6001 - 0.7000	6	6.25
0.7001 - 0.8000	0	0.00
0.8001 - 0.9000	2	2.08
0.9001 - 1.0000	1	1.04
TOTAL	**96**	**100.0**

Table 4.14 below presents the summary of technical efficiency scores among small scale salt producers in Elmina. The study indicates that, on average, the mean

technical efficiency among salt miners in the study area is 37.8% (.3779774). This suggests that, within the context of prudent and efficient salt production, salt mining in Elmina is technically inefficient. Thus, the level of technical inefficiency is 62.2% (1-. 3779774). The high level of inefficiency recorded could be attributed to the traditional salt mining practices coupled with a high illiteracy rate among small scale salt miners in Elmina. All the salt miners interviewed use the traditional inputs (head pan, shovel and brush) which are obsolete in mining. Moreover, the salt miners adopt the traditional system of salt mining where they trap the sea water from the lagoon during high tides. Hence, most of the salt brine is diluted in the process, leaving the salt miners with nothing. Additionally, the salt miners continue to depend heavily on concrete, cement to floor their walls instead of tarpaulin thereby recording high level of impurities in the process. The high level of inefficiency recorded is shown by the collapse of numerous small scale salt mining areas in most of the communities visited. Places such as Mankoadze, Manford and Akosua village in Winneba have collapsed.

Table 4.14 Summary of Technical Efficiency Scores

VARIABLE	OBS	MEAN	STD DEV.	MIN	MAX
te	96	.3779774	.1514162	.149245	.9549535

4.7 Examination of Determinants of Technical Efficiency

The second objective is to examine the determinants of technical efficiency among small scale salt producers in Elmina. Therefore, the study seeks to analyze the effects that salt producers' socio-economic variables have on their levels of technical efficiency. In view of this, STATA (Version 14) was used to estimate the technical efficiency among small scale salt miners in Elmina.

Table 4.15: Determinants of Technical Efficiency in Salt Production

TECHNICAL EFFICIENCY (TE)		COEF.	T	P>|T|
INTERCEPT	δ_0	.4558541	7.10	0.000
SALT SOCIO-ECONOMIC VARIABLES				
NUMBER OF PONDS (NOP)	δ_1	-.0473477	-4.09	0.000
INTEREST PAID ON LOANS (IPL)	δ_2	-.0373652	-2.66	0.009
EDUCATION (EDU)	δ_3	.072003	2.19	0.031
DISTANCE FROM CAMPSITE (DTX)	δ_4	.100536	1.88	0.064
LOAN ACCESSIBILITY (LNX)	δ_5	.0243732	1.50	0.137

Source: Computation using STATA

95% Confidence Interval R-square=0.3023

Prob>F=0.0000 Adj R-square=0.2636

Table 4.15 above shows the parameter estimates for technical efficiency using Cobb-Douglas stochastic production frontier for salt socio-economic factors. The pseudo R square is 0.3023 which indicates that the explanatory variables chosen for the model were able to explain about 30% of the variations in the technical efficiency model. However, the adjusted R-square is 0.2636 and the overall model is statistically significant at 1% (Prob>F=0.0000).

The results of the study indicate that, number of ponds (NOP) is statistically significant at 1% and has a negative relationship with technical efficiency with prior expectation met. This shows that, increase in the number of ponds increases the level of technical inefficiency among salt producers in the Elmina. The inference is that, since small-scale salt producers are under resourced, increasing the number of walls (ponds) would not necessarily translate into increased output. In view of this, most of the walls may not be properly attended to by the salt miners leading to inefficiency. Instead of increasing the number of walls, salt producers should rather concentrate on few walls this would enable them to produce efficiently with the limited resources at their disposal.

The study reveals that, loan interest (IPL) is significant at 5% and inversely correlated with technical efficiency with prior expectation met. This indicates that, a unit increase in a rate of interest on loans would lead to about 4% increase in inefficiency. The inference is that, small-scale salt producers who take loan to mine salt do so at a high interest rate leading to inefficiency. Instead of the small-scale salt miners using the credit facilities to undertake capital-labour investment, they end-up becoming indebted to various financial institutions because of high interest rate charge by these banks leading to inefficiency. The suggestion is that, government and other stakeholders (Minerals commission District Assemble and financial institutions) in the salt industry should provide interest free loans or loans at affordable interest rate to small-scale salt producers to undertake capital and labour investment to increase efficiency. The findings confirm an earlier study conducted by Arindam (2004) who came out that, farmers who have access to credit facilities at a low interest rate were able to adopt improved farming practices which enables them to be technically efficient.

The level of education (EDU) represents the number of years engaged in schooling by small scale salt producers. It serves as a proxy for decision-making on proper application of production inputs. Hence, higher level of education coupled with experience is expected to lead to better know-how on input combination. From the study, level of education is significant at 10% and positively correlated with technical efficiency with prior expectation met. The elasticity of .072003 indicates that, 1% increase in educational level would lead to 7% increase in technical efficiency. The implication of this finding suggests that, small-scale salt miners who had formal education are able to mine salt efficiently compared to those without formal education. The result confirm findings from an earlier study conducted by Awunyo-Victor et al. (2013) who came out that, level of education significantly contributes to technical efficiency among small-scale cowpea farmers in Ashanti Region, Ghana. The study also reveals that, gender is significant at 10% but negative.

The impact of distance (DTX) from homestead to the mining site is positive and significant at 10%. This reveals that, most of the small-scale salt miners stay closer to the mining site leading to efficiency.

4.9 Challenges Faced by Individual Salt Producers in Elmina

This section discussed the challenges faced by individual salt producers and measures put in place by the respondents to overcome the challenges. Table 4.17 below identifies the challenges faced by individual respondents in mining salt. The study indicates that, 34 respondents representing 35% of the total salt producers identified financial difficulty as one most important challenge facing salt producers. They lamented about high interest rates and inadequate capital. In view of this, 12.5% were unable to access any form of financial assistance in 2018. However, those who got access to credit had it at a high interest rate. This is followed by other challenges constituting about 23%. The other challenges identified by respondents include; sea waves, impurities and pollution of the environment by the surrounding communities making mining difficult. Marketing difficulty and low demand for salt constitute about 22% and 20% respectively.

Table 4.16: Challenges Faced by Individual Salt Producers in Elmina

INDIVIDUAL CHALLENGES	Frequency	Percentage (%)
LOW DEMAND	19	19.79
MARKETING DIFFICULTY	21	21.88
FINANCIAL DIFFICULTY	34	35.42
OTHERS	22	22.92
TOTAL	**96**	**100.00**

Source: Field survey, 2019

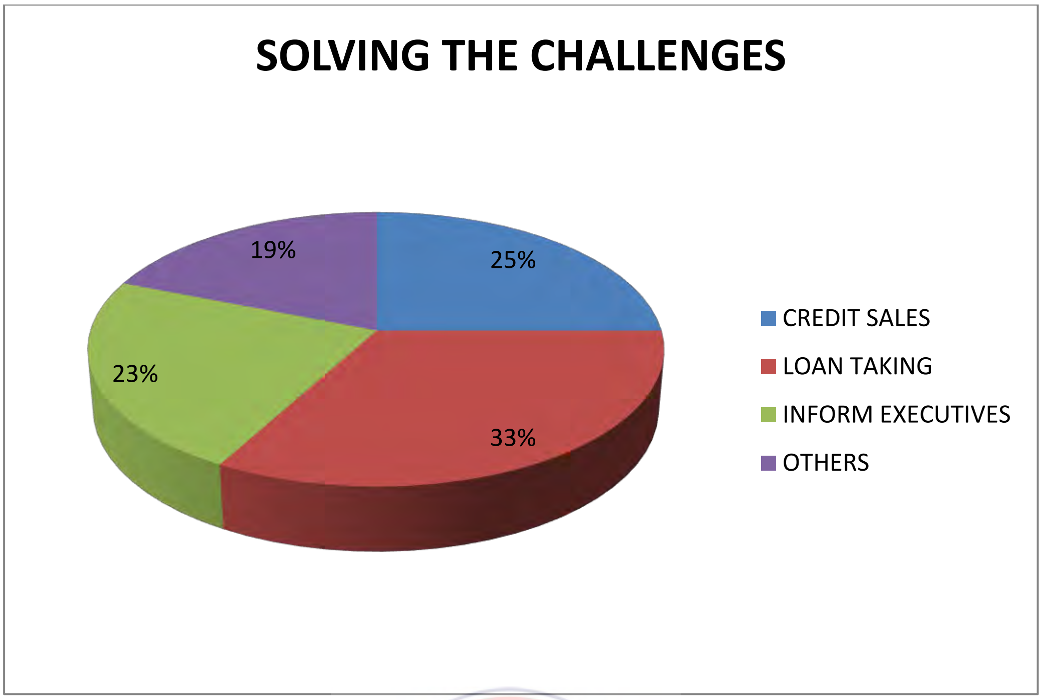
One respondent said: "The difficulty is the marketing. For the whole of this year, I have not sold anything because Chinese who are foreigners have flooded the market with cheap imported salt". How can we sell? (55 year old male respondent).

Another respondent said: "All my ponds are weak and I am unable to renovate them because of financial constraints". We are pleading with the government to come to our aid. (63 year old male respondent).

4.10 Measures put in Place to solve these Challenges

Figure 4.1 below discusses the various measures put in place by the individual salt producers to solve the challenges identified in table 4.15 above. The study reveals that, 25% of salt producers are engaged in credit sales due to low patronage of salt in Elmina and its environs. Additionally, 23% of the respondents argued that, they informed their executives about their difficulty in marketing the salt products. On the part of financial difficulty, 26% of the miners accessed credit to invest in salt mining. On the contrary, 19% of the respondents adopted other measures such as; reduction in salt prices and door-to-door marketing strategy to solve the problems confronting them.

Figure 4.1: Measures to Solve these Challenges



Another aggrieved respondent said: "For the past four (4) years now, I have been selling the salt on credit to customers of which some refused to pay". We are appealing to the government to do something about it. (47 years old female respondent).

4.11 Challenges Faced by Elmina Salt Producers Association (ESPA)

Table 4.18 below identifies the challenges faced by Elmina Salt Producers Association (ESPA). From the study, low salt patronage and market takeovers constitute about 38% and 28% of the major challenges facing the association. Some of the respondents argued that the low patronage of indigenous salt was due to salt importation by some Chinese into the country. The respondents maintained that, most of the Chinese involved in salt importation either subsidize prices or are engaged in credit sales. Furthermore, high interest on loan charge by financial institutions constitutes about 25% and is the third highest factor. However, unfavorable climatic condition is the last challenge representing 9.4%. Hence, salt mining is halted during raining season since small scale miners depend largely on solar evaporation of brine.

Table 4.17: Challenges Faced by Elmina Salt Producers Association (ESPA)

GENERAL CHALLENGES	FREQUENCY	(%)
LOW PATRONAGE	36	37.5
MARKET TAKE OVER BY FOREIGNERS	27	28.1
HIGH INTEREST ON LOAN	24	25.0
UNFAVOURABLE CLIMATE	9	9.38
TOTAL	**96**	**100.00**

Source: Field survey, 2019

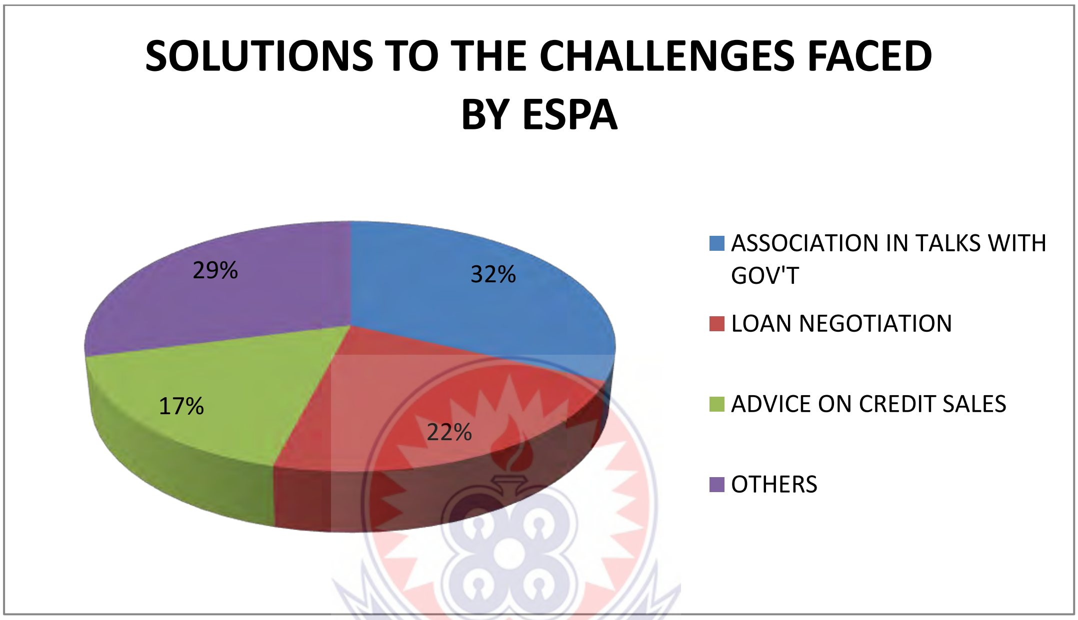
The secretary to ESPA said: For the past five (5) years now, the sea is not flowing into the lagoon as expected, so trapping the sea water for mining is becoming difficult. Moreover, high interest on a loan given to members is eroding the profit margin of miners. Most of the miners are now heavily indebted to the financial institutions in the area.

Another respondent said: The surrounding communities dispose their refuse into the lagoon and defecate on the walls of our ponds making mining in the areas difficult.

4.12 Measures taken by ESPA to solve these Challenges

Figure 4.2 below illustrates the measures taken by Elmina salt producers association (ESPA) to solve the challenges facing the association. From the study, 32% of the respondents indicated that the ESPA is in talks with the Ghana government over the importation of salt by some Chinese companies. Also, loan negotiation on behalf of members constitutes 22%. The association negotiates credit facilities for members from financial institutions at a low interest. With regard to credit sales, about 17% of the respondents stated that, the executives of ESPA advised them to engage in credit sales as a measure to curb low salt patronage. However, informal measures introduced by ESPA to solve these challenges constitute about 29%.

Figure 4.2: Measures Taken by ESPA to Solve the Challenges



4.13 Suggestions on Improving the Salt Industry

Table 4.19 below discusses the various suggestions offered by respondents on improving the salt industry. The results indicate that, out of 96 small scale salt miners, 44% of them suggested financial support from government as one most important factor necessary to improve the salt industry. Moreover, about 26% of the respondents argue that, government should provide market for them as a panacea to solving the low market situation facing the industry. 15% of the respondents came out that, the government should stop the importation of salt as a measure to boost local industry. Finally, 19% recommended other measures in addressing the challenges facing the salt industry.

Table 4.18: Suggestions on Improving the Salt Industry

SUGGESTIONS	FREQUENCY	PERCENT (%)
FINANCIAL SUPPORT	42	43.75
PROVISION OF MARKET	25	26.04
STOP IMPORTATION	14	14.58
OTHERS	15	15.63
TOTAL	**96**	**100.00**

Source: Field survey, 2019

The chairman of the ESPA said: 'The association suggested to the government to halt importation of salt of Chinese into the country and rather promote indigenous salt industries in the country. Moreover, the government should provide interest free loans to members to facilitate salt mining in the country'.

One respondent said: "I want government and other stakeholders to organize some form of workshop for us periodically on the best mining practices to enhance salt production in the country". (67 year old retired educationist).

CHAPTER FIVE

SUMMARY OF FINDINGS, CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

The chapter presents the summary of major findings, conclusions and recommendations for policy analysis and directions. The chapter concludes with the limitations and recommendations for future research.

5.2 Summary of Findings from the Study

The study focused on evaluating the level of technical efficiency among small scale salt producers in Elmina. The motivation for the study was based on two (2) objectives, namely; to estimate the level of technical efficiency of small-scale salt producers and to examine the determinants of technical efficiency among the small-scale salt producers in Elmina. Salt specific technical efficiencies involving some selected socio-economic variables were computed using cross-sectional data of small-scale salt miners in Elmina. A stochastic frontier approach was used to generate technical efficiency estimates using STATA (Version 14) software. The major findings of the study include:

1. Cobb-Douglas production function fits salt production in Elmina better than the Translog production function. In comparing the BIC of Cobb-Douglas production function and the Translog production function, the Cobb-Douglas production function is lower (1349.22<1359.204). This indicates that, Cobb-Douglas production function is the true model adopted by small scale salt miners in Elmina.

2. Technical efficiency is quite low among small scale producers in Elmina. The result of the mean technical efficiency shows that, small scale salt producers were 62.2% technically inefficient as compared to 37.8% technical efficiency.
3. Among the five (5) socio-economic parameters estimated in the technical efficiency model reveals that,
   i. The number of ponds is statistically significant at 1%, but negatively correlated with technical efficiency. The elasticity of -.0473477 indicates that, a unit increase in the number of ponds would lead to 5% increase in inefficiency among small-scale salt producers in Elmina. The suggestion is that, small-scale salt miners should be educated on the need to concentrate on a few walls (ponds) to enable them mine salt efficiently since they are under resourced.
   ii. Interest paid on loan has a coefficient to be negative but is significant at 5% level. This indicates that, high interest rate charged on loans by financial institutions leads to technical inefficiency among the small-scale salt producers in Elmina.
   iii. Level of education used as a proxy for decision-making on proper inputs application is significant at 10% and has a positive coefficient. The study indicates that, a unit increase in educational level would lead to 5% increase in efficiency. The inference is that, small-scale salt miners who had formal education are able to mine salt efficiently compared to those without formal education.
   iv. The coefficient of distance is positive but significant at 10%. The results of the study suggest that, small-scale salt producers stay closer to the mining site leading to technical efficiency.

4. The study also reveals that, 58% and 63% of the individual small-scale salt producers and Elmina salt producers association (ESPA) identified financial constraint, marketing difficulty and low patronage as major challenges deviling them. However, about 70% of the salt producers in Elmina agreed that, financial support from the government and provision of market are the panacea for solving the challenges facing the small scale salt miners in Elmina.

5.3 Conclusions

There is technical inefficiency among small-scale salt producers in Elmina. The small-scale salt miners are 62% technically inefficient and 38% efficient. The high level of inefficiency recorded is shown by the collapse of numerous walls (ponds) in most of the salt mining communities. The salt specific variables estimated in the technical efficiency model reveal that, number of ponds is statistically significant at 1% but inversely correlated with technical efficiency. However, interest on loan is significant at 5% but positively correlated with efficiency. The coefficients of education and distance are both positive but significant at 10% respectively. The results of the study reveal that, number of ponds and rate of interest on loans play an integral role in increasing the level of technical efficiency among small-scale salt producers in Elmina. In view of this, interest free loans or loans at affordable interest and reduction in number of ponds can help improve efficiency and profitability among small-scale salt producers in Elmina.

5.4 Recommendations for Policy and Directions

Based on the findings of this study, the following recommendations are made for policy action and direction to ensure that the salt industry increases their level of technical efficiency to maximize output.

1. It is recommended that, Government, Minerals Commission, and District Assembly should liaise with various financial institutions to provide interest free loans or loans at affordable interest rate for small-scale salt producers in Elmina. This will enable them to undertake more capital and labour investment necessary to increase efficiency.
2. Since the salt producers are under resourced, the study recommends that, the Minerals Commission and chiefs should educate the salt producers on the need to develop and mine few walls to improve efficiency.
3. It is recommended that, Elmina salt producers association (ESPA) should educate members on the need to adopt new marketing strategies such as door to door sales and credit sales to customers as a panacea for solving the difficulty in salt marketing.

5.5 Limitation of the Study

The study focused on evaluating the technical efficiency among salt producers in Elmina. What pertains in the study area may be different from other places due to certain peculiar practices or character of salt producers that relate to those areas. Therefore the recommendations of the study to increase technical efficiency and reduce inefficiency can only help to improve salt mining in Elmina and places where salt mining is individualistic and similar to that in Elmina.

5.5 Direction for Future Research

Future research into the same topic can be carried out, but in a different study area to find out the socioeconomic variables that influence technical efficiency among the salt producers in those areas.

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APPENDIX

APPENDIX I: INTERVIEW GUIDE FOR THE STUDY

I humbly request your attention on this instrument to solicit information on the topic "Technical Efficiency of Salt Production in Ghana: The Case of Small-Scale Salt Producers in Elmina". I am an M.Phil Economics student from the University of Education, Winneba. I will be grateful if you could answer the questions bearing in mind that your honest responses will go a long way to determine the overall success of this exercise. This work is strictly for academic purposes and so information given will be treated with absolute confidentiality. Thank you for your cooperation.

SECTION A: ADMINISTRATIVE SECTION

INTERVIEWER	DATE OF INTERVIEW	QUESTIONNAIRE CODE

Please tick the appropriate option of the answers provided for closed ended questionnaires below

SECTION B: BACKGROUND OF SALT PRODUCER

1. Number of years engaged in salt production…………………………………
2. Marital status? Single [0], Married [1], Separated [2], Widowed [3], Widower [4]
3. What was your age at last your birthday? ....
4. Educational status: None [0], Basic [1], Secondary [2], Tertiary [3]
5. Do you belong to any salt mining group or association? Yes [1], No [0]
6. If yes, please indicate the name of the association………………………

7. What is the importance of this group?

………………………………………………………………………………………

………………………………………………………………………………………

…………………………………………………………………...……………

………………………………………………………………………………………

SECTION C: THE PRODUCTION FUNCTION EMPLOYED BY SMALL SCALE SALT MINERS

Please indicate the quantity of salt and revenue margin for 2018

Number of ponds	Quantity of bags produced (in tons)	Quantity of bags sold (in tons)	Selling price per bag	Total sales GHC

Under normal circumstances, what quantity of salt would you have produced yearly using the same resources? ……………………………………….

Please indicate the capital asset used for salt production in 2018

Item	Quantity	Year of purchase	Unit price purchased (GHC)	Lifespan
Tarpaulin				
Willington Boot				
Head pan				
Shovel				
Working gear				
Any other				

What is the cost of land acquisition? ………………………………………..

Labor activity and requirement for 2018

Salt Mining Activity	Family Labor				Hired Labor					
	Male		**Female**		**Male**			**Female**		
	qty	hours worked per day	qty	hours worked per day	qty	hours worked per day	unit cost per day (GHC)	qty	hours worked per day	unit cost per day (GHC)
Land preparation										
Processing of salt										
Harvesting										
Any other										

SECTION D: THE LEVEL OF TECHNICAL EFFICIENCY OF SALT PRODUCERS

1. Did you take loan to mine salt in 2018? Yes [1], No [0]
2. If yes, where is the source of the loan? Family [1], Friends [2], Financial institution [3], Others [4]……………………………………
3. What was the amount received? GHC…………………………
4. How did you service the loan? In-Cash [1], In-Kind [2]
5. What was the interest rate on the loan in percentages (%)? ………………
6. If in-cash, how much did you pay on monthly basis and for how long? GHC…………………..
7. Has the loan helped in your production activities?

   ……………………………………………………………………......................................

8. Would you be receiving some more loan in 2019? ………………………….
…………………………………………………………………………………..
9. What is the dimension of your basin (meters)? ……………………………...

SECTION E: DETERMINANTS OF INEFFICIENCY IN SMALL SCALE MINING

Additional source of income in 2018

1. Do you have additional source of income? Yes [1], No [0]
2. If yes, what is the nature of work? …………………………………………
3. How much did you earned from it? GHC …………………………………..
4. Did you rent land to engage in salt mining? Yes[1], No [0]
5. If yes, how much did you pay for the land in 2018? GHC………………
6. Do you experience impurities in your salt brine? Yes [1], No [0]
7. If yes, roughly what percentage (%) of impurities do you get in your salt brine/output? ………………………………………
8. How does the impurities affect your output?
…………………………………………………………………………………..
……………………………………………………………………………………
……………………………………………………………………..………………
……………………………………………………………………………………
9. What is the distance from your house to the mining site (km)? ....

SECTION F: MERITS AND DEMERITS OF SALT PRODUCTION

10. Has salt mining been beneficial? Yes [1], No [0]
11. If yes, please explain………………………………………………………

…………………………………………………………………………………….

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……………………………………………………………………………………..

12. What have been the challenges faced by you as an individual producer?

………………………………………………………………………………………

………………………………………………………………………………………

………………………………………………………………………………………

13. What have you been doing to overcome these challenges? …………………..

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14. What are the challenges of salt production in Elmina in general? ……………

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15. What has your association been doing to overcome the challenges? …………

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………………………………………………………………………………………

16. How can the salt industry be improved? …………………………………….

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-END-

APPENDIX II

ESTIMATES OF PARAMETERS OF COBB-DOUGLAS STOCHASTIC PRODUCTION FRONTIER AND THE EFFICIENCY MODEL

```
. frontier ln_output ln_K ln_L ln_SB

Iteration 0:   log likelihood = -80.580779
Iteration 1:   log likelihood = -80.565689
Iteration 2:   log likelihood = -80.565686

Stoc. frontier normal/half-normal model          Number of obs      =         96
                                                 Wald chi2(3)       =     117.09
Log likelihood = -80.565686                      Prob > chi2        =     0.0000
```

ln_output	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
ln_K	.4123508	.1363939	3.02	0.003	.1450237	.6796778
ln_L	.8754688	.1167969	7.50	0.000	.646551	1.104387
ln_SB	-.1416169	.1200236	-1.18	0.238	-.3768588	.0936251
_cons	-3.720437	.9624075	-3.87	0.000	-5.606721	-1.834153
/lnsig2v	-1.477204	.3953177	-3.74	0.000	-2.252012	-.7023954
/lnsig2u	-1.435877	1.040428	-1.38	0.168	-3.475079	.6033244
sigma_v	.4777814	.0944377			.324326	.7038446
sigma_u	.4877566	.2537379			.1759528	1.352104
sigma2	.4661816	.1749114			.1233616	.8090016
lambda	1.020878	.3390342			.3563833	1.685373

```
LR test of sigma_u=0: chibar2(01) = 0.42                 Prob >= chibar2 = 0.258

. reg TE NOP IPL EDU DTX LNX
```

Source	SS	df	MS
Model	.658481516	5	.131696303
Residual	1.51957212	90	.016884135
Total	2.17805364	95	.02292688

```
Number of obs      =         96
F(5, 90)           =       7.80
Prob > F           =     0.0000
R-squared          =     0.3023
Adj R-squared      =     0.2636
Root MSE           =     .12994
```

TE	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
NOP	-.0473477	.0115795	-4.09	0.000	-.0703523	-.024343
IPL	-.0373652	.0140557	-2.66	0.009	-.0652892	-.0094411
EDU	.072003	.0329054	2.19	0.031	.0066308	.1373753
DTX	.100536	.0535853	1.88	0.064	-.0059206	.2069925
LNX	.0243732	.0162397	1.50	0.137	-.0078898	.0566363
_cons	.4558541	.064246	7.10	0.000	.3282181	.58349

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APPENDIX III

TRANSLOG STOCHASTIC PRODUCTION FRONTIER MODEL

Stoc. frontier normal/half-normal model — Number of obs = 96; Wald chi2(9) = 155.68

Log likelihood = -73.190223 — Prob > chi2 = 0.0000

ln_output	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
In_K	-1.046207	3.30266	-0.32	0.751	-7.519301	5.426887
In_L	.4053948	2.431155	0.17	0.868	-4.359582	5.170371
ln_sizebasin	-3.993072	1.756485	-2.27	0.023	-7.435719	-.5504248
cappitt	.6519501	.5331482	1.22	0.221	-.3930011	1.696901
labbit	.579087	.3386787	1.71	0.087	-.0847111	1.242885
sizzebax	.0984313	.4184813	0.24	0.814	-.7217771	.9186396
caplabb	-.5200181	.2725056	-1.91	0.056	-1.054119	.0140831
capsizx	.6091694	.2818814	2.16	0.031	.056692	1.161647
labssin	-.0923574	.222665	-0.41	0.678	-.5287728	.3440579
_cons	5.212558	12.92341	0.40	0.687	-20.11685	30.54197
/lnsig2v	-1.862368	.4638656	-4.01	0.000	-2.771528	-.953208
/lnsig2u	-1.130187	.6750706	-1.67	0.094	-2.453301	.1929271
sigma_v	.3940869	.0914017			.2501327	.6208884
sigma_u	.5683071	.1918237			.2932733	1.101269
sigma2	.4782774	.1606121			.1634834	.7930713
lambda	1.442086	.2742479			.9045697	1.979602

LR test of sigma_u=0: chibar2(01) = 1.06 — Prob >= chibar2 = 0.152

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