**ÇUKUROVA UNIVERSITY**
**INSTITUTE OF NATURAL AND APPLIED SCIENCES**

**PhD THESIS**

**Abdul-Basit Tampuli ABUKARI**

# MEASURING THE TECHNICAL AND ECONOMIC EFFICIENCIES OF MAIZE FARMING IN THE NORTHERN REGION OF GHANA: DETERMINISTIC AND STOCHASTIC APPROACHES

**DEPARTMENT OF AGRICULTURAL ECONOMICS**

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We certify that the thesis titled above was reviewed and approved for the award of degree of Doctor of Philosophy by the board of jury on 18/01/2017.

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# ABSTRACT

**PhD THESIS**

**MEASURING THE TECHNICAL AND ECONOMIC EFFICIENCIES OF MAIZE FARMING IN THE NORTHERN REGION OF GHANA: DETERMINISTIC AND STOCHASTIC APPROACHES**

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The study sets out to measure the technical, allocative and cost efficiencies of maize farmers in the Northern Region of Ghana. The region has 73% of its population as farmers, with maize being the most cultivated and consumed cereal. It is also among the poorest regions in Ghana. Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA) are employed in the estimation. Face-to-face interviews were conducted on a sample of 121 farmers. The sample was selected through a multi-staged stratified mixed sampling technique. Under the variable returns to scale assumption, the study found an average efficiency of 78.2%, 47.1% and 36.9% for technical, allocative and cost efficiencies respectively. For the Constant Returns to scale, the scores were 73.6%, 46.8% and 33.7% respectively. Cost and allocative efficiency estimates were very low especially for SFA. A relatively higher scale efficiency of 86.4% was recorded. A tobit regression analysis was used to analyze the causes of inefficiency. It was found that education and household structure of farmers determined their technical efficiencies. However, in the case of allocative and cost efficiencies, land area, marital status and maize farming experience were found to significantly affect efficiencies. Gross profits of the farmers were also estimated. It showed that small scale farmers are generally more profitable than the large scale farmers. The study also found that labor was excessively used in the production process. Recommendations were made following the findings of the study.

**Key Words**: Maize, Efficiency, Causes of Inefficiency, Stochastic Frontier Analysis, Data Envelopment Analysis, Ghana

# ÖZ

## DOKTORA TEZİ

**GANA'NIN KUZEY BÖLGESİNDE MISIR TARIMINDA TEKNİK VE EKONOMİK ETKİNLİĞİN ÖLÇÜLMESİ: DETERMİNİSTİK VE STOKASTİK YÖNTEMLER**

**Abdul-Basit Tampuli ABUKARI**

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Bu çalışma, Gana'nın kuzey bölgesindeki mısır çiftçilerinin teknik, tahsis ve maliyet etkinliklerinin ölçülmesi amacıyla yapılmıştır. Bölgede, nüfusun % 73'ü çiftçilik yapmaktadır ve mısır bölgede ekilen ve tüketilen tahıllar arasında birinci sıradadır. Bununla birlikte bu bölge Gana'nın en fakir bölgelerinden biridir. Etkinliğin arttırılması, verimliliğin artması ile doğrudan ilişkili olduğu için, bu çalışmada etkinlik tahmininde ve etkinliğin arttırılması önerilerinde bulunulmuştur. Çalışmada, tahminleri hesaplamak için, Veri Zarflama Analizi, (VZA) ve Stokastik Etkinlik Sınırı (SES) kullanılmıştır. Örneklem dâhilinde 121 çiftçi ile yüz yüze görüşülmüştür. Örneklemin kapsamı ise çok aşamalı tabakalı örnekleme yöntemi ile belirlenmiştir. Ölçeğe değişken getiri varsayımına göre, teknik, tahsis ve maliyet etkinlikleri için sırasıyla % 78,2, % 47,1 ve % 36,9'luk ortalama tespit edilmiştir. Sabit değişken getiri varsayımına göre ise sırasıyla % 73,6,% 46,8 ve % 33,7'lik ortalama tespit edilmiştir. Maliyet ve tahsis etkinlik sonuçları, özellikle SFA için, oldukça düşüktür. Sonuç olarak ölçek etkinliği değeri, % 86,4 olarak bulunmuştur. Etkinsizlik nedenlerini analiz etmek için tobit regresyon yöntemi kullanılmıştır. Etkinsizlik nedenleri arasında yalnızca hane halkı yapısı değişkeni anlamlı bulunmuştur. Aile yapısı ve eğitim değişkenleri, çiftçilerin teknik etkinliklerini etkilemiştir. Tahsis ve maliyet etkinliklerinin analizinde, arazi alanı, medeni durum ve mısır çiftçiliğindeki deneyimin önemli etkisi olmuştur. Çiftçilerin brüt kârları da tahmin edilmiştir. Tahmin sonucunda küçük ölçekli çiftçilerin genellikle büyük ölçekli çiftçilerden daha kârlı oldukları tespit edilmiştir. Çalışmada tespit edilen bir diğer bulgu ise, üretim sürecinde aşırı yoğun işgücü kullanılmakta olduğudur. Araştırma bulguları ışığında öneriler geliştirilmiştir.

**Anahtar Kelimeler:** Mısır, Etkinlik, Etkinsizlik Nedenleri, Veri Zarflama Analizi, Stokastik Etkinlik Sınırı, Gana

## GENİŞLETİLMİŞ ÖZET

Tarım sektörü, tüm gelişmekte olan ülkelerde olduğu gibi, Gana ekonomisinde de çok önemli bir rol oynamaktadır. Tarım sektörü Gana ekonomisinde Gayri Safi Yurtiçi Hasılaya (GSYH) katkısı en az olan sektör iken, istihdama katkısı en büyük sektördür. Tarım, sanayi ve hizmet sektörlerinin Gana GSYH'na katkısı sırayla %22, %28,6 ve %49,4'tür (Ghana Statistical Service, 2014a, p.5). Ekim 2013 itibariyle, tarım sektörü toplam işgücünün %44,7'sini istihdam etmektedir (Ghana Statistical Service, 2014b, p.51). Gana'da özellikle arazi kullanımında, üretim ve işgücü tahsisinde verimliğin oldukça düşük olması, tarımsal üretimde etkinlik ve verimlilik tahminlerinin hesaplamasını zorunlu kılmaktadır. Gana'da tarım sektöründe etkinsizliği ve verim düşüklüğünü etkileyen nedenlerin ortaya çıkarılması ve bu sorunların çözümü için öneriler geliştirilmesi bu çalışmanın temel amacıdır.

Toplamda 10 coğrafi bölgeden oluşan Gana'da, inceleme alanı olan kuzey bölgesi yoksullukta 3. sıradadır (Osei 2011, p.6). Yoksulluğun yoğun olarak yaşandığı bu bölge aynı zamanda tarımsal üretim açısından çok önemlidir. Gana'da üretilen mısır, patates, manyok, sorgum gibi tarım ürünlerinin büyük kısmı kuzey bölgesinde üretilmektedir. Ayrıca Gana'nın coğrafi açıdan en büyük bölgesi kuzey bölgesidir. Buna rağmen sosyo-ekonomik göstergeler açısından en kötü durumda olan bölgedir. Bu durumun nedenleri arasında iklim, siyasi nedenler, altyapı eksiklikleri gibi pek çok neden gösterilmektedir. Kuzey bölgesinde ekonomi küçük aile tarım işletmeciliğine dayalı iken, güney bölgelerinde imalat sanayi, madencilik, ticaret gibi diğer ekonomik aktiviteleri de yoğun bir biçimde içermektedir (Ramatu ve Xinshen, 2007, p.1). Kuzey bölgesinde nüfusun yaklaşık %73'ü tarım sektöründe çalışmaktadır. Gana'nın diğer bölgeleri için bu oran değişmektedir. Kırsal istihdam oranları sırasıyla Ashanti bölgesi için %3,03, Büyük Accra bölgesi için %5,2, Orta bölge için %42, Doğu bölgesi için %45 ve Batı bölgesi için %47'dir (Ghana Statistical

Service, 2012, p.76, 77). Geçtiğimiz yıllar içerisinde Gana, düşük gelir düzeyine sahip bir ülke iken, günümüzde düşük-orta gelir düzeyinde bir ülke konumuna gelmiştir. Birleşmiş Milletlerin yeni binyıl hedefleri arasında dünyadaki yoksulluğu yarıya indirmek vardır. Bu hedef doğrultusunda Gana 2015 yılında yoksul sayısını yarıya indirme hedefine oldukça yakındır. Ancak bu durum bölgeler bazında incelendiğinde bir eşitsizliğin olduğu görülmektedir. Bölgeler bazındaki bu eşitsiz durum, bölgeler arası göçü tetiklemektedir.

Gana'da, mısır üretimi, toplam tahıl üretiminin yaklaşık % 55'ini oluşturmaktadır. Üretilen mısırın %90'dan fazlası insan beslenmesinde kullanılmaktadır. Bu durum mısır üretiminin, Gana'daki gıda güvenliği açısından en önemli üretim olduğunu göstermektedir. Mısır bitkisinin hayvancılık sektöründe de kullanılıyor olması, mısır üretiminin önemini artırmaktadır (Akramov ve Malek, 2011, p.7). 104.000 Hektar ekim alanı ve 70.000 ton üretim miktarı ile mısır, tahıllar arasında, kuzey bölgesinde en çok yetiştiriciliği yapılan üründür (FAO / WFP, 2002). Ancak mısır bitkisinin Gana için bu kadar önemli olmasına rağmen, mısır üretiminde verimlilik oldukça düşüktür. Yapılan bilimsel araştırmalara göre Gana'da mısır üretiminde potansiyel verim 6 t/ha iken, mevcut durumda Gana'da ortalama mısır verimi 1,7 t/ha'dır. Yani Gana'da mevcut mısır verimi, potansiyel verimin %29'u kadardır (MOFA, 2011, p.12). Verimlilik, temelde, çıktıların girdilere oranıdır. Genel olarak, belirli bir ürün açısından başarılı işletmeleri (DMU) gösterebilir. Ancak verimlilik, detaylı bir karşılaştırma yapmak için, iyi bir ölçü değildir. Etkinlik ise, verimliliğin aksine, benzer koşullara sahip, aynı ürünü üreten işletmelerin birbirleri ile karşılaştırılmalarına olanak sağlayan bir yöntemdir. Etkinlik hesabı ile her bir işletmenin, en iyi, en "etkin" işletme ile karşılaştırılması yapılabilir. Etkinlik hesabı, girdi ve çıktı yönelimli olarak iki yönlü yapılabilmektedir. Bu yönelimler, işletmelerin mevcut girdiler ile elde edebilecekleri maksimum çıktı miktarının göz önüne alındığı yöntem veya mevcut çıktıları minimum girdiler ile nasıl elde edeceklerinin hesaplanması şeklindedir. Ayrıca, etkinlik hesabın fiyat bilgileri de

dahil edilirse işletmelerin mali durumları da ölçülebilir ve karşılaştırabilir. Bu sebeple, işletmelerin karşılaştırılması açısından, etkinlik ölçümü verimlilik ölçümünden daha kullanışlı bir yöntemdir.

Bu çalışmada, en yaygın etkinlik ölçüm teknikleri (Veri zarflama-VZA ve Stokastik Sınır Analizi-SSA) kullanılmıştır, üç farklı etkinlik değeri (Teknik, Tahsis ve Ekonomik etkinlik) tahmin edilmiştir.

Teknik etkinlik, belirli bir girdi düzeyi ile maksimum çıktı elde etmek olarak veya minimum girdi kullanılarak belirli bir çıktı düzeyinde üretim yapmak olarak tanımlanır. Bu etkinlik hesabına girdi ve çıktı fiyatları da dahil edilerek işletmelerin optimum girdi kombinasyonuna nasıl ulaşacakları da hesaplanabilmektedir. Bu hesaplama yöntemine tahsis etkinliğini denir. Tahsis etkinliği ve teknik etkinlik birbirleri ile işleme tabi tutulduğunda ekonomik etkinlik hesaplanır (Coelli et al, 2005, p.5). Bu çalışmada her iki yöntemle de elde edilen (Veri Zarflama ve Stokastik Sınır Analizi) sonuçlar karşılaştırılmıştır. Her iki yöntemin de kullanılacak olmasının amacı tahmin edilen etkinlik değerlerinin gerçekliğinin arttırılmak istenmesidir. Hesaplanan etkinlik değerlerinin gerçeğe yakın olması, etkinsizlik nedenlerinin tahminlerinin de gerçeğe yakın olmasını sağlamıştır. Bu nedenle bu çalışmada Gana'nın Kuzey Bölgesinde mısır üreticilerinin etkinlik düzeyleri ve etkinsizliklerine neden olan faktörler belirlenmiştir.

Temel olarak, çalışmanın dört amacı vardır; 1. Gana'nın Kuzey Bölgesinde, mısır tarımında teknik, tahsis ve ekonomik etkinliğin ölçülmesi; 2. Etkinsizlik nedenlerinin belirlenmesi; 3. Etkinliği artırmak için önerilerin geliştirilmesi; 4. Tarım analizlerinin yapılmasıdır.

. Örneklemin kapsamı çok aşamalı tabakalı örnekleme yöntemi ile belirlenmiştir. Örneklem seçimi kapsamında, Gana'nın kuzey bölgesinden 20 ilçe içerisinden 10 ilçe seçilmiştir. Aynı yöntem kullanılarak, 100 çiftçi görüşme için seçilmiştir. Hatalı anketler veya eksik bilgi içeren anketler olabileceği göz önüne alınarak toplam 130 anket yapılmıştır. Neticede, analizde 121 çiftçi anketi

kullanılmıştır. Etkinliklerin hesaplanması için gerekli veriler anket yolu ile üreticilerden elde edilen birincil verilerle oluşturulmuştur. Teknik ve ölçek etkinliğinin hesaplanması için mısır üreten işletmelerin birim alandan elde ettikleri ürün miktarı dikkate alınmıştır. Tahsis etkinliği ve ekonomik etkinlik için ise üretim birimi başına maliyet dikkate alınmıştır. Tahsis etkinliğinin hesaplanması için girdilerin birim fiyatları dikkate alınmıştır.

Etkinliklerin hesaplanması için, kullanılan değişkenler: mısır miktarı, arazi büyüklüğü, işgücü, makine, saf azot, saf fosfor ve pestisitler olarak belirlenmiştir. Birinci analiz için çıktı, diğer analiz için girdiler kullanılmıştır. Ancak tüm değişkenler birim alan olan, bir acre (1 acre= 4,05 dekar) için hesaplanmıştır. Bu nedenle, girdi sayısı 5'e düşürülmüştür. Etkinsizlik nedenlerinin belirlenmesi için, sekiz sosyo-ekonomik değişken teşhis edilmiştir. Bunlar tarımsal yayım, mısır ekim alanı, aile işgücü oranı, eğitim, cinsiyet, medeni durum, aile yapısı ve mısır çiftçiliği deneyimidir. Bu değişkenlerin etkinlik skorları üzerindeki etkileri de analiz edilmiştir. Ancak, son analizde aile işgücü oranı değişkeni kaldırılmıştır. Çünkü bu değişkenin üretim girdileri ile yakından ilişkili olduğu tespit edilmiştir.

Ortalama çıktı miktarı 526,97 kg/ac iken, maksimum ve minimum çıktı miktarları sırasıyla 1000 kg/ac ve 117,25 kg/ac olarak belirlenmiştir. Girdiler için acre başına ortalama işgücü, makine, azot, fosfor ve pestisit miktarı sırasıyla 178,84 saat/ac, 4,42 saat/ac, 18,55 kg/ac, 8,69 kg/ac ve 1,03 lt/ac olarak belirlenmiştir. Kullanılan girdilerin standart sapmaları, ortalama değerlerden farklı olmasına rağmen, daha fazla bir dağılım göstermemektedir. Ancak, varyasyon katsayısı bunu, tam olarak yapabilmektedir. Varyasyon katsayısı değerlerine göre, en dağınık girdiler pestisit ve işgücüdür. Pestisitin özelinde, çiftçiler ekonomik durumlarından dolayı farklı miktarlarda pestisit satın almaktadırlar. Pestisitler diğer girdiler kadar önemli sayılmamaktadırlar. Genellikle kullanılan işgücü, aile işçiliğidir. Ailelerin üye sayısı her aile için oldukça değişken olduğundan, kullanılan işgücünün varyasyon katsayısı da

yüksektir. Makine, azot, fosfor girdi miktarları, arazi büyüklüğü ile doğru orantılıdır, bu nedenle, varyasyonu katsayıları diğer girdilerden daha fazla değildir. Sosyo-ekonomik değişkenlere ait özet istatistiklerin yüzde değerleri, küçük ölçekli işletmelerde, büyük ölçekli işletmelerden fazladır. Sırasıyla %69 ve %31'dir. Diğerleri için bu oranlar; eğitim (okuryazar %63; okuryazar değil, %37), cinsiyet (erkek %77, kadın %23), medeni durum (evli %81; bekâr %19), aile yapısı (çekirdek aile %61; geniş aile %39), çiftçilik deneyimi (deneyimli %48; az deneyimli %52) şeklindedir. Tüm yukarıdaki değişkenler kukla değişkenler olarak modele dâhil edilmişlerdir. Geri kalanlar ise, tarımsal yayım ve aile-işgücü işgücü oranı, sürekli değişkenler olarak modele dâhil edilmiştir.

Çeşitli etkinlik tahminleri hesaplamadan önce, stokastik sınır analizi yöntemiyle bir üretim fonksiyonun oluşturulmuştur. Cobb-Douglas tipi üretim fonksiyonu incelenmiştir. Bu üretim fonksiyonu tipi seçimi SSA'da kullanılan yöntemle belirlenmiştir. Yöntem, üretim ve maliyet fonksiyonları arasında dualite teorisi kullanmayı gerektirir. Cobb-Douglas üretim fonksiyonunun dışında, diğer yöntemlerin bu özelliği yoktur. Dağılım varsayımları açısından, yarı normal dağılım varsayımı kullanılmıştır. Ölçeğe sabit ve değişken getiri varsayımları dikkate alınmıştır. İki ölçeğe getiri varsayımlarında da tüm katsayılar pozitiftir; bu herhangi bir girdi artarsa, çıktının da artırcağı anlamına gelmektedir. İşgücü dışında, diğer girdiler istatistiksel olarak anlamlıdır. Anlamlı katsayılar arasında, yüksek değerler sahip olanlar azot ve fosfordur. Sonra sırasıyla pestisit ve makine gelmektedir. İşgücü, anlamsız olmasının yanı sıra aynı zamanda en düşük katsayıya da sahiptir. Katsayıları pozitif olması rağmen, her girdiyi artırmak ekonomik olarak akıllıca değildir. Marjinal Etkinlik Katsayıları (MEK) (Input Allocative Efficiency Coefficient- IAEC), kullanılan girdilerin miktarının azaltılması veya artırılması sorununa bir cevap olabilir. MEK dahilinde işgücü, makine, azot, fosfor ve pestisit katsayıları sırasıyla 0,03, 1,43, 6,74, 6,36 ve 10,10 olarak bulunmuştur. Bu sonuca göre, işgücü aşırı kullanılmakta ve azaltılması gerekmektedir. Makineler, azot, fosfor ve pestisitin

ise gerekli miktarlardan daha az kullanıldığı ve artırılması gerektiği tespit edilmiştir.

Gamma parametresi 0,79 olarak bulunmuştur. Bu parametre üretilen çıktı ve üretim fonksiyonu arasındaki farkın %79'unun teknik etkinsizlikten kaynaklandığını göstermektedir. Ayrıca bu değer istatistiksel olarak anlamlıdır. Ölçeğe sabit getiri varsayımı için bu değer 0,77'dir. Üretim fonksiyonda ölçeğe getiri 0,94 bulunmuştur. Bu değer, ölçeğe azalan getiri demektir. Tüm girdiler aynı oranda arttırıldığında ve çıktı seviyesindeki oransal artış girdilerdeki oransal artıştan az ise ölçeğe azalan getiri mevcut demektir. Ancak hipotez testi, bu değerlerin istatistiksel olarak birbirinden farklı olmadığını göstermektedir. Yani istatistiksel olarak, fonksiyon sürekli olarak ölçeğe sabit getiri göstermiştir. Mısır üretim fonksiyonunda etkinsizliğin varlığını belirlemek için, logaritmik olasılık fonksiyonları kullanılarak bir hipotez testi yapılmıştır. Test, mısır üretiminde etkinsizlik olduğunu göstermiştir.

Genelde hem VZA'da hem de SSA'da nispeten yüksek teknik etkinlik skorları bulunmuştur. Farklı ölçeğe getiri varsayımlarına göre, farklı tahminler bulunmuştur. Ölçeğe değişken getiri varsayımında %79,3 (VZA) ve %77,1(SSA) değerleri bulunmuştur. Ölçeğe sabit getiri için, %68,5 (VZA) ve %78,7 (SSA) değerleri bulunmuştur. Normalde VZA skorunun SSA'den düşük olması beklenmektedir. Ancak, ölçeğe sabit getirinin aksine, ölçeğe değişken getiri için durum böyle değildir. Bu problem hem VZA'ne hem de SSA'ne atfedilebilir. VZA'nde sınır verileri daha çok zarflanmıştır. SSA için en uygun üretim fonksiyonu türü seçilmemiş olabilir. İki yöntem ile de yaklaşık %31 etkinsizlik bulunmuştur; yani girdi miktarları değişmeden mısır çiftçilerinin verimliliği %31 artırılabilir.

Tahsis etkinlikleri tahminleri için ölçeğe değişken getiri varsayımında %67,2 (VZA) ve %27 (SSA) değerleri bulunmuştur. Ölçeğe sabit getiri için, %64 (VZA) ve %29,6 (SSA) değerleri bulunmuştur. Maliyet etkinlikleri için ölçeğe değişken getiri varsayımında %53 (VZA) ve %20,8 (SSA) değerleri

bulunmuştur. Ölçeğe sabit getiri için %44 (VZA) ve %23,3 (SSA) değerleri bulunmuştur. Genelde, tahsis ve maliyet etkinlikleri düşüktür. Ancak, SSA değerleri görece daha düşüktür. Ortalama olarak ölçeğe değişken getiri varsayımına göre teknik, tahsis ve maliyet etkinlikleri için sırasıyla % 78,2, % 47,1 ve % 36,9'luk ortalama değerler tespit edilmiştir. Sabit değişken getiri varsayımına göre ise sırasıyla % 73,6, % 46,8 ve % 33,7'lik ortalama değerler tespit edilmiştir. Sonuç olarak ölçek etkinliği değeri % 86,4 olarak bulunmuştur.

Etkinsizlik nedenlerini analiz etmek için tobit regresyon modeli kullanılmıştır. Teknik etkinsizlik nedenleri arasında yalnızca hane halkı yapısı değişkeni anlamlı bulunmuştur. Aile yapısı ve Eğitim değişkenleri, çiftçilerin teknik etkinliklerini etkilemiştir. Ayrıca, tahsis ve maliyet etkinliklerinin analizinde arazi alanı, medeni durum ve mısır çiftçiliğindeki deneyimin önemli etkisi olmuştur. Çalışmada, çiftçilerin brüt kârları da tahmin edilmiştir. Tahmin sonucunda küçük ölçekli çiftçilerin genellikle büyük ölçekli çiftçilerden daha kârlı oldukları tespit edilmiştir.

İki yöntemin skorlarının benzerliklerinin belirlenmesi için, spearman sıra korelasyonu kullanılmıştır. VZA ve SSA metotları arasındaki korelasyon oldukça güçlü bir ilişki olduğunu göstermektedir. En yüksek değer %77 iken, en düşük değer %37'dir. Genelde ölçeğe sabit getiri tahminleri, ölçeğe değişken getiriden tahminlerinden güçlüdür.

Çalışmada tespit edilen bir diğer bulgu ise, üretim sürecinde aşırı yoğun işgücü kullanılmakta olduğudur. Bunu azaltmanın en temel yolu üreticilerin çiftçiliği aynı zamanda bir ticari iş olarak görmeleridir.

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## LIST OF ABBREVIATIONS AND SYMBOLS

| | |
|---|---|
| AE | : Allocative Efficiency |
| BCC | : Banker, Charnes, Cooper |
| CCR | : Charnes, Cooper, Rhodes |
| CE | : Cost Efficiency |
| Coef | : Coefficient |
| COI | : Cost of inefficiency |
| COV | : Coefficient of Variation |
| CRS | : Constant Returns to Scale |
| DEA | : Data Envelopment Analysis |
| DMU | : Decision Making Unit |
| DRS | : Decreasing Returns to Scale |
| Eqn | : Equation |
| GDP | : Gross Domestic Product |
| IAEC | : Input Allocative Efficiency Coefficient |
| IRS | : Increasing Returns to Scale |
| LHS | : Left Hand Side |
| LLH | : Log Likelihood Function |
| ML | : Maximum Likelihood |
| MoFA | : Ministry of Food and Agriculture |
| MPSS | : Most Productive Scale Size |
| MRTS | : Marginal Rate of Technical Substitution |
| NIRS | : Non-Increasing Returns to Scale |
| OLS | : Ordinary Least Square |
| PAR | : Parameter |
| PDF | : Probability Density Function |
| RHS | : Right Hand Side |
| RTS | : Returns to Scale |

| | |
|---|---|
| SE | : Scale Efficiency |
| SFA | : Stochastic Frontier Analysis |
| SRID | : Research and Information Directorate |
| Std Dev | : Standard Deviation |
| Std. Err | : Standard Error |
| TE | : Technical Efficiency |
| VRS | : Constant Returns to Scale |

# 1. INTRODUCTION

## 1.1. Background of the Study

Like all developing countries, agriculture plays a very important role in the Ghanaian economy. The value of agriculture has so much to do with the number of people it employs than its contribution to the economy. It is the least in terms of contribution to GDP, but the highest in terms of population employed. Agriculture, industry and services contribute 21.9%, 28.6% and 49.5% respectively to GDP (Ghana Statistical Service, 2014a, p.5; World Bank Ghana Development Indicators, 2014). Agriculture however, employs 44.7% of the labor force as at October 2013 (Ghana Statistical Service, 2014b, p.51). This superficially reflects low productivity in the sector, especially that of labor. Industries therefore have to import most raw materials for production, which otherwise could have come from the agricultural sector. This has resulted in continuous growth in the service sector, inconsistent growth in industry and continuous decline in agriculture. If the sector that support about half the population of the country is in such a bad shape, it is obvious who the direct victims of this situation are; the rural community poor. Overall, Ghana's economy is doing well in recent years with the most contribution coming from the service sector and the newly found crude oil. But those figures have a lot of internal inconsistencies when compared to their real effects on the entire population, especially the rural communities who are mostly farmers. That is, the growth in the economy is not pro-poor.

According to Klasen (2007, p. 196), pro-poor growth is the growth that leads to a disproportionate increase in the incomes of the poor and at the same time decrease inequality. It leads to a situation where the incomes of the poor grow at a higher rate than those who are considered not poor (Hadnes and Klump, 2008, p. 107; Ravallion, 2008, p.2). This type of growth is faster, sustainable and more effective in reducing poverty and inequality than any form of growth. To promote

this type of growth attention is given to the region in which the poor live, how and where they earn their livelihood (OECD, 2006, p.22). In the case of Ghana, agriculture is obviously the sector to be given that attention, and the three Northern Regions and other rural communities in the country should be the targeted locations.

Agriculture is the sector that can improve the general wellbeing of the Ghanaian population if proper attention is given to it. Without a strong agricultural base, the transformation of the Ghanaian economy cannot be robust and sustainable (McKay and Aryeetey, 2004, p.48; Diao, 2010, p.5 and Breisinger et al. 2011, p.23). The sector is however bedeviled with lots of problems. The focus of this thesis is fundamentally based on two broad issues; improving the productivity and efficiency of the agricultural sector, and bridging the economic inequality in the country; these together define pro-poor growth or development concept. The former is the basis for the selection of maize for the study whiles the selection of the Northern Region as the study area stems from the latter.

Agriculture indeed has special powers in reducing poverty irrespective of the level of development of the country (World Bank, 2008). Ligon and Sadoulet (2007) demonstrated this conducting a cross-country survey of 42 developing countries from 1981 to 2003. They found that agricultural led GDP growth is at least twice more effective than non-agricultural led GDP growth when it comes to poverty reduction. Cervantes-Godoy and Dewbre (2010) after comparing the agricultural economic indicators of a highly diverse mix of developing countries concluded that despite their diversity, they all agree on the contribution of agriculture to poverty reduction. A time series analysis was further conducted, which revealed that economic growth resulting from growth in agricultural incomes was the most effective in reducing poverty. Similar studies like Christiaensen and Demery (2007) has found the effectiveness of reducing absolute poverty among the poorest than other groups. Bravo-Ortega and Lederman (2005),

Schneider and Gugerty (2011) and Hasan and Quibriam (2004) are some other few examples that arrived at similar conclusion.

For agriculture to improve agriculture and ultimately lead to poverty reduction, the starting point is to improve the productivity of some of the most important agricultural inputs, which have direct effect on the livelihood of the population. However as noted by Ramaila et al. (2011, p.14), increase in agricultural productivity is a product of technological change, improved input use efficiency and conservation of natural resources which are achieved through investments in agriculture related researches and extension as well the human capital involved in the agricultural value chain. As experienced in the Far Eastern countries like India, China, Taiwan, Malaysia, Vietnam, Philippines, Thailand, etc., increase in agricultural productivity has made their growth relatively pro-poor (OECD, 2006, p.24). Agricultural productivity is the base on which growth in other sectors will thrive, hence becoming the led sector for overall growth of the economy, especially in agriculture-based countries (McKay and Aryeetey, 2004, p.48; World Bank, 2008, p.6). In developed agricultural economies like Turkey, India and Brazil, which are also developing countries, agricultural productivity is the least of their problems in the agricultural sector now. The agricultural policies and programs used by these countries placed emphasis on increasing productivity which acted as a spring board to their current enviable status in agriculture. Turkey for example, after its independence in 1923, embarked on an agenda of empowering the small scale farmers to increase output and productivity, and create a domestic market to enhance production and trade (Öztürk, 2012, p.59). These were the most pressing problem they had to deal with for the start. They however did not reap the full benefits until 1950's. In the case of India, the severe 1965/66 drought forced them to realign their policies towards achieving self-sufficiency especially, in rice and wheat which were seen as very important for their survival. This move was known as the Green Revolution or The New Agricultural Strategy and was spearheaded by the Punjab province in 1966/67 and later spread to other

provinces. The main objective of this was to apply science and technology to increase productivity (Tripathi and Prasad, 2009, p.66). This initiative has been largely credited as being responsible for turning India from food import based economy to not only a self-sufficient one, but an exporter in food grains (UNDP, 2004, p. 17).

According to Ghana's Ministry of Agriculture, about 60% of crops produced in Ghana are below 50% of their potential. These include important ones like maize, rice, cassava yam, tomato, and cocoa (MoFA, 2011, p. 12). Improving productivity of these crops requires a multidimensional approach which involves careful and balanced way of providing logistics, training and infrastructure to the farmers. In improving the productivity of maize for example, access to water, improve seeds, technology, extension services are very paramount. Inadequate provision of any of these may not achieve the required results.

To the second issue of inequality, Ghana's development has historically been skewed towards the south where there are a lot natural resources and cash crop production compared to the north. Aside the presence of gold, diamonds, bauxites, manganese and oil, the south is the only viable place for the production of Ghana's most important and precious cash crops; cocoa and coffee. Ghana's economy is strongly dependent on these resources even though most part of it is exported in their raw form. The Northern regions however, have agriculture as their most dependable source of livelihood.

From table 1.1, about 70% of the populations in the Northern regions (the bottom 4) are farmers, compared to about 32% for the southern regions. They make up the first three poorest regions in the country; Upper East, Upper West and Northern Regions. The regions also lag behind in terms of other socio economic indicators and social infrastructure. While the country is on track to meet the first goal of the Millennium Development Goals (MDGs) of the United Nations (UN), the benefits have not been well spread. Between 1992 and 2006, number of poor in the south reduced by 2.5 million people, while the combined number of poor in

Upper East, Upper West and Northern Regions rather increased by 900,000 people (IFAD, 2012, p. 5). In the specific case of Northern Region, which has a population of 2,479,461 witnessed the lowest reduction rate in poverty rate relative to the whole country, from 1992 to 2013 (Cooke, et al. 2016). This means that for any development policy that seeks economic equality must have an agricultural policy through which the people in the Northern Regions and other rural communities in the country can be economically uplifted.

Table 1.1 Proportion of Population in Agriculture, by Regions

| Region | % of Men | % of Women | Total (%) |
|---|---|---|---|
| Greater Accra (Capital) | 6.87 | 3.6 | 5.21 |
| Ashanti | 3.21 | 2.87 | 3.04 |
| Eastern | 53.31 | 37.42 | 45.15 |
| Western | 50.9 | 43.1 | 47.05 |
| Central | 47.68 | 37.46 | 42.15 |
| Volta | 57.07 | 43.69 | 50 |
| Brong Ahafo | 65.34 | 56.58 | 60.92 |
| Northern | 77.83 | 68.45 | 73.11 |
| Upper East | 72.31 | 65.98 | 68.95 |
| Upper West | 76.53 | 67.54 | 71.78 |

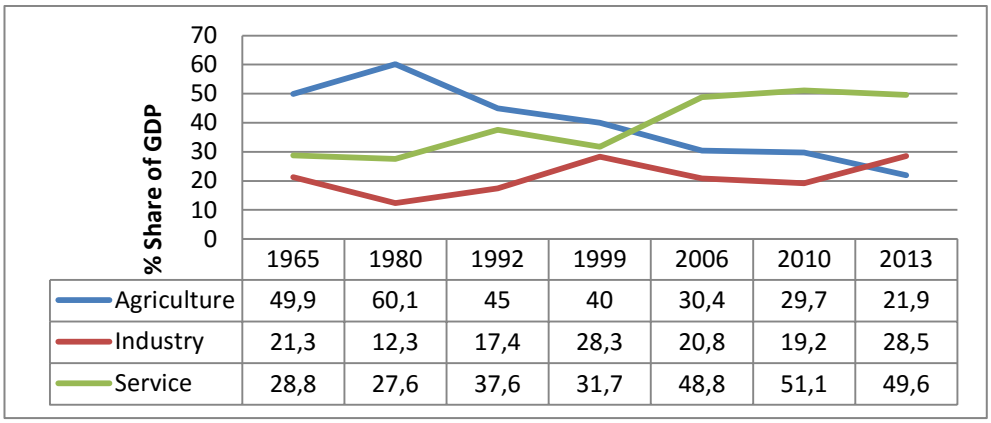
Source: Authors calculations from Ghana Statistical Service, 2012, p.76 and 77

A national agricultural policy is important for both the north and the south but it is much needed by the Northern Regions since it is the most dependable and sustainable option they have currently.

### 1.2. Statement of the Problem

Ghana has been considered one of the promising economies in Sub Saharan Africa with impressive growth rates in recent years. However sectorial contributions to these growth comes from the commercial crops (especially cocoa), mineral extraction (mostly gold and oil) and the service sector, that constitutes about half of the economy's GDP. Almost half of the country agricultural labor is not direct beneficiaries of this growth since the growth is nonagricultural. It is known that

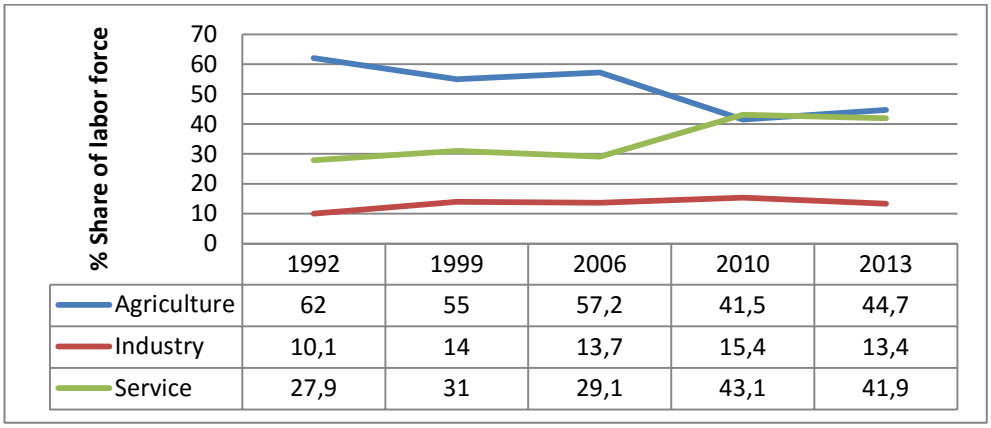
this development trajectory is not only unsustainable but widens inequality in economies (World Bank 2005, p.28).




| | 1965 | 1980 | 1992 | 1999 | 2006 | 2010 | 2013 |
|---|---|---|---|---|---|---|---|
| Agriculture | 49,9 | 60,1 | 45 | 40 | 30,4 | 29,7 | 21,9 |
| Industry | 21,3 | 12,3 | 17,4 | 28,3 | 20,8 | 19,2 | 28,5 |
| Service | 28,8 | 27,6 | 37,6 | 31,7 | 48,8 | 51,1 | 49,6 |

Source: Figures from 1966 to 2010 were extracted from the World Bank Ghana Development Indicator (2014)

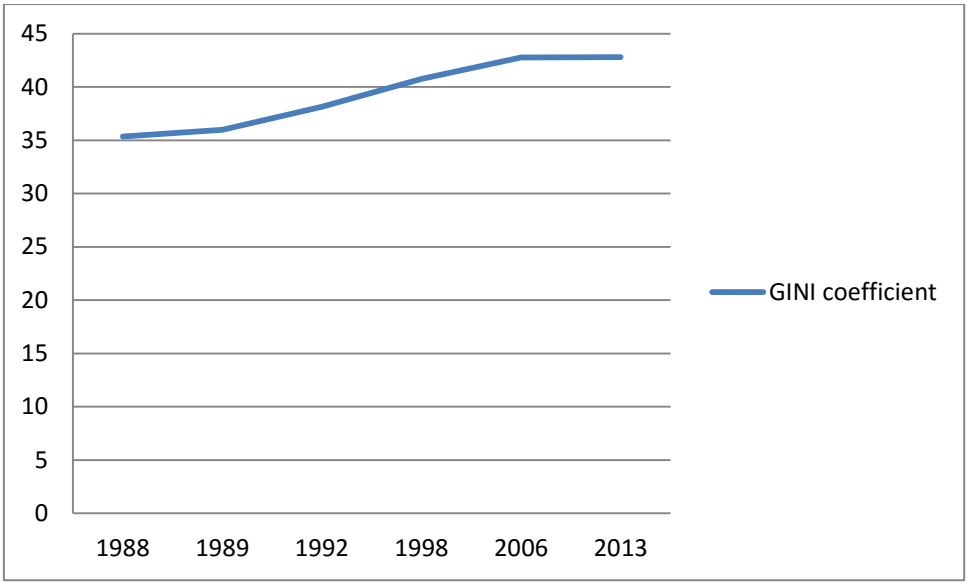
Figure 1.1 Sector Contributions to GDP




| | 1992 | 1999 | 2006 | 2010 | 2013 |
|---|---|---|---|---|---|
| Agriculture | 62 | 55 | 57,2 | 41,5 | 44,7 |
| Industry | 10,1 | 14 | 13,7 | 15,4 | 13,4 |
| Service | 27,9 | 31 | 29,1 | 43,1 | 41,9 |

Source: Figures from 1992 to 2010 were extracted from the World Bank Ghana Development Indicators (2014) and that of 2013 from Ghana Statistical Service (2014b, p.51).

Figure 1.2 Labor Force Employments by Sectors




Source: Figures from 1988 to 2006 were extracted from the World Bank Ghana Development Indicators (2014) whiles that of 2013 is from the UNDP Human Development Report (2014, p. 170)
Figure 1.3 GINI Coefficients

In classical growth and development sense, this structural change as observed from Figure 1.1 and 1.2 is promising, but Figure 1.3 reveals that there is rising inequality in income distribution. As seen from Figure 1.2 about 45% of the labor force are currently been negatively affected by these non-pro-poor growth. Growth in agriculture will not only add to the growth in the economy but will arrest and reduce the increasing income inequality (Breisinger et al. 2011, p.84). The immediate effect of this in the Ghanaian economy recently is the increasing food prices and general cost of living, resulting from food importation. Another effect is the negative consequences of urbanization in the few big cities especially the capital, Accra, were lots of youth especially girls migrate to the cities from the north in search of non-existing jobs. This phenomenon is widely referred to as 'kayaye' in Ghana. According to Breisinger et al. (2011, p.11), development in agriculture counteracts rural urban migration and closes the poverty gap between the urban rural communities.

The agricultural productivity led growth, otherwise known as the Green Revolution is therefore key to the sustainable development of Ghana. For such an economic structure, poverty levels are highly correlated with growth in agriculture (Page, 2006, p.23). Agricultural productivity growth as the name suggests, it refers to the growth of total factor productivity through a deliberate change in the amount and the quality of agricultural inputs, driven by technology. It also includes improving the soil productivity and irrigation facilities (Toenniessen, Adesina and DeVries, 2008, p. 234). It is an established fact that when agriculture is less developed than other sectors in an economy, the growth and development tend to be less pro-poor (OECD, 2006, p.24). Unlike the nonagricultural growth, this type of development benefits the whole economy through linkages with the other sectors and at the same time a necessary condition to stimulate growth in the nonagricultural sectors (Breisinger et al. 2011, p.106; Mckay and Aryeetey, 2004, p. 50). The worst part is the source of the modest growth in agriculture since 1966. It is estimated that land expansion has been the driving force as opposed to land productivity. While cultivable lands have increased about 60% from 1994 to 2006, land productivity actually fell between 1997 and 2002 and only regain later, thanks to growth in the cocoa sector (Breisinger et al. 2011, p.51). With the accompanying environmental effects of farming, if this trend continues, the cost will be enormous. Ghana's economy will be more robust and sustainable if its current development is supported by agricultural productivity growth. This approach would tackle the two broad issues the thesis seeks to address; improving the agricultural sector through increased productivity and reducing the inequality that exist between the northern and southern part of the country.

After making a decision to embark on a productivity led growth in agriculture, the first thing is to strategically select the most important crops that have a direct effect on the livelihood of the people. Whiles wheat and rice were selected in the case of India, Turkey concentrated on wheat and later on sugar beets, tobacco, cotton, hazelnuts and figs. Turkey is among both the high wheat

producing and consuming countries in the world, indicating how important it is to the Turkish economy (International Business Publications, 2003, p. 204). Ghana produces commercial crops like cocoa, coffee and cashew, but most of it is exported in their raw form coupled with their unstable prices in the world market. The most important food crops in Ghana are; maize, rice, millet, sorghum, cassava, cocoyam, yam, plantain, sweet potato, cowpea, groundnut and soybeans (MoFA, 2011, p. 12). The strategy is to focus on the productivity of some these crops so as to make the economy self-sufficient in their production.

For the purpose of this study, I choose from among the three Northern Regions Northern Region as the research area because it has the largest proportion of it population as farmers in the whole country (refer to table 1.1). Furthermore, the poverty situation in the region is worsening as compared with all regions in Ghana. In terms of poverty rate, it moved from being the fourth poorest region in 1992 to the second in 2013 (Cooke, et al. 2016). Even though Northern Region is not the highest producer of maize in Ghana, maize is the highest both in terms of planting area and output among cereal production in the region; 110,430 hectares and 202,316 tons respectively (MoFA, 2010). Furthermore, maize is the highest in terms of household farming activities in the region; maize (75%), yam (38%), groundnuts (28%), and rice (25%) (Choudhary et al. 2015, p. 120). Nationally, maize is the most important cereal crop, representing about 55% of total grain production. Over 90% of it is consumed as food making it the most important crop for food security. It is also the major component in the feed of poultry and livestock (Akramov and Malek, 2011, p.7). It is also the crop with the highest planted area among all crops in Ghana (Braimoh and Vlek , 2006). It is obvious how an increase in the productivity of maize will directly impact the lives of the people in the region and Ghana as a whole. However, according to Morris et al. (1999), between 62% and 86% of maize growing household end up buying maize before the next farming season. This implies that maize output is not enough for household consumption.

### 1.3. Purpose of the Study

Productivity is basically the ratio of outputs to inputs. Generally, it determines the most productive Decision Making Unit (DMU) in terms of output produced. In productivity and efficiency analyses, the term 'firm' is mostly replaced with the term 'DMU'. This term is preferred because of the general application it has in efficiency analysis. It is referred to any productive entity capable of converting inputs into outputs and whose performance can be evaluated. This makes it possible for productivity and efficiency analyses to be applied in so many disciplines. A DMU can be a maize farm that converts agricultural inputs into maize output or a hospital that converts inputs of doctors and nurses into outputs of inpatients and outpatients. The use of the 'firm' however has a limited application (Coelli et al. 2005, p.1; Cooper et al. 2007, p.22). The DMUs in this case are the maize farmers. However for a detailed comparison amongst the DMUs, productivity is not a good measure. Unlike productivity, efficiency compares all the firms with a benchmark, which is normally the DMU with the highest productivity. This benchmark represents the optimal input and output under the given circumstances. Every observed output and input combination is then compared with the optimal input and output combination. Efficiency allows the DMU to either produce using the minimum input possible, given output or produce the maximum output with the given inputs. Furthermore, efficiency also allows the comparison of DMUs in terms of scale of production. Lastly, in the presence of price information on inputs and outputs, the financial and economic situations of the DMUs can be compared (Coelli et al. 2005). These make efficiency measurement more advantageous. As would be explained later, in the calculation of efficiency, productivity is implicitly calculated for every DMU, i.e. increasing efficiency means increasing productivity. Put in another way, the efficient use of inputs automatically translates into increased productivity.

The results from efficiency and productivity analyses can form the fundamental input into the formulation of an agricultural policy aimed at increasing

productivity. Technical efficiency measures the efficiency in converting inputs to outputs by producing with minimum inputs or obtaining the most output from a given input (Ramanathan, 2003, p.78). In either of these definitions productivity which is the ratio of total output to total inputs, automatically increases. While the former seeks to minimize the denominator in the productivity ratio, the latter maximizes the numerator, all of which indicate increase in productivity. In the presence of price information allocative and economic efficiencies can be computed.

Furthermore for every efficiency measurement, there are two methods of constructing the most efficient frontiers. These are nonparametric and parametric approaches, which are popularly known as DEA and SFA respectively. DEA uses linear programming to construct the frontier whiles SFA technique uses econometric models with two components representing both random effects and technical inefficiency (Silva et al. 2013a, p.5). The study is employing both methods, because of their comparative advantages and disadvantages they both have over each other. Their results would then be compared.

From the data obtained, the study intends measuring the technical, scale, allocative and economic efficiencies of the sampled farmers. For all these efficiencies, the inputs to be considered are; planting area, labor, machinery, nitrogen, phosphorus and pesticides. However, different outputs will be considered for different efficiency measures. The study will consider output per-unit area of sampled maize farmers as the basis for the measurement of technical and scale efficiencies; whiles per-unit cost of its production will be the basis for allocative and economic efficiencies. However, the calculation of allocative and economic efficiencies will require information about the unit prices of inputs used in production.

The combination of these efficiency measures will therefore achieve the purposes of measuring and assessing how productivity of the maize farmers can be increased through technical efficiency and how this translates to the economic

situation of the farmers through economic efficiency. This in my would address the two broad issues spelt out earlier; That is, increasing the productivity of farmers and increasing their economic status so as to bridge the gap between the northern and the southern Ghana. The results of these can form basis for policy formulation.

### 1.4. Significance of the Study

To promote the idea of growth in agricultural productivity to support the current trajectory of development of the Ghanaian economy, this type of study is obviously important for policy directions to achieve the goal of a pro-poor growth. The study is also very significant in the sense that it is targeting a region not fully benefiting from growth, and at the same time having the largest proportion of its population as farmers in the whole country.

Despite maize being the largest cereal both in terms of output and land area in the region, much attention has not been given to improving its productivity and efficiency. Attempts are made by some localized, limited budget and short lived projects which are normally foreign sponsored. These projects often do not fit into government's strategy and lack consistency. The research in this topic with respect to maize is very scanty in Ghana.

This research will fill a big vacuum in the measurement of maize efficiency in the region. Unlike previous works that only measures technical efficiency, this study seeks to measure with the same data, the technical, scale, allocative and economic efficiencies. All these efficiencies are going to be calculated using both stochastic and deterministic approaches. Considering the pros and cons of these approaches, the results from both methods will then be compared. Lastly, policy recommendation from this type of study is rooted in the causes of various inefficiencies and productivity. The study would make an attempt to find them.

### 1.5. Research Questions and Objectives

The main aim of this research is to promote pro-poor growth through improving agricultural productivity and various efficiencies of maize farmers in the Northern Region of Ghana. This leads to the main research question of this thesis; how can efficiency and productivity of maize farmers in Northern Region be improved? As mentioned out earlier, improving efficiency is synonymous to increasing productivity. On that basis the study will try answering the question by these specific objectives;

1. Measure technical, scale, allocative and economic efficiencies of maize farmers in the Northern Region of Ghana, using both stochastic and deterministic approaches.
2. Determine the causes of the estimated inefficiencies
3. Recommend ways to improve efficiency
4. Some farm analyses that may explain the first two objectives

### 1.7. Thesis Outline

The rest of the thesis is arranged as follows: chapter two deals with the review of similar studies. Because of the multifaceted nature of this study, it has a lot in common with many studies. Chapter three is the methodology and material section. Variables and their measurement units are reviewed in the material whiles the methodology section deals with the detail review of the DEA, SFA and general efficiency studies. It allocated some sections for the historical evolvement of the efficiency measurement techniques. Chapter four contains the results and the discussions thereof from the analysis, whiles the final chapter draws conclusion and recommendation from the discussions in chapter four.

# 2. PREVIOUS STUDIES

## 2.1. Introduction

This chapter reviews previous studies conducted in line with some or all the objectives of this thesis. In this regard, a lot of literature qualifies to be reviewed. The chapter has been organized in an orderly manner. The first part deals with the genesis of comparative efficiency studies, which applied different techniques on the same data and compared. This historical review is necessary so as to appreciate how it evolved. In the same vein, a sub section under methodology is also dedicated to the history and the evolvement of efficiency measurement. The second part involves general studies that involve the use of the two methods. This part is then divided into two; those that involve maize productions and the others that deal with other crops especially cereals. The next part dealt with literature concerning the determinants or causes of inefficiency irrespective of the methods used and the last part considered efficiency studies in the research area, Ghana.

## 2.2. History

Agriculture has been at the forefront since the inception of productivity and efficiency measurement studies. The seminal paper by Farrell in 1957, which marked the beginning of modern productivity and efficiency measurement studies, used agricultural production data. He applied it on agricultural production in 48 states of the United States for the year 1950 (Darku et al. 2013, p.5). From that time, productivity and efficiency measurement has undergone so many improvements and new methods. The dominant till date are the deterministic and stochastic methods otherwise known as nonparametric (DEA) and parametric (SFA) methods respectively. Each of these methods has their advantages and disadvantages depending on the type of study, the purpose and the type of data used. However, it wasn't until the 1990's that the idea of using both parametric and

nonparametric methods on a single dataset and comparing the results emerged (Darku et al. 2013, p.71). Since this thesis intends employing this type of study, it would be prudent to review the earlier studies done with this methods giving preference to those that were related to agriculture.

Sharma, Leung and Zaleski, (1997): The study was conducted on Hawaii's swine industry, which at that time was experiencing a decline both in terms of the number of farms and hogs (a domesticated castrated male pigs reared for slaughter). Data were collected from 60 commercial swine producers for the fall of 1994. On the profitability analysis, they found out that most of them especially the small and medium farms were running losses. Comparatively the large farms were more profitable as they enjoyed the scale advantage. In terms of the efficiency analysis, SFA was used to calculate the technical, allocative and economic efficiencies of the farms. Using both input and output-orientations, DEA was used to calculate technical, scale and overall technical efficiencies. This means that the only comparison possible between the two methods is that of technical efficiency. The stochastic methods yielded 0.704, 0.76, and 0.531 for technical, allocative and economic efficiencies respectively. For the input-oriented DEA, the results for technical, scale, and overall technical efficiencies were 0.748, 0.842 and 0.635 respectively, and were 0.726, 0.895, and 0.644 respectively for the output orientation. The technical efficiency estimate of the stochastic method was 0.704, compared to the technical efficiency in the output DEA results (0.726). This difference according to them was not significant. Farm size had a positive influence on productive efficiency whiles farmers' experience and education level did not have any effect.

Sharma, Leung and Zaleski (1999): Unlike their previous work **(**Sharma, Leung and Zaleski, 1997), they calculated on the same data, technical, allocative and economic efficiencies using both DEA and SFA. This research was also conducted on the swine production in Hawaii. The results of the two methods were compared to establish a range within which the three efficiency estimates lie.

Factors affecting technical efficiency of swine production were also analyzed. For each of the two methods, Variable Returns to Scale (VRS) and Constant Returns to Scale (CRS) assumptions were considered. Under the VRS assumption for DEA, technical, allocative and economic efficiencies were 0.759, 0.803 and 0.603 respectively, and were 0.759, 0.758 and 0.571 respectively with SFA. For the CRS assumption, the DEA results for Technical, allocative and economic efficiencies were 0.643, 0.714 and 0.457 respectively whiles SFA recorded 0.745, 0.739 and 0.547. The two methods when compared under the same scale assumption appear to agree with each other, since the correlation between the results were very high especially the results of technical efficiency under CRS assumption. When potential outliers were removed, technical efficiencies results from SFA and the allocative efficiencies results from DEA were improved. But generally, DEA results were found to be more robust than those of SFA, contrary to popular belief.

Farm size was found to have a strong positive effect on productive efficiency. This agrees with their earlier work (Sharma, Leung and Zaleski, 1997). Type of pigs produced also had an effect on efficiency: those producing for the market were more efficient than those producing feeder pigs.

Kalaitzandonakes and Dunn (1995): They calculated the technical efficiency of 82 corn producers in Guatemala using three different efficiency methods; Deterministic Statistical Frontier (DSF), DEA and SFA. The DSF method measures efficiency from the Corrected Ordinary Least Square (COLS). Efficiency was then regressed against the possible determinants of efficiency. Even though this research estimated only technical efficiency of the corn producers, it went further to investigate whether the choice of method may change the effects of the determinants of efficiency, especially education. For the DSF, the mean technical efficiency was 0.52, with a minimum of 0.21 to maximum of 1.00. In terms of the distribution of the efficiency results, a lot of the farmers were found to be inefficient because 89% of them had efficiency values below 0.7. They however expressed the possibility of the inefficiency exaggerated because of the method

used; for every deterministic frontier, any deviation is considered inefficiency when it not actually the case, especially in the field of agriculture. In the case of SFA results, the mean technical efficiency was 0.73. Whiles the minimum was 0.37, the maximum efficiency score was 0.93. Inefficiency in terms of mean and the number of inefficient farmers seems to have reduced compared with the previous method as 61% of the farmers were operating below 0.7 efficiency level. It therefore suggests that much of what the deterministic procedure considered inefficiency has actually been statistical noise as revealed by SFA. The DEA results recorded the highest efficiency value of all. It recorded a mean efficiency of 0.93 with a minimum of 0.49 and a maximum of 1.00. Spearman correlation coefficients between DSF and SFA were very high but each recorded low coefficient when correlated with DEA results.

They found out that relationship between technical efficiency and education was positive for DSF and SFA but negative for DEA. This clearly shows that the effects of determinants of efficiency are defined by the method used. They therefore proposed the latent variable analysis approach.

Singh, Coelli and Fleming (2000): This research sort to measure the performance dairy firms in both cooperatives and private sectors in India. The data were collected between the 1992/93 to 1996/96 seasons. Considering the competition between the private firms and the cooperatives, they chose to measure the performance by how cost efficient the firms were, i.e. they measured their cost efficiencies. This efficiency which is also known as economic efficiency was decomposed into technical and allocative efficiencies. They employed both DEA and SFA for their analysis. The sample included 23 firms comprising 13 cooperatives firms and 10 private firms. Although the difference was insignificant at 5% significance level, the cooperatives firms were more cost efficient than the private firms. They found out that over that period mean technical, allocative and economic efficiencies for cooperatives were 0.887, 0.927 and 0.822 respectively with SFA, while it recorded 0.888, 0.657 and 0.585 respectively for DEA. With the

private firms, SFA results for technical, allocative and economic efficiencies were 0.885, 0.883 and 0.780 respectively whiles that of DEA were 0.943, 0.707 and 0.67. Per each method, the cooperatives were more efficient in all the efficiencies than the private firms under SFA. However it was the reverse in the case of the DEA; it showed that the private ones were more efficient in all the three efficiencies than the cooperatives. They however, upon observing abnormally large and erratic measures especially in the allocative measures, made them not put their trust in the DEA results, hence the conclusion by the SFA results.

They concluded that, the effort the government is putting in encouraging more private dairy firms is not worth it since they are relatively cost inefficient.

Wadud and White (2000): Using farm level data, they estimated the technical efficiency of rice farmers in Bangladesh. Both CRS and VRS assumptions were considered. They used both SFA and DEA and compared their results. Technical efficiency estimates were then regressed against farm-specific socioeconomic factors, environmental factors and irrigation infrastructure. Under the DEA method the mean technical efficiency estimates for the CRS and VRS assumptions were 0.789 and 0.858 respectively. 41 farms were recorded as fully efficient under VRS against 20 farms under CRS. With a mean scale efficiency of 0.921, most of the farms were characterized by decreasing returns to scale, followed by constant returns and few with increasing returns to scale. For the SFA results, mean technical efficiency was 0.791, with scale efficiency of 0.889. Both methods imply substantial technical inefficiency and at the same time a mild decreasing returns to scale phenomenon. The results from the two methods seem to agree because the correlation coefficient between the SFA and DEA results was high.

Technical inefficiency was found to be positively affected by age. That is, older farmers tend to be more inefficient then the younger ones. They attributed this to the less receptive nature of older farmers to technology compared to the younger ones. Education was also found to be positive. Implying more education

means more technical inefficiency. Land fragmentation (plot sizes) and soil quality which is a dummy variable, were all negative. This indicates that farmers with greater plot size and good soil tend to be less inefficient. Irrigation fuel recorded a positive coefficient implying that diesel driven irrigation schemes are more inefficient.

Reinhard, Lovell and Thijssen (2000): Even though this research is environmentally inclined as opposed to output and cost inclination of this thesis, it is worth reviewing because it is one of the earlier studies with focus on agriculture. They used both DEA and SFA to calculate both technical and environmental efficiencies of the Dutch dairy farms. The environmentally detrimental inputs considered for the environmental effects were nitrogen surplus, phosphate surplus and the total (direct and indirect) energy use. They defined environmental efficiency as the ratio of the minimum feasible to observed use of multiple environmentally detrimental inputs, conditional on observed levels of output and the conventional inputs. From the DEA and SFA, technical efficiency from the output oriented approach was found to be 0.78 and 0.89 respectively. However, environmental efficiency was 0.52 and 0.80 respectively. In the calculation of the environmental efficiency by the SFA method, they realized that phosphate surplus defied the monotonicity assumption in more than half of the data. This forced them to drop it leaving only nitrogen surplus and total energy use. Considering them separately, nitrogen surplus had a very low inefficiency compared to energy use, which fell marginally below the overall environmental efficiency. This indicates that environmental efficiency is largely determined by energy use.

In the DEA analysis all the environmentally detrimental inputs were considered. Nitrogen surplus and phosphate surplus recorded low efficiencies. Energy use however recorded an efficiency level higher than the overall mean efficiency. In both methods, it can be seen the farmers are not so much concern with the efficient use of nitrogen and phosphate, but concentrate more on energy

use. Technical efficiency scores from SFA were about 10% higher than that of DEA. In the case of the environmental efficiency, it was about 30% higher.

### 2.3. General DEA and SFA Studies

In this subsection agriculture related papers employing both DEA and SFA are reviewed. However more preference is given to those that employed the combination of both methods, with maize as the crop under study. Next attention is given to studies that used both methods but with other cereals, especially rice and wheat.

#### 2.3.1. DEA and SFA Analyses with Maize as Crop

Orhun and Orhun (2013): Technical, allocative and economic efficiencies of maize farmers in 15 villages of the province of Canakkale, Turkey, were examined in this study. Maize yield represented output, whiles the inputs were, labor, machine, amount of seed and nitrogen usage. In both methods CRS and VRS assumption were made. SFA results yielded 0.769, 0.871 and 0.778, while DEA approach estimated 0.842, 0.782 and 0.647 respectively for technical, allocative and economic efficiencies. At 1% significance level, the efficiency values were highly correlated indicating an agreement between the two methods.

Farm size, number of irrigations and irrigation interval were found to have a positive and significant effect on technical efficiency. The effect of farm size on efficiency agrees with Wadud and White, (2000), Sharma, Leung and Zaleski, (1997) and Sharma, Leung and Zaleski, (1999) studies. However number of irrigations had a negative and a significant effect on allocative and economic efficiencies. Even though the age of farmers had a positive effect on efficiency levels, it was insignificant. Education level of farmers was the only determinant to have a negative and an insignificant effect on all efficiency values. This implied that farmers with higher education were more inefficient than those with lower

level of education. They inferred that, farmers with lower education concentrate more on farm activities than the educated ones who normally have additional jobs or responsibilities. The effect of education contradicts that of Wadud and White (2000).

Kaçıra (2007): This study also measured technical, allocative and economic efficiencies of maize producers in Şanlıurfa, Turkey, employing DEA and SFA. For the DEA analysis, she calculated the results for both output and input orientation. The mean technical, allocative and economic efficiencies for SFA were 0.84, 0.78 and 0.64 respectively, whiles DEA results were 0.81, 0.87 and 0.77 respectively. The two results were found to be highly correlated, indicating the extent to which the two methods agree. Tobit regression analysis was also used to determine the causes of inefficiency. It was found that the number of irrigation, watering frequency and land size had positive effect on technical efficiency. However all except land size was significant. In addition to not having significant effect on efficiency, education and age of farmers were negatively related to technical efficiency. In the case of economic efficiency, all but watering frequency was significant even though it had a negative effect on economic efficiency. Among the insignificant determinants, all but education had a negative effect on economic efficiency.

Hassan, Y. et al. (2014): The study calculated only technical efficiency of maize production in the whole of Nigeria. The data used was secondary and panel from 1971 to 2010. Both DEA and SFA were used in the analysis of the technical efficiency. In the DEA analysis CRS and VRS assumptions were employed. Data were collected on the following variables; maize output, quantity of maize seed, area harvested, quantity of fertilizer, labor used (No. male and female economically active in agriculture) and the number of tractors in use. Because the data were panel, they found it necessary to test some hypotheses just to be sure that a problem within the data did not evolve in time that could jeopardize the statistical inference to be conducted on the results, especially that of SFA. The Augmented Dickey

Fuller (ADF) unit root test was used to test the null hypothesis that the data are not stationary. This was rejected by the test. To investigate whether there could be a long term relationship between the variable, Johannes co-integration test was used to test whether there has been a no co-integration among the variables. This null hypothesis was also rejected.

The mean technical efficiency score for SFA was 0.64. Those of DEA under CRS and CRS were 0.77 and 0.87 respectively. Both methods indicate the presence of inefficiency. DEA efficiency results were higher than those of SFA, however SFA did not record a fully efficient farm as compared to DEA which recorded 6 and 15 under CRS and VRS respectively. Across the two methods most of the farmers were found to be in the range of 0.71 and 0.80 efficiency levels.

Ngeno et al. (2013): Even though maize production is the major agricultural activity in Kenya, it does not meet the domestic demand. The study was done in Uasin Gishu District in Rift valley province, which is considered one of Kenya's bread basket districts. The researchers aimed at measuring its technical efficiency. Across different categories of maize farmers, a sample of 540 farmers was chosen through a multi-stage random sampling. These categorizations were small, medium and large scale farmers, defined as less than 20 acres, between 21 and 49 acres, and above 50 acres respectively. DEA and SFA were used to independently analyze technical efficiency. The results of these two methods were compared. Overall, the mean technical efficiency was 0.85. In terms of the categorizations, the mean efficiencies for small, medium and large scale farmers were 0.8, 0.83 and 0.95 respectively. This clearly indicates the efficiency advantage the large scale farmers have over the medium and small scale farmers. It was also found that the proportion of farmers with higher efficiency score were more in the large scale category than the other two categories.

Another important discovery they made was in relation to what was responsible for the deviation from the stochastic frontier. The gamma ($\gamma$) parameter calculated from the SFA, indicates the extent to which deviation from the frontier

is caused by inefficiency or statistical noise. The closer it is to one, the more likely the deviation is caused by inefficiency, and the closer it is to zero, the more likely the deviation is caused by random statistical noise. The gamma ($\gamma$) ratio for the large, medium and small scale farmers were 0.970, 0.997 and 0.696 respectively. Even though the effect of inefficiency is more in all the three categories, those of large and medium scale farmers were profound.

Ogunniyi and Ajao (2011): Maize being a strategic crop in Nigeria, the researchers decided to measure the technical efficiency of its production in Oyo State. Having reviewed the pros and cons of DEA and SFA, they decided to employ the mixed method. Using a two-stage random sampling technique, they randomly selected 5 villages. From these villages 16 maize farmers were randomly selected from each making a total sample size of 80 farmers. The variables they consider for the efficiency measurement were; maize output, farm size, labor, seed, fertilizer and pesticide. In the DEA analysis CRS and VRS assumptions were considered. They also calculated the scale efficiency too.

Averagely, the technical efficiency score were 0.659, 0.326 and 0.829 for SFA, CRS and VRS respectively. While 9 farmers and 32 farmers under CRS and SFA respectively were fully efficient, the highest efficient farmer under SFA was 0.829. The very large difference between the results of DEA-CRS and DEA-VRS explain the existence of substantial amount of scale inefficiency. With a mean scale efficiency of 0.384, 10 farmers exhibited CRS while the rest of the 70 farmers were operating under IRS (Increasing Returns to Scale). This indicated that farmers could be more efficient by increasing their farm size. Spearman correlation coefficients between the results of the two methods revealed a positive relation, indicating how the two methods agree. The strongest correlation was between SFA and DEA-CRS results. The researchers also identified the issue of input slacks. All the inputs used recorded slacks with varying proportions. Seed had the highest with 17.16% excess used. The rest are farm size (9.10%), labor (10.08%), pesticide (16.80%) and fertilizer (9.58%).

Geta et al. (2013): This research was conducted on smallholder maize farmers in Southern Ethiopia. They set out to measure the productivity and technical efficiencies of these farmers, as well as determine their causes. Using random sampling techniques a sample of 385 farmers was drawn. They used the parametric method (SFA) to calculate the productivity and employed the non-parametric method (DEA) in the estimation of technical efficiency. This method is a little bit different from the other application. In the case of the parametric methods, a normalized translog production function was employed in the estimation of productivity and its determinants, whiles in the identification of causes of inefficiency a tobit regression model was used. Maize output represented the dependent variable of the function whiles the inputs were fertilizer, labor, seeds and oxen power. The determinants of productivity were planting method, hybrid variety, farm size, tropical livestock unit, integrated soil fertility management, frequency of extension contact, distance to development center, credit and off-farm income. There were common variables between the determinants of productivity and that of technical efficiency; agro-ecology, rain distribution, sex, age, education, family size, oxen power, farm size, hybrid variety, frequency of extension contact, distance to development center, credit and consumption expenditure.

The productivity results showed that productivity was significantly influenced by the use of labor, fertilizer, and oxen power. Even though the coefficient for seed was positive, it was insignificant. On the determinants of productivity, planting method, hybrid maize seed and the application of integrated soil fertility management practices were positive and significantly influence maize productivity. As expected, off-farm income was the only determinant with a negative and significant effect on maize productivity. For the DEA results, the mean technical efficiency was found to be 0.4. This indicates a great amount of inefficiency, only about 7% of them scored above 0.9, with majority of them in the range of 0.2 to 0.3. Among the determinants of efficiency, farm size, hybrid maize,

agro ecology, oxen power and consumption expenditure were positive and highly significant. Even though some recorded negative, they were not significant.

### 2.3.2. DEA and SFA Analyses with Focus on Other Crops

Ismail et al. (2013): The researchers expressed the importance of technical efficiency measurement for policy purposes, especially if the policy is aimed at country's food self-sufficiency. The technical efficiency of a strategic crop like paddy in Malaysia is worth calculating. Using DEA and SFA methods, the study compared the technical efficiencies of paddy farmers in the east coast and the west coast of the Peninsular in Malaysia. A translog stochastic function was used in the SFA analysis. The sample for the two locations was 230 farmers. The results of the two methods were then compared. The maize yield was considered output against farm size, expenses on seeds, expenses on fertilizer and the number of workers as inputs. For the determinants of efficiency, pesticide, education, experience and training/seminar were considered. The mean technical efficiencies were 0.56 for DEA and 0.69 for SFA. The difference is expected even though it is a little bigger. The fact that DEA considers all deviations from the frontiers as inefficiency is expected to have a lower efficiency value than SFA. In both methods, farmers in the east coast were more efficient than their counterparts in the west coast. The west coast recorded 0.58 and 0.66 for DEA and SFA respectively while the east coast recorded 0.51and 0.72 respectively.

Pesticide, experience and training/seminar were found to have a positive and significant influence on technical efficiency. There were however disparities in the two locations. Education is the only determinants with a negative influence on technical efficiency. This is in line with the findings of Orhun and Orhun (2013).

Parlakay and Alemdar (2011): This study employed DEA and SFA to estimate the technical, allocative and economic efficiencies of 90 peanut farmers in Adana and Osmaniye provinces in Turkey. These two provinces together produce

about 80% of the total peanuts output in Turkey. Data used were peanut yield, pure nitrogen, pure phosphorus, machinery operating time, labor and pesticide cost. In the case of the efficiency causes, they considered education, planting area, appropriate nitrogen use, family labor, number of irrigations and number of plots. Even though they estimated for both input and output orientations for the DEA, they used only the results of the output orientation in the comparison with the SFA results. For the DEA, they also assumed both CRS and VRS separately in their analysis. After the analysis, they found technical efficiency within the range of 0.81 and 0.86, and economic and allocative efficiencies were 0.60 and 0.74 respectively. Correlation between the results was high, indicating that the two methods agree.

On the determinants of efficiency, it was revealed that, a negative relation existed between efficiency and education, planting area, and use of appropriate nitrogen levels. The effect of education agrees with Ismail et al. (2013) and Orhun and Orhun (2013). All but use of appropriate nitrogen level was insignificant. This means an increase in any of these should not be encouraged since they will lead to increase in inefficiency. Technical efficiency was however positive with family labor, number of irrigations, and number of plots. But only family labor was significant.

Alemdar and Ören (2006a): Data were gathered from 75 wheat farmers from the Southeastern Anatolia region of Turkey. At the farm level, data were collected from the wheat farms for 2003/2004 planting season. Using DEA and SFA methods, they estimated their technical efficiencies. Their scale efficiencies were also calculated. For the DEA analysis, both CRS and VRS assumptions were considered. One output and six inputs were used in the analysis. Wheat yield was the output whiles seed, fertilizer-N, fertilizer-P, labor, machine and pesticide represented the inputs.

CRS and VRS assumption under DEA recorded 0.72 and 0.79 respectively, with an average scale efficiency of 0.92. The mean estimate for the SFA was 0.73.

Even though no farmer was fully efficient under SFA results, 21 farmers under CRS and 28 under VRS were fully efficient for DEA. The highest efficiency firm under SFA was 0.93. The study did not agree with the conventional lower DEA results compared with SFA results. It was rather the opposite which they suggested is not abnormal especially in cases where the DEA frontier envelopes data tightly.

The SFA revealed that all inputs but fertilizer-N had positive effect on wheat output. Out of which only pesticide was statistically insignificant. The negative of fertilizer-N suggest an existent of input slacks that could be reduced without reducing output levels. At 5% significance level, the null hypothesis that there is no technical inefficiency in model was rejected giving way to proceed to determine the causes of inefficiency. The scope of the study however did not cover finding the determinants of efficiency.

A strong positive correlation between the results showed the extent to which the methods agreed. They were all significant. Again, the researchers sort to find out the extent to which the two methods would agree in identifying the best and worst performing farmers. While 67% of the best performing farms were common among the techniques, the percentage for the worst performing farms was 78%. This further confirms the consistency of the two methods. They however suggested more research to determine the causes of inefficiency.

Ören and Alemdar (2006): DEA and SFA methods were used to measure the technical efficiency of tobacco farmers in Southeastern Anatolia, Turkey. Data were gathered from 149 farmers for the 2000/2001 production season. Ten villages were chosen from Adıyaman Province, which produces about two-thirds of total tobacco in Southeastern Anatolia. Simple and stratified random sampling techniques were used. Outlining the advantages and disadvantages of both methods, they defended the need to use the both methods and compare their results. The CRS and VRS assumptions were separately considered in the case of DEA analysis. Whiles tobacco yield was used as output in the analysis, fertilizer-N, fertilizer-P, labor, draft power and pesticide, represented the inputs.

For DEA CRS and VRS assumptions, mean efficiency scores were 0.45 and 0.56 respectively, while that of the SFA was 0.54. The variation in the DEA results under CRS and VRS indicates the presence of scale efficiency which they calculated to be 0.82. Whiles only 18 farmers were operating at the optimal scale, 50 and 81 farmers were operating under increasing returns and decreasing returns to scale respectively. Further analysis revealed that no farmer was fully efficient under SFA and the highest score was 0.88. However for DEA, 17 farmers under CRS and 33 farmers under VRS were fully efficient. In terms of slack analysis, all the inputs had sufficiently large input slacks. The highest was fertilizer-N, which was used in excess of 35.5%, while the lowest was fertilizer-P, with 16.6% excess usage. To pave way for the possibility of further research on the causes of technical efficiency, the null hypothesis that there is no technical inefficiency in the model was rejected at 5% significance level. This meant that determinants of technical efficiency could be researched, but the scope of this paper did not include that.

The two methods also agreed in identifying best and worst performing tobacco farmers. The proportions of farmers identified by both methods were highly correlated and significant as well. A Spearman correlation coefficients of the technical efficiencies from both methods showed a very strong correlation and significant as well. They however expressed the need for further research to determine the causes of inefficiency.

Minh and Long (2009): They estimated technical, allocative, and economic efficiencies of agricultural production in Vietnam using both DEA and SFA. A time series data were taken from sixty provinces from 1990 to 2005. In both methods, CRS and VRS assumptions were employed. The SFA used Cobb-Douglas stochastic production frontier in the estimation. In the analysis, output was defined as the sum of the value-added of major agricultural production activities like farming, forestry, animal husbandry, fishing, and sideline activities within each district. For the inputs, labor used in all the above mentioned activities, total

number of fertilizers used and the total land area on which these activities are taking place.

The mean estimates were 0.663, 0.8052, and 0.5392 respectively for DEA whiles SFA recorded 0.4688, 0.9035, and 0.4218 respectively. Under both CRS and VRS assumptions, the slope coefficients of all the inputs in the stochastic production frontier were positive and highly significant. These coefficients which represent output elasticity were very high for labor than fertilizer usage. This meant that production under the time reviewed was labor intensive. Using the maximum likelihood estimates (MLE), they tested the null hypothesis that there is no inefficiency in the model under consideration. This was however rejected indicating that, the production function would not be appropriate without the inefficiency term.

In the results of DEA, the mean efficiency under CRS and VRS were 0.663 and 0.726 respectively, which resulted in a scale efficiency of 0.909. In the case of SFA, the mean technical efficiencies were 0.373 and 0.468 for CRS and VRS respectively. It can be seen that under the same returns to scale, the two methods produced significantly different results. Even though a spearman correlation showed a high degree of correlation between the two methods under CRS and VRS, they concluded that returns to scale is critical in explaining differences in efficiency scores under the two methods.

Ajibefun (2008): With the use of both DEA and SFA, he estimated the technical efficiency of small scale Food crop production in Nigeria. Considering the pros and cons of both methods he used both methods and sought to analyze the sensitivity of technical efficiency scores to the choice of method used. A multi-stage sampling which involved the use of both random and purposive sampling method was used to select 200 farmers. Data were collected on output, which represented the monetized form of various outputs of different food crops. Land, labor, implements, fertilizer and seed were the inputs used in the analysis. For the

determination of the causes of efficiency, data were also collected on farmer's age, level of education, household size and farm size.

After comparing the results of the two methods, the mean technical efficiency was found to be 0.68 for SFA and 0.65 for DEA. Whiles four farmers were fully efficient under DEA analysis, there was none under SFA. However, they all revealed that the efficiency scores of most of the farmers fell within the range of 0.61-0.70. The input slope coefficients in the stochastic production, which represent output elasticity, were all positive and significant at 5% significant level. This means that an increase in any of the inputs would lead to an increase in output. Even though the scale efficiency depicted increasing returns it was not significantly different from constant returns to scale.

Age of farmers and their education level were found to have significant influences on the level of technical efficiency. Age was negative while education was positive. In terms of the effects of age, the findings here agrees with Wadud and White (2000), who suggested the inability of the older farmers to adopt to new technologies could explain this relationship. However the conclusion on the effects of education is in sharp contrast with their findings. Comparative Frequency Distribution of the efficiency score of the two methods was plotted; it revealed how the two methods agree. The pattern was almost perfectly the same.

Vu (2012): This technical efficiency study was conducted on rice farming households in Vietnam. Rice is grown on 84% of agricultural lands, constitutes 85% of all food grain output as well as providing 85% of daily calorie consumption of Vietnamese. Both DEA and SFA were used in the analysis. To increase the statistical precision of DEA estimates, a bootstrap method was used. In the end, there were three methods to be compared; DEA, DEA semi-parametric bootstrapping procedure and SFA results. In the second stage where he sought to find the causes of inefficiency, he used the results of DEA and SFA as the dependent variables. Scale efficiencies were also estimated. Harvested rice represented the output whiles the inputs were fertilizers, pesticides, seed,

equipment, family labor, hired labor, owned fixed asset, hired asset, small tool and energy, and rice land.

The mean technical efficiency for DEA and SFA were 0.765 and 0.634 respectively. The bootstrapping method or the bias-corrected TE was 0.678, which is lower than the original DEA but closer to the SFA results. Average scale efficiency was 0.890, however larger farmers were more scale efficient than smaller ones. Under the DEA, only 23% were operating optimally, whiles as much as 59% were operating under increasing returns to scale. The summation of the coefficients of the Cobb-Douglas stochastic production function was 1.098 indicating increasing returns to scale. A hypothesis test revealed that this is significantly different from constant returns to scale. It was also found that bigger farms were more technically efficient than smaller farmers. They also had a larger proportion of farmers being fully efficient.

In determining the causes of efficiency, the research used 18 variables. Out of which all the three methods recognizes the positive impact of education on technical efficiency even though variations exist in the primary, secondary and higher education. Farm size, irrigation and labor intensive variables recorded positive coefficients. The effect of extension and non-farm income ratio on efficiency were not significant

**2.4. Determinants of Efficiency with DEA and SFA Analyses**

Boundeth, Teruaki and Shigeyoshi (2012): The researchers observed a changing trend in the production of cash crops in Laos. Maize is ranked second among the cash crops in Laos. They observed more inputs (labor, land, fertilizer etc.) are now required to increase maize production which directly reflects falling productivity and efficiency. The authors considered their work as the first of its kind in Laos, i.e. measuring technical efficiency of maize in Laos. Only SFA was used for the measurement. They argued in favor of SFA as the best method for agricultural analysis in developing countries, and therefore saw no need for other

methods. They considered Cobb-Douglas and translog stochastic production functions. They also tried finding the determinants of efficiency of maize production. For the efficiency analysis they gathered data on yield, labor, seeds, fertilizer, and machinery services. For the determinants of efficiency, they used farm size, farm experiences, age of farmer, household size, farmer education, farmland elevation and hybrid or improved seeds.

The mean technical efficiency was 0.65, indicating a substantial amount of inefficiency in maize production. The distribution of these efficiency estimate showed that only 30.6% of the farmers had their score above 0.8. The gamma ($\gamma$) was 0.687, indicating that; about 68% of variation from the stochastic frontier is caused by inefficiency rather than random statistical noise, like luck, bad weather, disasters etc.

Before establishing the determinants of efficiency, likelihood ratio (LR) test, which is defined by chi-squared ($\chi 2$) distribution, was conducted to affirm or deny the significance of the inefficiency estimates calculated above. The test rejected the null hypothesis that, the existing inefficiency has no significant effect on the data available. This then gave way for them to determine the causes of efficiency. Under the Cobb-Douglas and translog stochastic production functions, all the coefficients agreed with the exception of Farmer age which recorded a positive effect on efficiency under Cobb-Douglas and negative under translog. Generally farm experience, education and land elevation are found to be significant, and positively affects efficiency.

Alemdar and Isik (2008): This research was carried out on peanut farmers in İçel, Adana and Osmaniye provinces which produces about 80% of all peanut output in Turkey. Using stratified random sampling, 75 peanut farmers were selected for the study under 2000/2001 production season. Peanut yield represented output whiles the inputs consisted of seed, fertilizer-N, fertilizer-P, labor, machinery and pesticide. The variables for the determinants were age of the farmer, education level of farmer, peanut farming experience, total land size, number of

peanut plots and location of the farm. With the DEA method, they were able to estimate the mean technical efficiency at 0.79 for CRS assumption, 0.92 for VRS assumption and scale efficiency of 0.86. In terms of slacks all the inputs recorded excess usage among some farmers. However, fertilizer-N was widely misusage by 33.3% by 42 farmers.

On the determinants of efficiency, VRS DEA technical efficiency scores were regressed on the above mentioned variables with a two-tailed tobit model. It revealed that farmer age, peanut farming experience, farm location and farm size had a strong and significant effect on efficiency. However farmer age and farm location had negative and the rest had positive effects.

Alemdar and Ören (2006b): Following 2000-2001 farming season, the researchers gathered data from wheat farmers in the Southeastern Anatolian region of Turkey. This research is a follow up research on Alemdar and Ören (2006a) they conducted in which they recommended further research into the determinants of technical efficiency of wheat farmers in Southeastern Anatolia. Using different data set of different planting season they researched into the determinants. In the previous work they decided to use DEA and SFA in estimating the technical efficiency, but they only employed DEA in this since much emphasis is not on estimating the efficiency but finding its causes. The same variables are used in the two papers for the efficiency estimation. Tobit regression analysis was used. For the efficiency determination, age of the farmer, education of the farmer, share of family labor, number of plots, land size and specialization were the possible determinants analyzed.

The mean technical efficiency for CRS and VRS were 0.65 and 0.83 respectively, resulting in a scale efficiency of 0.78. Input slacks were recorded with machinery being the most wasted input by 67 farmers. In the case of tobacco by these same researchers (Ören and Alemdar, 2006) in the same region, fertilizer-N was the most wasted input.

For the causes of efficiency, age of farmers recorded a positive coefficient indicating that older farmers are more efficient then the younger one. This result however was not significant. This is a direct contrast to the findings of Wadud and White (2000) as well as Ajibefun (2008), who think that younger farmers are more efficient because their ability to easily adopt to technology. Formal education was found to negatively affect technical efficiency. Even though this was also not significant, the researchers explained that educated people do not take farming as full time job because they have other opportunities with their education certificates. Family labor was found to be more efficient than hired ones especially in the sense of cost reduction. This effect was significant under 10% significant level. They also discovered that the number of plots (land fragmentation) had a negative and significant effect on technical efficiency. This finding improved the internal consistency of the analysis by the fact that machinery was the most wasted input. The time machines spend moving from different plots to the other is a complete waste from the cost point of view. In this regard they recommended a comprehensive land consolidation policy.

Koç, Gül and Parlakay (2011): This research was conducted in two provinces (Adana and Hatay) in the Eastern Mediterranean region of Turkey. After wheat and barley, maize is the third most important grain in terms of planting area and output in Turkey. By way of stratified random sampling procedure, eighty nine (89) second crop maize farmers were chosen. Following the 2004-2005 growing season, data were collected from second crop maize farmers by way of questionnaires. The input oriented DEA technical efficiency was estimated. After which, a tobit regression analysis was employed to establish the causes of technical efficiency. Maize yield was used as the output whiles pure nitrogen, pure phosphorus, seed, labor and machinery represented the inputs. To determine the causes of efficiency, they considered Farmers' age, education level, maize areas, number of irrigation, number of pesticide and off-farm income. Both CRS and VRS assumptions were considered.

On average, technical efficiency was 0.72 under CRS and 0.88 under VRS, with a resulting scale efficiency of 0.81. However, 88% of the farmers were operating below the optimal scale. Fertilizer-P and labor were the inputs most misused in terms of input slacks. Maize areas, age and off-farm income were found to have a positive effect on efficiency. However, all but maize area were significant. Pesticide application, number of irrigation and education level recorded a negative and an insignificant relationship with technical efficiency.

Erdal (2010): Data were collected from wheat farmers following the 2004/2005 agricultural season in the Çukurova region of Turkey, specifically Adana and Hatay provinces. Using input oriented DEA, he estimated the technical efficiencies of these farmers. A tobit regression model was then used to determine the causes of inefficiency. Stratified sampling procedure was used to select a total of 103 wheat farmers. Inputs used were pure nitrogen, pure phosphorus, seed, labor, machinery and pesticide. The socio economic variables were education level, number of wheat plots, location of land, experience of the farmer, wheat harvested land and farmer age

The mean technical efficiency under CRS and VRS were 0.59 and 0.80 respectively. This resulted in a scale efficiency of 0.72. About 85% of the farmers were operating under the optimal scale. Pesticide and labor recorded the highest percentage of input slacks. Formal education had a positive and significant effect on technical efficiency. This finding however, did not agree with that of Alemdar and Ören (2006b) who concluded that educated farmers are less efficient because they have extra jobs to do with their academic qualifications. To support his findings, he attributed it to the readiness of educated farmers to adapt to new technologies and innovations. Number of plots (land fragmentation) recorded a negative effect, which was also significant at 5% significance level. The two findings (with the studies of Alemdar and Ören, 2006b) however agreed on this one. This was expected because the more the number of plots the more expensive it is to use machinery and labor. It was also found that the higher the elevation of

farm land, the lesser the technical efficiency, this effect too was also significant at 10%. Experience of the farmer, wheat harvested land and farmer age had positive effects, but none was significant.

Lira et al. (2014): In their bid to improve the productivity of rice production in Malaysia, they suggested an improvement in the efficient use of agricultural inputs as well formulate policies to address the determinants of efficiency. In this regard they measured the technical efficiency of these rice farmers, their production and substitution elasticities as well as determine the causes of technical efficiency. They did this by employing on SFA method. Land, seed, fertilizer, pesticide and labor were the five inputs used, whiles rice yield represented output. In determining the causes of efficiency, age household size, job, extension, experience, land ownership, access to credit and education. Both Cobb-Douglas and translog production frontiers were separately employed.

The results of the production elasticity analysis revealed that, all but labor was significant under the Cobb-Douglas. Fertilizer recorded the highest of 0.20, indicating that a 1% increase in fertilizer application could result in 0.20% increase in rice output. In the case of the translog production frontier all but labor and fertilizer were significant. All of them recorded an elastic elasticity with land being the highest; 1.5. On the issue of gamma ($\gamma$) ratio, which measures the proportionate effect of inefficiency and random errors on the deviations from the frontier, all the two production frontiers found them significant. It was 0.93 for Cobb-Douglas and 0.91 for translog. This means that more than 90% of deviations from the frontier are causes by inefficiency. This gives way for the determination of causes of efficiency. The hypothesis test on the inefficiency effect model for the absence of technical efficiency was rejected. On average the technical efficiency of the sampled farmers was 0.854. Large percentage of them scored above 0.9, while no farmer scored below 0.5.

To determine the causes of inefficiency a hypothesis test was conducted as to which of the two frontiers suits the data more. It was found out that translog was

better than Cobb-Douglas, hence the use of the former in the determination of the causes of inefficiency. Access to credit and education level of farmers were the only variables with significant and negative effects on technical inefficiency. They argued that farmers who take credit for farming are very conscious of input minimization so as to be able to repay the loan. This increases their efficiency. Educated farmers are equipped with better skills, well informed and good farm managers, which ultimately leads to decrease in inefficiency as seen from the results. However this did not agree with Alemdar and Ören (2006b).

Coelli and Battese (1996): SFA was used on farm level data to calculate the technical efficiency as well as determine its causes in India's agricultural production. Unlike the popular two-stage analysis, where technical efficiency is first calculated and then regressed upon the determinants of efficiency, the method used in this paper combines the variables in the stochastic frontier production function and those in the inefficiency effect model. With stratified sampling they chose 273, 289 and 268, from Aurepalle, Kanzara and Shirapur villages respectively. Data were collected from predominant crops from these villages; castor, sorghum, paddy, cotton, pigeon pea, chickpea, wheat and vegetables.

Value of these crops were used as output, whiles land, irrigated land, labor, hired labor, bullock labor, cost of other inputs, age and education level of farmers, year of observation and farm size represented inputs. The last four variables represented the determinants of inefficiency.

The results of the production analysis show that, for all the three villages the coefficients of land and labor were positive. Irrigated land had a positive sign and significant for two villages, but negative and significant for Shirapur village, which to them a strange result which demands further research. Hired labor was found to be less efficient than family labor. Bullock labor is negative for all the three villages but significant for only one. Cost of other inputs recorded positive but significant for only two. The year of observation was positive except for one. The positive indicates technological progress. The gamma ($\gamma$) ratio which was 0.9

indicates the important effect inefficiency is having in the agricultural process, stressing the need to find the causes of inefficiency.

On the determinants of inefficiency, age negatively and significantly affected technical inefficiency in two villages but was positive in Shirapur. This mixed effect is not surprising as various researches found different effects of age depending on the location. Koç, Gül and Parlakay (2011) and Alemdar and Ören (2006b) agreed with the case of the two districts that older farmers are more efficient whiles studies like Wadud and White (2000) and Ajibefun (2008) supported the case in Shirapur that older farmers are less efficient. Education was negative for Aurepalle and Shirapur, but positive for Kanzara. This is also not surprising because, some researchers argue that people with higher educational level turns to pay less attention to farming hence less efficient, while others also argue that educated people are more receptive to technology and innovation in farm management which makes them more efficient. Studies like Ajibefun (2008) and Vu (2012) conform to the findings in Aurepalle and Shirapur where more educated farmers are more efficient. However Orhun and Orhun (2013) and Ismail et al. (2013) concluded educated farmers are less efficient like in the findings in Kanzara. That of land was negative for all the three villages, indicating that larger farmers are more efficient than smaller ones. For the year of observation parameter, the effect was negative for all the three villages, indicating that farmers tend to be more technically efficient over time.

Mburu et al. (2014): The aim of the research was to determine the causes of economic efficiency of Wheat Farmers in Nakuru District of Kenya. Technically, they had to calculate technical, allocative and economic efficiencies. The data were collected from 138 farmers comprising large and small scale producers. Cobb-Douglas stochastic production frontier and cost function were used in the estimation of those efficiencies. Whiles wheat output represented the output of the function, fertilizer, seed, chemicals, foliar, hired labor and family

labor represented the inputs. In the Cobb-Douglas cost frontier function, the cost of the above variables represented the parameters in the function.

Among the inputs, only family labor had a negative and an insignificant relationship with the wheat output. However, seed, fertilizer and chemicals were significant. In the stochastic cost function, as expected all the inputs had a positive relationship with cost of wheat production. On average, technical, allocative and economic efficiencies were 0.85, 0.96, and 0.84 respectively. In terms of farm size, larger farmers were more technically and economically efficient than the small ones, but it was the reverse in allocative efficiency. All these differences were statistically significant. Out of the eleven socioeconomic variables considered as the possible causes of efficiency, few were significant. Farm size was significant for only allocative efficiency. Education was significant for technical and economic but not allocative efficient. Main occupation was significant for only allocative, whiles distance to extension service was significant for both technical and economic efficiencies. Among the significant factors only distance to extension service was negative for all the three efficiencies. Main occupation was negative for only allocative efficiency whiles the rest of the significant factors were all positive. They therefore concluded that education, distance to extension advice as well as farm size have strong effects on the efficiency levels.

### 2.5. General Efficiency Studies in Ghana

Efficiency and productivity studies in Ghana's agriculture have been very scanty. This has led to less application of more robust techniques in the studies. As far as I have researched, there are no efficiency studies in Ghana that fully fit the methodological layout of this study. That is, calculating the three efficiency measures from the same data and at the same time applying both parametric and nonparametric methods. Few of them investigate the causes of inefficiencies. Nonetheless, some studies would be reviewed, with preference given to those on crops.

Al-hassan (2008): He estimated farm-specific technical efficiency of rice farmers on irrigated and non-irrigated lands in Northern Ghana using data from the 2005/2006 farming season. The determinants of efficiency were also determined. This study area comprises of three regions namely; Northern, Upper East and Upper West Regions. Using a multi staged sampling techniques, a total of 11 districts were chosen across the three regions. Out of which, 252 farmers practicing irrigation and 480 non-irrigators were selected for the study. He employed the SFA method with a translog functional form. Labor, seed, chemical fertilizer, pesticides, animal power (bullock), machine power (tractor), manure and irrigation expenses were initially considered the inputs for the analysis. However seed, pesticides, bullock plough and manure were excluded later for various reasons. Rice output per hectare represented the output for the translog production function. In order to determine the causes of technical efficiency, the study considered education of farmers, number of contacts with extension personnel, size of household, soil quality, amount of credit received for farming, and gender of farmers. An interactive variable between age and education was also included

The research revealed significant amount of inefficiency in rice farming. The average efficiency level for the total sample was 0.528, with non-irrigators slightly more efficient than irrigators, i.e. 0.534 and 0.512 respectively. Even though the difference existed, it was not statistically significant. Whiles the lowest was 0.12, the highest was 0.88, indicating no farmer achieved full efficiency. The other revealing part of this research was the results of the gamma ($\gamma$) ratios in both groups of farmers. The non-irrigators recorded 0.448, whiles the irrigators recorded 0.848. This reveals that, even though they both seemingly recorded the same inefficiency scores, that of the non-irrigators was largely due to factors beyond their control (i.e. statistical noise). That of the irrigators however, could be explained more by their inefficiencies than statistical or random noise.

Among the causes of efficiency variables, all but credit and gender recorded positive. However they were not significant at both 1% and 5%

significance levels. It was therefore concluded that education, extension contact, age and family size were the main causes of inefficiency. He recommended formal and informal education to farmers as well as training of more extension agents to improve efficiency.

Shamsudeen et al. (2013): This study applies only SFA in determining the technical efficiency of 360 maize farmers in the three Northern Regions of Ghana (Northern, Upper East and Upper West Regions). The study period covered the 2011/2012 cropping season. A Multi-stage sampling procedure was used in the selection of the sample. A likelihood ratio test conducted on the data revealed that translog production function was more appropriate than the Cobb-Douglas productions function. Maize output represented the output of the function whiles the inputs were represented by five inputs; farm size, quantity of seed, quantity of fertilizer, cost of labor and cost of weedicides. The variables considered for the determination of technical efficiency were, access to tractor services, number of years of maize cultivation, number of years in school, number of agricultural extension visits, gender of the farmer and the value of credit received for that particular farming season.

The mean technical efficiency estimate was 0.74, with 0.2 and 0.99 as the minimum and maximum scores respectively. The majority however fell between 0.8 and 0.9 score. Significant regional variations existed as 0.71, 0.74 and 0.85 were recorded for Northern, Upper East and Upper West Regions respectively. The returns to scale coefficient of 1.383 indicates increasing returns to scale implying that farmers were operating below the optimal scale. With a gamma ($\gamma$) ratio of 0.786, it means that deviations from the stochastic frontier were more explained by inefficiency than stochastic random noise. A test to establish whether the inefficiency in the model significantly affects the production function was conducted. It was revealed that the presence of inefficiency was statistically significant, hence the need to proceed to determine it causes.

All the determinants had a negative relation with inefficiency (positive with efficiency). However education, extension and credit were not significant. This implies that, aside the insignificant ones, an increase in any of the other variables would lead to increase efficiency of maize farmers in the three regions.

Sienso et al. (2014): This study was conducted on maize farmers in the Nkoranza District of Brong Ahafo Region of Ghana. The authors used the SFA method, adopting a translog production function for the 2008 cropping season. They also estimated their input allocative efficiencies (resource use efficiency), input elasticities as well as the determinants of technical efficiency. A sample of two hundred (200) farmers was chosen from twenty two (22) communities in thirty two (32) operational areas of the Ministry of Food and Agriculture. The first two stages were done purposefully while the final selection was done randomly. In the translog production function, maize output represented the output of the function while farm size, labor, fertilizer, agrochemicals and seed were the inputs for the function. The variables considered for the determination of causes of efficiency were maize variety, farmer's education, external support, gender, farming experience, household size, distance to farm, extension frequency, association membership and health status.

All the inputs had a positive relation with maize output except labor, which was also insignificant. In terms of the output elasticity which measures the percentage change in output when those inputs increase by 1%, the recorded values were 0.05, 0.02, 0.16, 0.011 and 0.059 for farm size, labor, fertilizer, agrochemicals and seeds respectively. Average technical efficiency was found to be 0.91. It was however observed that farmers using improved seeds had a lower efficiency than those using local ones. A t-test for the equality of means indicated they were statistically different.

With the exception of maize variety, gender, farming experience, distance to farm and extension, the rest were insignificant. All the significant determinants satisfied a priori expectations except maize variety. Its coefficient was positive

indicating that the use of improved seed would lead to increase inefficiency. An explanation was given to this abnormality from the data itself. It was found out that these improved seeds produce the potential output if it is accompanied by increased application of other inputs especially fertilizer. However, farmers who generally complained of high input cost are not ready to increase these accompanying inputs. They also suspected that the farmers may lack the skills needed to manage those seeds. They also found from the resource use efficiency that, whiles labor was over utilized, fertilizer and seed were underutilized.

Kuwornu et al. (2013): The study analyzed technical efficiency and its causes of maize farmers in the Eastern Region of Ghana. A total number of 226 maize farmers were selected through a multi-stage random sampling. The SFA with a translog production function was used. The selection of the translog over Cobb-Douglas was as a result of fitness test. Quantity of maize output represented output, whiles seed, fertilizer, agro-chemicals, other inputs and hired labor represented the inputs of the production function. Sixteen variables were investigated in relation to the causes of efficiency. The first four variables were locational variables.

Seed, fertilizer and family labor were found to be negatively related with output even though they were all statistically not significant. The rest were positive and significant. The efficiency scores reveal a substantial amount of inefficiency among maize farmers in the region. An average of 0.51 efficiency score was recorded. The gamma ($\gamma$) ratio of almost 1 points to inefficiency as the sole factor responsible for producing under the frontier. The scale efficiency of 0.47 indicates how much production is far below the optimal scale point.

All the locational variables are positive indicating that farmers in these areas have lesser efficiency scores. Only one was not significant. Extension visits and FBO membership were significant and positive, which is not in line with a priori knowledge. Formal training in maize farming, cash credit, in-kind credit, cash and in-kind credit and frequency of meetings were negative and significant

indicating that an increase in these variables would improve technical efficiency. Among the inputs considered in this study only agro-chemicals and hired labor were considered underutilized from the results of the resource use efficiency.

Asante, et al. (2014): This research was project based. It sought to find out the impact of Multi-National NERICA Rice Dissemination Project (MNRDP) on the efficiency of rice farmers in Ghana. They purposively chose some major rice producing areas (project districts) in the country, out of which 200 rice farmers were chosen for the study. Firstly, the technical efficiency of farmers was estimated. After which the NERICA adoption in addition to other determinants of efficiency were examined. SFA with a Cobb-Douglas production function specification was adopted in the estimation of efficiency. The output of the function was represented by the quantity of rice harvested, whiles the independent variables (inputs) consisted of land area, labor, seeds, herbicides and fertilizers. In addition to the NERICA adoption variable, other variables included in determining the causes of efficiency were gender, age, education, access to road, distance to markets, nonfarm income, household size, agricultural projects, FBOs, NGOs, fertilizer use, herbicide use and extension.

The maximum-likelihood estimates (MLE) reveal that, all but fertilizer positively affected rice output. No farmer attained full efficiency as the maximum score was 0.937 and the minimum, 0.127. The mean efficiency was therefore 0.691. A test to find out whether using the traditional production function without efficiency was enough was rejected, explaining the need to further pursue the causes of efficiency. The gamma ($\gamma$) ratio 0.367 meant the effect of inefficiency on deviations from the frontier is low compared with statistical noise. As expected from the maximum likelihood results, all but fertilizer had positive output elasticities, indicating that a 1% increase in any of the inputs would lead to a corresponding increase in rice output except fertilizer that would rather decrease output by the corresponding elasticity. Returns to scale was 0.130, indicating the need for farmer to decrease scale to improve efficiency. The factors with a

significant positive of efficiency were NERICA adoption, gender, education, access to road, NGOs, extension and the use of herbicide. Only household size recorded a significant negative effect. The NERICA adoption variable which was the focus of the study recorded the highest coefficient of 0.114, which means that farmers who adopted this program had about 11.4% increase in their technical efficiency.

Kwabena and Victor (2014): Selecting districts from the various ecological zones of Ghana (Forest, Transitional and Savannah Zone), the researchers estimated the technical efficiency of maize farmers in those zones. The district considered were Bekwai Municipality, Nkoranza South District and Gushiegu District representing each ecological zone. The pooled sample from the selected district was 453 maize farmers. The data which were collected for the 2010 cropping season was fitted into a translog production function to estimate technical efficiency as well as determine its causes. Whiles maize yield represented output, labor, seed, fertilizer and cultivating area were the inputs of the functions. Gender, access to credit, extension services, off-farm work engagements, practicing of mono cropping, education of farmers and use of improved seeds were the variables considered for the causes of efficiency analysis.

With the exceptions of seed all the other three inputs recorded a negative relationship with maize output, but only that of farm size was significant. The estimated mean efficiency was 0.641. Per each zone, the efficiency estimates were 0.722, 0.839 and 0.616 for forest, transitional and savannah zones respectively. The Savannah zone which consists of the area under study for this study (Northern Region) recorded the least, which the researcher blames partly on rainfall pattern. The results when compared with the study of Shamsudeen et al. (2013) which were also done in the savannah zone, the mean efficiency differs by a wider margin. The efficiency was 0.74 for Shamsudeen et al. (2013) compared with 0.62 for this study. All of them used the same method (SFA), the same production function (translog), the same crop (maize) and were all under the Savannah zone. The other

similarity was the variables used; the previous used only one input more than this study i.e. cost of weedicides. Aside, all the other four were the same. Normally such a wider margin is not expected if all these are common among the studies.

The gamma ($\gamma$) ratio of 0.951 reveals how deviations from the frontier are almost the results of inefficiency. They also set out to test for the equality of technical efficiencies between male and females and also between those who have off-farm engagements and those who do not have. In terms of the gender, it was revealed that there is a significant difference between the mean technical efficiencies of male and female farmers. The same conclusion was drawn for the differences between those with off-farm engagement and full time farm engagement.

On the determinants of efficiency, all but gender and off-farm work had a positive effect on efficiency. However the effect of gender was not significant. The same effects of credit access on technical efficiency was also reported by Lira et al. (2014), who further explained that farmers who take credit for farming are very conscious of the consequences of defaulting and would therefore do whatever possible to minimize input use which ultimately leads to increased efficiency.

Donkoh et al. (2013): Following the 2007/2008 farming season, data were collected from rice farmers in the Tono Irrigation Project located in the Kassena-Nankana District of Upper East Region of Ghana. Their technical efficiencies were measured, and their causes determined. A one-step SFA estimation method was used. The inputs for the production function were land, seed, fertilizer, labor and other expenditures. Rice output represented the output or the dependent variable of the function. Experience in farming, number of years in school and gender of farmers were the variables suspected to be the determinants of technical efficiency. Three different hypotheses were tested and all rejected the null hypotheses. It was therefore concluded from the test that, translog fits the data more than Cobb-Douglas, there was inefficiency in the model and lastly the determinants had an effect on inefficiency.

All but land had a negative coefficient, implying an increase in land leads to fall in rice output. However, only that of fertilizer was insignificant. The lowest efficiency score was 0.4 while the highest was full efficiency. The mean estimate was 0.81. About 56.7% attained efficiency scores greater than the mean estimate. The gamma ($\gamma$) parameter of 0.99 meant the differences between actual and frontier output was mainly due to farmers' technical inefficiency rather than factors beyond their control (statistical noise). Men were slightly more efficient than women, but the difference in efficiency between non-school goers and educated was very large, i.e. those with secondary and tertiary education were more efficient than those without education. Among the three determinants it was only farming experience whose effect on inefficiency was not significant. However, education and sex had a positive and negative effect respectively.

Etwire et al. (2013): The focus of this study was on the measurement of the technical efficiency as well as determination of its causes, of soybean farmers in two districts of the Northern Region of Ghana. The sampling frame consisted of farmers participating in Agricultural Value Chain Mentorship Project (AVCMP). Through a multi staged sampling procedure, 200 soya beans farmers were chosen for the study, during the 2012 farming season. SFA method was used with a translog stochastic production function. Quantity of soybeans produced per hectare represented the output of the function whiles cost of hired labor, cost of family labor, combined cost of other inputs, farm size and the cost of soybeans seed represented the inputs. Eleven variables were used in the technical inefficiency effect model, which seeks to analyze the causes of technical efficiency. Most important of them for the focus of the research was the locational variable and the project participation variable, i.e. the farmers' district of operation and whether they are participating in the AVMP. The rest were gender of farmers, age, soybeans farming experience, marital status, education of farmers, residence status, electricity access, credit access and access to agricultural extension service.

The null hypothesis supporting the use of Cobb-Douglas production function was rejected in favor of translog. Another hypothesis denying the existence of inefficiency in the model was also rejected. The MLE of the production function reveals a negative relationship between all the inputs except family labor and land. However, only the effects of land and other inputs were significant. Though all were not significant, the results reveal that all the inputs would contribute negatively to soybeans output in the long run except land. The output elasticity of land was stronger, positive and significant. The technical efficiency analysis recorded a mean value of 0.53 indicating a considerable amount of technical inefficiency that characterizes the production of soybeans in the two districts. Nearly half of the sampled farmers scored below 0.5 efficiency score. A returns to scale of 0.75 explains the scale of operation of the farmers. They are operating at decreasing returns to scale and may have to reduce their scale in order to be more efficient. Age, participating in AVCMP and the location of the farm were the variables among the determinants that had significant effects on the levels of inefficiency. Whiles age and AVCMP participation variable recorded negative, the location district was positive. This indicated that older farmers as well as farmers who participate in the project turns to increase their efficiency levels.

Bempomaa and Acquah (2014): The title ‘‘Technical Efficiency Analysis of Maize Production: Evidence from Ghana.’’ maybe misleading in the context of the study area, which relates the research results as evidence for Ghana. It was actually conducted in only one district, Ejura-Sekyedumase. An SFA was used in the estimation of the technical efficiencies of the maize farmers. The data were fitted into a Cobb-Douglas production function. 306 maize farmers were selected for the study for the 2013 farming season. One output and six inputs were considered in all. The inputs were land size, labor, seed, agrochemicals, equipment and fertilizer. Maize output represented the output or the dependent variable of the function. In all, suspected nine determinants of efficiency were analyzed; educational level, age, gender, number of extension contacts, access to credit, off-

farm work engagements, household size, maize farming experience and FBO membership.

The MLE reveals that only the effects of land, equipment and agrochemicals were significant on the output of maize produced. Only agrochemical amongst them was negative. A mean technical efficiency of 0.67 was recorded with no farmer attaining full efficiency. It is also revealed that inefficiency has a great role to play in increasing productivity as the gamma ($\gamma$) parameter was 0.6324. In the analysis of the output elasticities, all but land was inelastic. This means that apart from land, a 1% in all other inputs would cause maize output to increase less than 1%. In the case of land, output would increase more than 1%. The returns to scale analysis also shows that the scale of operation of the farmer are far below the optimal scale, thus increasing their land size would improve productivity. Returns to scale was 1.2218. The MLE of the inefficiency effect model indicated a disappointing result. Most of the determinants the researchers suspected could have been having an effect on technical efficiency were all not significant save one. That is off-farm work engagement. Its coefficient was positive, confirming an a priori expectation. This means that the more farmers engage in off-farm activities the lesser efficiency he or she would be.

Nkegbe (2012): In order to examine the effects of soil management and good farming practices being promoted in the three Northern Regions of Ghana (Northern, Upper East and Upper West), the researcher decided to measure the technical efficiency of households. Other socio-economic variables were considered for the determination of technical efficiency. He employed the SFA method and adopted the translog production function for the data of 2008/2009 cropping season. Through a multi-stage sampling procedure, a total of 445 household were selected to represent the sample. The output of the production function represented the value of all crops (cereals, legumes, roots and tubers, and vegetables) grown by the households. The inputs or the explanatory variables were land, purchased input, household labor and capital. The variables considered for the

efficiency effect model were education of household head, proportion off-farm income, credit and practice of soil management and good farming.

A test conducted rejected the Cobb-Douglas production function for the more flexible translog. Under all the three distributional assumptions, normal-half normal, normal-truncated and normal-gamma, all the inputs recorded a positive and a significant effect on the total crop output of households. However the results under the normal-half normal assumption are relevant for this study since the test for distributional assumption for inefficiency settled for it. The average efficiency estimate was 0.63 under the normal-half normal assumption, even though the other assumptions recorded different mean values. No household achieved full efficiency. A further attention was given to practicing of soil management practices by comparing the mean efficiencies of adopters to non-adopters. The mean efficiencies were 0.64 and 0.58 respectively. This difference was statistically significant at 5% significance level. A test for constant returns to scale was also rejected. The actual returns to scale was 0.89, which indicates a decreasing returns to scale.

Among the determinants considered, only the effect of education was insignificant. Among those with significant effects, only off-farm engagement had a positive effect. This means that access to credit and practicing soil management and good farming would lead to increase in efficiency whiles more off-farm engagements would in line with an a priori expectation, lead to increased inefficiency

# 3. MATERIALS AND METHODS

This section starts with the material for this study, which involves the definition of all the variables used in this study. The methodology section outlines the various methods that are employed in the calculation of various estimates in this study. Before that, a section is devoted to the historical evolvement of productivity and efficiency measurement. This is lacking in most theses on efficiency and productivity analyses. The outlined methods are executed by various software programs. The Data Envelopment Analysis Program (DEAP Version 2.1) is the main software used for the DEA estimates. In the case of SFA, most of the estimates were done with NLOGIT 5.0. However, FRONTIER Version 4.1 and STATA 12 were also used for some details that could not be provided by NLOGIT. Some part of the estimation involved manual estimation, where Microsoft Excel was very useful.

## 3.1. Materials

Technical, allocative and economic or cost efficiencies of maize production in the Northern Region of Ghana are measured in this study. The study would consider output and inputs per acre of sampled maize farmers as the basis for the measurement of technical efficiencies, whiles total and per-unit cost of inputs would be the additional information needed to estimate allocative and economic efficiencies. A maize farmer in the context of this research is defined by the following:

1. The farmer must earn more than 50% of his or her farm income from maize production
2. They should not be practicing mix cropping, i.e. growing maize with other crops on the same field at the same time.
3. Their production must be rain fed.

The first two definitions are to make sure that only serious farmers are considered since everyone has the potential of growing maize in the region. The third makes sure that farmers are assessed under similar conditions. Irrigation is an insignificant part of Ghana's cereal production. Already less than 0.5 % of agricultural land in Ghana is under irrigation, most of which are for vegetable production. With the advantages of irrigation, if irrigated farmers are included, there are bound to be outliers in the data which is not good for efficiency analysis.

One (1) output and six (6) inputs were used in the estimation of all the efficiencies. The output is harvested maize output (kg). The inputs are farm size (acre), labor (hours), machinery (hours), nitrogen (kg), phosphorous (kg) and pesticides (liters). For the allocative and cost efficiencies, the total cost and the per-unit cost of all the inputs in Ghanaian cedi (GH₵) are the needed variables. The other variables of interest are the causes of efficiency. These variables and the costs would not be used in its nominal form. In order to correct for scale advantage larger farmers may have over smaller ones in terms of efficiency estimates, all variables and cost are corrected to per-unit acre. As a result, the number of variables to be used in the analysis would be reduced to five (5). Furthermore, it has to be acknowledged that some perceived important variables are not included because of technical challenges. Maize seeds for example are important inputs in the production of maize, however the data on it lacks variability. That is the amount of maize seeds per acre is almost the same for all farmers. This makes it impossible for regression analysis. That of potassium is explained later under chemical fertilizer as a variable. Other important causes of efficiency variables not included are credit access, number of maize plots and membership to a Farmer Based Organization (FBO). These variables do not vary so much among the farmers making it impossible for a tobit regression analysis.

### 3.1.1. Variables

#### 3.1.1.1. Output and Input Variables

The variables are measured in different units. Whiles some are direct physical quantities, other are measured in hours. The first group consists of output, land size, nitrogen, phosphorous and pesticide. Labor and machinery belong to the second group. The prices of variables like output, machinery and pesticide are directly estimated from the prevailing market price. That of nitrogen and phosphorous are indirectly estimated from the available information from the fertilizer market. Finally the opportunity costs of land size, labor hours are used in the approximation of their prices.

Maize output (kg): This refers to the weight of the harvested grains from the farm for that particular farming season. This is normally measured in bags and bowls which weigh 100kg and 2.5kg respectively. For instance, a farmer who produced 3 bags and 20 bowls would be imputed as 350kg.

Farm size: This is the total land area on which only the maize is cultivated. It is normally measured in acres. Since most of them use tractors for ploughing, there is a standard for the measurement by the tractor operators. There is a slight difference when it is ploughed by hand and animal plough. On the issue of cost, there was no official source from where this information could be gotten. In fact, no one hires land for farming. If you are not from a particular community and you want to farm there, all you need to do is go to the chief for permission. According to them however, the common practice is to give a bag of maize on each acre to the chief after harvest. If it is on the land of a particular family, you give them too any quantity you desire after harvest. From this information the cost of 'hiring' an acre of land for farming is estimated at GH₵ 80 (which was the price of a bag of maize at that time). However, some farmers gave additional bags to family land owners. I

therefore added the quantity they gave to the families to the one they gave to the chief; this increased their cost of using the land.

Labor hours: This measure the amount of labor hours used in the process of producing the maize output. Labor is basically divided into two; family and hired labor. This was estimated by soliciting information from the farmer about the number of people who worked on the farm at each production stage, how many hours in a day and for how many days. The number of working hours in a day and number of days vary with each activity. For instance, fertilizer application normally takes a shorter time than sowing, weeding and harvesting. Since labor consists of different genders across all age group, the standard labor conversion coefficient in table 1.2 were used in the aggregation of the labor units.

Table 3.1. Labor Conversion Coefficient

| | Coef. | |
|---|---|---|
| Age Group | Male | Female |
| 0-6 | - | - |
| 7-14 | 0.5 | 0.5 |
| 15-49 | 1 | 0.75 |
| 50+ | 0.75 | 0.5 |

Source: Açil and Demirci (1984)

Most farmers use family labor and would only resort to hired labor in the weeding stage, when the weeds are growing faster than the crops. The information on the charges of hired labor for each activity was used to estimate that of the family labor. The study assumes the quality of both types of labor is the same. Therefore the per-unit cost of labor was the total cost of labor divided by the number of labor employed.

Machinery: There are many different types of machinery used in the production of maize. However, machines are less used in the context of Northern

Region where production is more labor intensive. They hardly use planters, harrows, harvesters and trucks in the process. The main machine component of the production process is ploughing and sometimes, trucks for transporting produce from the farm to the house. In the case of the ploughing, the information was taken from the operators about the number of hours they spend in ploughing an acre of land. In most cases, the farmers are not present when the ploughing is done, or they do not keep record on how long their plot was ploughed. The information on the number of hours trucks use for transportation was taken from the farmers themselves. For the information on the cost, there is a fix amount of tractor operators charge for ploughing an acre, however, the amount charged for transporting produce to the house differs from farmer to farmer. The total cost divided by the number of hours gives the per-unit price of machinery input.

Chemical fertilizer: The most commonly used chemical fertilizers for maize are the NPK (15-15-15) and NPK (23-10-5) compound fertilizers made up of nitrogen (N), phosphorous (P) and potassium (K). These are subsidized yearly by the government and distributed through the ministry of agriculture through certified agro input dealers. It is measured in kg. Each bag of fertilizer is 50kg. The study segregates and measures individual elements in the compound fertilizer except potassium. Unlike the other elements, the unused potassium can be held up in the clay components of the soil for years and feed any plant that is planted and watered (Rosen, et al. 2008). This makes it difficult to estimate the actual amount of potassium applied in the farm. More so, Ghanaian soils are known have potassium in abundance (FAO, 2005). The segregation is done as follows:

The proportions represent what percentage of the fertilizer is made up of those nutrients. For example the nitrogen is 15% of the total 50kg bag of NPK (15-15-15). However, apart from these 3 main nutrients, there are other things that make up the total weight of the compound fertilizer bag. They mostly weigh more than the 3 nutrients. They are mainly fillers, or inert ingredients, which basically helps in dispersing the chemicals. In order to estimate the weights of the nutrients,

the fillers have to be included. While the per-unit cost of nitrogen, phosphorus and potassium would be represented by N, P and K respectively the cost of the fillers would be denoted by F.

For example, an NPK (15-15-15) fertilizer bag of 50kg contains 15 % nitrogen, 15% phosphorus, 15% potassium and 55% fillers or other ingredients. This therefore means that in terms of weight, the bag contains 7.5kg of nitrogen (15/100 *50), 7.5kg of phosphorus, 7.5kg of potassium and 27.5kg of the other ingredients. The cost of a 50kg of 15-15-15 is GH₵ 95 at the subsidized price. This translates into ;

$$7.5*N+7.5*P+7.5*K+27.5*F=95 \quad (3.1)$$

For NPK (23-10-5) fertilizer which also cost GH₵ 95, it contains 11.5kg of nitrogen, 5kg of phosphorous, 2.5kg of potassium and 31kg of fillers.

$$11.5*N+5*P+2.5*K+31*F=95 \quad (3.2)$$

For urea (46-0-0) fertilizer which also cost GH₵ 95, it contains 23kg of nitrogen, 27kg of fillers and nothing of phosphorous and potassium.

$$23*N+27*F=95 \quad (3.3)$$

Ammonium Sulfate (21-0-0) cost GH₵ 85. By its nutrient proportion it contains 10.5kg nitrogen,

$$10.5*N+39.5*F=85 \quad (3.4)$$

Solving these four equations simultaneously, the per-unit cost of nitrogen, phosphorus, potassium and the fillers are GH₵ 2.3, GH₵ 3.6, GH₵ 1.2 and GH₵ 1.5 respectively. However, of interest to this thesis are the first two. Therefore, for

a farmer who used 3 bags of NPK (23-10-5), it means he used 34.5kg of nitrogen [(23/100 *50)*3], 15kg of phosphorous [(10/100 *50)*3]. For this farmer the cost of these inputs would be GH₵ 73.9 for nitrogen (34.5kg *2.3) and GH₵ 54 for phosphorous (15kg*3.6)

Pesticide Use: This consists of all chemicals used for the control of weeds, insects, fungi, rodents and others. Because of the unregulated nature of these chemicals in the country, their measurements in terms of quantity and prices are very difficult. More so, they come in different forms; liquid, powder, grains etc. these are measured in liters, grams, packets etc. This makes the unit of measurement difficult. A solution to this would be to consider the monetary value of all pesticides used. However, this will only work for the measurement of technical efficiency. In the case of allocative and cost efficiencies, per-unit cost and quantity are needed, and the monetary value cannot satisfy this requirement. The other challenge is that farmers do not know or remember the name of the particular chemical they used. In the light of this, a particular chemical was considered and measured for this input. It was used by all farmers in the sample. Even though it has different names and brands, it is liquid and all farmers use it before ploughing. It is a total weed killer and regardless of the name or brand, it is popularly known in local parlance as ‘condemn’. However, price varies with the brand and districts.

### 3.1.1.2. Causes of Inefficiency Variables (Environmental Variables)

Extension services: This refers to the number of times the farmer has been in contact with an extension officer during the cropping season. The word contact is used in the sense that some farmers rather reach to the extension agents on the problems they encounter on their farms. Due to the limited number of extension agents they may not cover all areas in their visits.

Land size: This measure is to separate large scale farmers from small scale ones. Farmers with more than 5 acres are considered large scale and those below

are small scale farmers. It is measured as a dummy variable; below 5 acres=0, 5 acres and above=1

Labor ratio: This measures the ratio of family labor hours to the total labor hours. This is to access the effect of family labor as against hired labor. A higher fraction means higher amount of family labor and the vice versa.

Education: This variable makes a distinction between literate and illiterate farmers. The variable is based on the ability of the farmer to read and write. Literates are assigned 0, and illiterates, 1

Gender: Gender in this sense refers not only to the owner of the farm, but the one who makes decisions about the farm as well. Culturally, in rural communities in developing countries, women may have farms but do not have control over the decisions thereof. In that case, they are more or less care takers. This was taken into consideration in the data collection process. In the context of this thesis, gender is not only viewed as male and female, but male farm manager and female farm managers. Male are assigned 0, and females 1.

Marital status: This variable separate married from unmarried farm managers. Married =0, and single=1

Credit access: the credit variables sort find out whether farmer received any form of credit (cash or input or kind). The dummy variable 1 represents those who received credit and 0 is for those who did not receive.

Number of maize Plots: This variable represents the number of separate plots use in the production of maize for a single farmer.

Farmer Based Organization (FBO): Membership to an FBO. The dummy variable 1 represents those who are members of an FBO and 0 is for those who do not.

Table 3.2. Summary Representation of Variables

| Output | Inputs | Unit Cost of Inputs (GH₵) | Causes of Inefficiency |
|---|---|---|---|
| Maize output (kg/acre) | Farm size (acre) | Cost of acre of land | Extension services (number of times of extension contact) |
| | Labor (hours/acre) | Cost of labor/hour | Land area- (below 5=0, 5 and above=1) |
| | Machinery (hours/acre) | Cost of machine usage/hour | labor ratio (family to total labor) |
| | Nitrogen( kg/acre) | Cost of nitrogen /kg | Education level- literates=0 and illiterates=1 |
| | Phosphorus ( kg/acre) | Cost of phosphorus /kg | Gender(male=0 female=1) |
| | Pesticides (liters/acre) | Cost of pesticide/liter | Marital Status- (married=0 or single=1) |
| | | | Household structure (extended=0 nuclear=1) |
| | | | Maize Farming Experience (below 15=0 15 and above=1) |
| | | | Credit access(yes-1/no-0) |
| | | | Number of maize plots |
| | | | FBO membership (yes-1/no-0) |
| | | | Improved seed (own-0/hybrid-1) |

Improved seed: This variable sort to identify farmers who used improved or hybrid maize seeds as opposed to those who used their own seeds. 1 represents those who used hybrid seeds and 0 is for users of own seed.

Household structure: The structure of the household in this sense refers to the family members the farmers stay with. It may either be nuclear or extended family. Those farmers in the nuclear family system normally have more independence in their decision making then those in the extended family system. In the extended family household, there is normally a family farm on which everybody contributes resources and labor, giving them less time to attend to their own farms. Farmer in the nuclear family household may not have the advantage of using more family labor, but will have more time and control over their farms. Extended family household=0 nuclear family household=1

Maize farming experience: This represents the number of years the farmer has been producing maize. Farmers' age was initially considered as an environmental variable. However the near perfect correlation it had with maize farming experience meant that it could not be used together, hence dropped. Therefore, this variable can sometimes be interchanged with farmers' age depending on the discussion. Below 15 years=0, 15 and above=1

## 3.2. Methodology

### 3.2.1 History

Efficiency and productivity measurements are two different but related concepts used in assessing the performance of a DMU. Most scientists, since time immemorial have naturally sorted to use the latter in performance measurement. The former which is the focus of this thesis, later emerged. All researchers in this field, agree that the seminal papers by Farrell in 1957 marked the birth of modern efficiency measurement; both in terms of definition and methodology (Coelli et al. 1998 p. 51; Sampaio, 2013 p.14; Cooper et. al. 2011 p.4; Sharma, Leung and

Zaleski, 1999; Lovell, 1993, p. 10; Hjalmarsson et al. 1996). They however differed in terms of its antecedence. Whiles most agree to the fact that the work of Debreu (1951) and Koopmans (1951) marked the beginning of discussion on efficiency measurement, Cooper, Seiford, Zhu and some few others dates it back as far as 1906. They are of the view that, just as Farrell (1957) built upon the works of Debreu (1951) and Koopmans (1951), the work of the Swiss-Italian economist, Vilfredo Pareto was the inspiration behind the work of Koopmans. The 'Pareto criterion' expounded in his Manual of Political Economy (1906) was adopted by Koopmans in his 1951 paper (Cooper et. al. 2011, p.4). This resulted in the famous Pareto-Koopmans Efficiency which states that 'A DMU is fully efficient if and only if it is not possible to improve any input or output without worsening some other input or output'. In almost the same time, Debreu (1951) also came out with the idea of "coefficient of resource utilization", which was defined as a measure of technical efficiency for a whole economy. From his theoretical explanation, a deviation from one was interpreted as a waste by the economy resulting from the inefficient use of resources (Ray, 2004 p. 3).

M.J. Farrell in 1957 harnessed these concepts into a coherent and definitive presentation, which formed the basis for all efficiency estimations methods till date. He manifested his concept by diagrammatically presenting it in an input-output space and supporting it with observed agricultural data (Ray, 2004 p. 3; Cooper et. al. 2011 p.5). This was the first time efficiency measurement concepts were put to reality, that is, until his "The Measurement of Productive Efficiency" in the Journal of the Royal Statistical Society, all explanations were conceptual. Unlike preceding concepts, his was entirely input output relation devoid of price information. Realizing the fact that the theoretical full efficient point being referred to by Koopman and Debreu was not practically known, he argued that the efficiency should be based on the available information with references to other DMUs. This concepts was later termed as ''relative efficiency'' or "Farrell measure of efficiency" (Cooper et. al. 2011, p.5; Cooper et. al. 2007, p. 69). Even

though Farrell's methodology was not that encompassing, most researchers agreed to his definitive definition of inefficiency as the realized deviation from a frontier isoquant, constructed by the observed data (Sampaio, 2013, p.14; Lovell, 1993, p. 10). Farrell in his presentation used an input orientation and assumed constant returns to scale. He then formulated a system of linear programming (LP) models, which identified the benchmark to which references would be made in the estimation of technical efficiencies (Ray, 2004 p. 26; Fried et al. 2008 p. 20; Murillo-Zamorano, 2004, p. 35)

It has to be acknowledged that, not only did he present a practical estimation to technical efficiency, he went further to define most other forms of efficiencies that is being used today. With the exception of scale efficiency which he laid the foundation for, he explicitly defined technical, allocative and cost efficiencies. He explained that firm's efficiency is divided into two; technical and allocative efficiencies. While the former reflects the ability of the firm to minimize the use of inputs, the latter assesses the ability to optimally combine these inputs in their right proportions, given prices and technology. The combination of these two efficiencies results in cost or economic efficiency (Coelli et al. 1998 p. 51). In his literature, he used productive, price and overall efficiencies for the now widely used technical, allocative and economic/cost efficiencies respectively (Murillo-Zamorano (2004, p.3). This thesis would stick to the modern terminologies. It must be noted further that, even though his illustration was two inputs one output scenario, he extended his discussion to cover multiple inputs, multiple outputs. Then again, he also proposed the discussion with non-constant returns to scale assumption, even though he used Constant Returns to Scale (CRS). Under his discussion on Returns to Scale (RTS), he acknowledges the fact that output orientation could produce different results from input orientation (Farrell, 1957, p. 259; Coelli et al. 1998 p. 51). RTS measures a change in output levels resulting from a 1% simultaneous increase in all inputs used in its production. If this 1% increase leads to 1% increase in output, then the production is experiencing CRS. It

may also be Variable Returns to Scale (VRS) in the sense that output may increase more or less than 1% in response to the 1% increase in all inputs; the former is Increasing Returns to Scale – IRS and the latter, Decreasing Returns to Scale – DRS (Kapelko and Oude-Lansink , 2013). Even though the original work of Farrell, (1957) and the subsequent Charnes et al. (CCR) (1978) used the CRS assumption, subsequent authors ditched this assumption for the VRS led by the Banker et al. (BCC) (1984). This is because in practical terms, it is often difficult to find a justification for CRS especially in agricultural production.

It can therefore be seen that Farrell covered most part of efficiency studies in terms of definitions and discussion, but not methodology. Concepts and definitions in efficiency studies preceded him, but he is definitely the starting point of efficiency estimation methods. Different methods have since emerged. Though some methods are far away from the linear programming techniques he used, they all have his work as the reference point.

### 3.2.2. Methodological Evolution

Until the definite definition and estimation of efficiency by Farrell, there were methods used in the estimation and comparison of entities' performances, which they believed represented their efficiencies. The most common was productivity of inputs, and later the introduction of index numbers and cost comparisons. Farrell referred to productivity as an efficiency approximation as the least satisfactory among all the attempted methods. He further stated that, the unsatisfactory nature of the productivity methods hastily led to the employment of index numbers. This method, though seek to solve the problems in the previous was too complicated to be practicable. This method sort to aggregate inputs with a scalar into a single quantity, and then make comparison amongst firms to determine their efficiencies or performance. The suitable method of aggregation as Farrell pointed out, was the main setback of this method. The cost comparison

method looked more credible under one condition; all firms under study face the same factor prices. This condition however is not practically guaranteed (Farrell, 1957, p. 264). It is argued and expressed by Farrell himself that, the inspiration behind his paper was the desire to perfect these estimations that were approximated for efficiency. This drove him to employ the Koopmans' "activity analysis concepts", which later resulted in his final work in 1957 (Cooper et. al. 2011, p.4).

Farrell opened the floodgate for methodologies. Like Farrell, some of the researchers were still searching for better ways of addressing the poor performances of the index numbers and productivity approaches. Others were interested in the modifications and extensions of Farrell's work. This resulted in the establishment of two broad categorizations depending on a chosen criterion; parametric and nonparametric models if the functional form of the frontier is considered, deterministic and stochastic models if the presence or absence of statistical noise in the data is considered, Cross-sectional and Panel Data Models when the type of data is taken into consideration. The third classification is considered when technical and productivity changes are of interest to the researcher (Daraio and Simar, 2007 p. 28; Pascoe et al. 2003 p. 3; Coelli et al. 2005, p.6). The thesis would also adopt terminologies from the first and second criteria; that is, the thesis is interested investigating the production functions as well as the statistical noise that characterizes the highly stochastic field like agriculture. This means that depending on the situation, nonparametric and parametric approaches would be interchangeably used with deterministic and stochastic approaches respectively. This classification which is adopted in this thesis is not the only one in terms of taxonomy. Other literatures use non-statistical versus statistical approach, non-frontier versus frontier, non-econometric versus econometric, as well as non-stochastic versus stochastic (Jacobs, 2001 p. 2; Pascoe et al. 2003 p. 3).

For all the categorizations above, three main methods were identified in the historical evolvement of efficiency techniques; Data Envelopment Analysis (DEA),

Deterministic Frontier Analysis (DFA) and Stochastic Frontier Analysis (SFA). The first represents non-parametric (deterministic) and employs linear programming, whiles the third represents parametric (stochastic) approach and uses econometric techniques. However, DFA, which is similar in many ways to both DEA and SFA, was gradually replaced by DEA (Hjalmarsson et al. 1996). Before continuing the discussion on the three main techniques, it has to be acknowledged that there are other approaches which necessarily do not fall under the above categorization of parametric and nonparametric approaches or econometric and non-econometric approaches. Rather these techniques are an amalgamation of the two main categorizations. Two of the widely known and applied techniques are The Goal Programming (GP) and the Nonfrontier efficiency techniques. Whiles the former originated from Aigner and Chu (1968) the latter is believed to have been proposed by Hopper (1965) (Lovell, 1993 p. 36). Continuing with the three main techniques, the DFA technique was the antecedence to SFA, in terms of methodology but the same as DEA in terms of interpretation. Both DFA and SFA uses econometric analysis, but interpret the error term differently. Both DFA and DEA assume all deviations from the frontier reflect inefficiency, while SFA separate this deviation into inefficiency and stochastic noise. Aigner and Chu (1968) started formal econometric modeling of efficiency in a deterministic form (DFA approach) using linear and quadratic programming. Using maximum likelihood, Afriat (1972) modified it by assuming a gamma distribution for the inefficiency term. Two years later, Richmond (1974) used the modified ordinary least squares (MOLS). Almost the same time, Gabrielsen (1975) introduced the Corrected Ordinary Least Squares (COLS) in estimation of deviation from the frontier. Even though the logic of the COLS model was introduced by Winsten in 1957, Gabrielsen(1975) is credited with its application in DFA (Coelli et al. 1998 p. 241; Greene, 2005 p. 19; Porcelli, 2009 p.19). Further refinement of DFA led to the emergence of SFA in 1977 as a tool to overcome the challenges in the use of DFA to estimate individual efficiencies. It was originally and independently

proposed in three separate continents by Meeusen and Van den Broeck (June 1977), Aigner et al. (July 1977) and Battese and Corra (1977). However, most researchers give the credit to the first two sources (Sampaio, 2013, p.19). In this approach, the deviation from the frontier which hitherto was entirely attributed to inefficiency is now divided into two; a symmetric random error that accounts for statistical noise and inefficiency. A competing econometric technique was proposed by Koenker and Basset (1978) known as quintile regression. Unlike SFA, it did not require a distributional assumption on the inefficiency term. This was its major advantage. However, its inability to investigate relationship among variables and efficiency estimates made its use unpopular (Darku et al. 2013, p.4).

Other researchers were extending the methodologies and the proposals Farrell made in his paper. The most pursued was the piece-wise-linear convex hull approach he proposed. There was a break through at almost the same time the econometrics methods were evolving. In 1978, Charnes, Cooper and Rhodes came out with codified technique that they call DEA. The model they proposed came to be known as the 'CCR model' which is an acronym made up of their names. Like Farrell, they also assumed CRS, input orientation and employed linear programming. Before this breakthrough, Boles (1966), Shephard (1970) and Afriat (1972) were known to have applied this technique (Coelli et al. 1998 p. 162). This method requires the construction of a nonparametric piecewise frontier over the observed data, using linear programming. Inefficiency is therefore estimated as the deviation of any DMU from that established frontier (Silva et al. 2013a p.4). It can therefore be seen that DEA has the same efficiency concept as DFA; they all interpret inefficiency as the deviation from the constructed frontier. However DEA has the extra advantage of constructing the best practice benchmark. This gradually led to the preference of DEA over DFA. It is worth mentioning that, just as the quintile regression by Koenker and Basset (1978) became a competing technique to the parametric approach (SFA), so was the Free Disposal Hull (FDH) technique proposed by Deprins, Simar and Tulkens (1984) to the nonparametric (DEA)

approach. Till date, the DEA and the FDH remain the most popular nonparametric estimators of frontiers. FDH relaxes the convexity assumption in DEA, hence imposes no restriction on scale of operation (Daraio and Simar, 2007 p. 29). Like DEA, it is a deterministic (nonparametric) approach, it does not assume a functional form for the frontier and it also does not take into consideration the statistical noise. However the relaxation of the convexity assumption makes it difficult to estimate scale of operation and scale efficiency for that matter (Lovell and Vanden –Eeckaut, 1993 p. 450). DEA has the edge over FDH in terms of wider applicability, scale efficiency analysis and the general implicit assumption that production sets are convex (Kneip et al. 2015). The convexity assumption has been in place since the origin of efficiency estimation and many studies have not relaxed it because the investigation of scale is usually very necessary. The work of Koopmans, Shephard and Farrell all relied on the convexity assumption (Daraio and Simar, 2007 p. 17). The thesis therefore would consider DEA for the nonparametric aspect of the analysis and SFA for the parametric.

### 3.2.3. Terminologies and Efficiencies to be Estimated

#### 3.2.3.1. Technical Efficiency and Orientations

The discussion above has been concentrated on technical efficiency which is the reference point for all other efficiencies. During the process of evolvement, some assumptions were relaxed whiles others were introduced. Diagrams would be used to explain the various forms of efficiencies as well as efficiency related terminologies that would be used frequently under the methodology and results presentation. Reference is made to some figures below for the understanding of some of the terminologies. The first of the figures is figure 3.1, which shows a simple relation between output (Y) and input(X). The production function Y=f(X), mirrors a typical production with all the three stages of production. This reflects a Variable Returns to Scale (VRS). To begin with, productivity and efficiency are

terms many use interchangeably, probably because, until the emergence of formal efficiency measurement, productivity was used as an approximation for it. Even though they are two cooperating concepts, there is a difference between them. Authors like Sengupta (1995) and Cooper, Seiford and Tone (2011) still define both as the ratio between output and input (Daraio and Simar, 2007, p. 14). In a single input single output case, productivity is virtually the ratio of output to the input used in the production of an output. This could be 'partial' or 'total' factor productivity. The former takes into account only one input and one output in the ratio while the latter considers all outputs and all inputs. The major problem with the partial productivity measurement is its lack of satisfactory interpretation. The fact that so many inputs contributed in the production of the output means that the losses or gains may be attributed to the chosen input in the ratio which actually could be attributed to other inputs. For example, the maize output per labor could be high when actually the real contributor to that output could be other inputs other than labor. The contribution of labor could even remain unchanged or deteriorate within that period of measurement. The 'total' factor productivity in an attempt to solve this problem run into the problem of assigning weights to all the inputs and the outputs involved (Cooper et. al. 2007, p. 7). In a hypothetical case of one input one output case, this ratio is basically the slope of a line from the origin through the said point. Consider firm 1 in figure 3.1. It uses $X_3$ of input to produce $Y_2$ of output, which by the definition above productivity = $Y_2/X_3$. To Justify its equality with the slope of line 0R from the origin; the slope of firm 1 is calculated as; Slope= $(Y_2-0)/X_3-0) = Y_2/X_3$= productivity. From the same conclusion, the slope of lines OS and OT represent the productivities of firms 2 and 3 respectively. It therefore follows that the higher the slope the higher the productivity, and vice versa. That is, firm 1 has the highest productivity followed by 2, 3, 5 and then 4.

Efficiency as seen before is a relative concept in the sense that the productivity of the said firm is compared to the productivity of a point on the constructed frontier (optimal values for the observed outputs and inputs). All firms

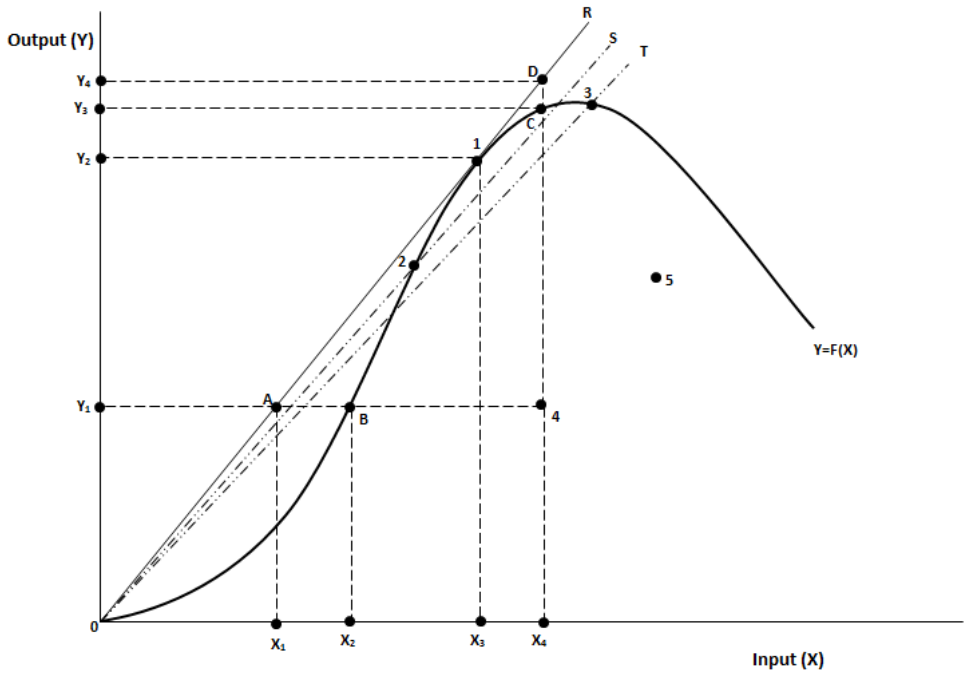
under this frontier are considered inefficient. The comparison between the firms and the frontier is done by a straight line from the origin through the firms' coordinates to the frontier. This concept is known as distance functions expounded independently by Malmquist (1953) and Shephard (1953). Farrell productive efficiency was later found to be the same as the application of the distance function. Along this line there is a radial contraction and expansion in inputs and outputs in the direction of the frontier. That is, a maximum possible equiproportionate reduction in all variable inputs, or the maximum feasible equiproportionate expansion of all outputs. This measure is unit invariant. This maximum feasible contraction of inputs and expansion of output is basically Farrell's measure of productive efficiency (Daraio and Simar, 2007, p.14), and (Kumbhakar and Lovell, 2000 p. 6). According to (Coelli et al. 2005, p.56), authors like Fare and Lovell (1978) and Kopp (1981) have used thhe non-radial techniques instead of the radial procedure. Others like Fare, Grosskopf and Weber (2004) employed the directional distance functions which also involve the expansion of outputs and contraction in inputs at the same time. However the property of unit invariant inherent in the radial measure gives it a notch ahead of the other techniques.

Since the established frontier is the ultimate for every firm, it means that the closer a firm to the established frontier, the more efficient it becomes. Unlike productivity, efficiency has a limit. That is if a firm makes it to the frontier, its efficiency will be one, hence fully efficient. Efficiency estimates are positive but less than or equal to one. In figure 3.1, it can be seen that firms 1, 2 and 3 are fully efficient whiles 4 and 5 are not. Considering and inefficient firm 4, there are 3 options it has in order to increase its efficiency or get closer to the frontier; moving up towards point C on the frontier, moving leftward towards point B, or moving to any point bounded by the area B21C4. In the first instance, firm 4 uses the same amount of input ($X_4$) to get a much higher output ($Y_3$). In the second scenario, the firm reduces the input use to $X_2$ and still gets the same amount of output ($Y_1$) as

before. The last option involves simultaneously increasing output and decreasing input. In order to be fully efficient in this case, the firm will end up at any point between B and C on the frontier. This last scenario however is not of interest to this study. Concentrating on the first two scenarios, the technical or the productive efficiency of firm 4 is $\overrightarrow{X44}/\overrightarrow{X4C} = Y1/Y3$ for the first, and $\overrightarrow{Y14}/\overrightarrow{Y1B} = X4/X2$ for the second scenario. In efficiency measurement literature, these two options of the firm in measuring its efficiency is known as output and input oriented respectively. Since the frontier Y=f(X) reflects a VRS, these efficiencies are identified as such. This means that efficiency varies with scale of operation, hence the name 'pure' technical efficiency. This is opposed to 'global' technical efficiency measured with reference to the CRS frontier (Ramanathan, 2003, p.78; Cooper et. al. 2007, p. 153).

According to Coelli et al. (2005, p.6), output oriented measure of efficiency answers the question "By how much can output quantities be proportionally expanded without altering the input quantities used?" whiles input orientation answers "By how much can input quantities be proportionally reduced without changing the output quantities produced?'' From the figure, the answers are at follows; firm4 could proportionally expand output from Y1 to Y3 with the same input X4- output orientation. It could also proportionally reduce input from X4 to X2 without changing the original output (Y1) - input orientation.

According to Cooper et al. (2011, p.27), for any radial measure of efficiency there are two distance functions; one from the origin to the firm's location (lines X44 and Y14), and one from the origin to the frontier (lines X4C and Y1B). These are for the output and input orientations respectively. It has to be noted further that because it is a single output single input presentation, the point X4 acts as the origin for output orientation since output is zero at that point. The same goes for the input orientation. This picture will be clear in subsequent diagrams with two input one output and one output two inputs presentation.




Source: Author's Illustration
Y is output and X is input, Numbers represents firms, letters represent point intersections, y=f(X) is the production function, lines RST are lines from origin which represents productivity
Figure 3.1. Productivity and Efficiency Comparisons

As mentioned earlier, efficiency estimates are bounded between zero and one. However, a closer look at the estimates of the Farrell input orientation in figure 3.1 indicates that the ratio is greater one. That is $Y_1 4/Y_1 B = X4/X2 > 1$. However, the actual efficiency score is the inverse of the ratio of the two distance functions (Coelli et al. 2005, p.59; Forrsund, 1993 p. 355). In other words the estimate above should rather be expressed as; $Y_1 B / Y_1 4 = X2/X4 < 1$. This idea applies to all input oriented efficiencies; allocative, cost and scale. Henceforth the inverse relation would be directly applied.

It is worth repeating that the frontier Y = f(X) has assumed a VRS, and hence the efficiencies thereof, irrespective of the orientation are identified as such. This equally means that the same efficiency estimate can be estimated under CRS

assumption. This brings the issue of CRS frontier. Unlike VRS frontier, CRS frontier is a straight line from the origin that is tangential to that part of the VRS frontier that exhibits the CRS. This point is often referred to as the optimum scale; the point where increasing all inputs by a certain proportion would lead to increase in output by the same proportion. This point is located in the second stage of a classical production function like $Y = f(X)$ in figure 3.1. It can therefore be seen that line 0R is the CRS frontier in the figure. Technical efficiency under CRS assumption is therefore estimated in reference to 0R. For the output oriented efficiency measure of firm 4, the firm will moves towards point D on 0R whiles keeping input constant at $X_4$. In this case efficiency is $X_4 4/X_4 D = Y_1/Y_4$. In the same vein, the input oriented technical efficiency is $Y_1 A/Y_1 4 = X_1/X_4$. Under the CRS assumption the output and input oriented measure of technical efficiencies are equal (Coelli et al. 2005, p.54)

The other terminology worth explaining is scale efficiency. Even though Fare et al. (1983) are the brainchild of this estimate, it is often attributed to Banker (1984), whose study focused much on estimating the Most Productive Scale Size (MPSS) (Cooper et. al. 2011, p.4). A firm can be technically efficient, but could still increase productivity just by modifying the scale of inputs. It is therefore regarded as the measure of impact scale size has on the productivity of a DMU (Thanassoulis, 2002, p.140). Under the VRS assumption, productivity is determined by scale of production. From figure 3.1, even though firm 2 and 3 are both fully efficient technically, the productivity of firm 2 is higher than that of 3 simply because they are operating on different scales. It is therefore, prudent to find a point on the frontier with the highest productivity can be attained. This point is referred to as the MPSS. At this point, a scale change, whether increasing or reducing will decrease productivity, hence fully scale efficient. At this point, scale efficiency is one. According to Santos, et al. (2013, p. 44), MPSS is the dividing line between increasing returns to scale region of the frontier and the decreasing returns to scale region. It is the point where the VRS and the CRS efficiency

frontiers are equal. All firms on The CRS frontier are assumed to be operating at the optimal scale. The position of firm 1 on figure 3.1 indicates this point. Scale efficiency is then estimated as a deviation from MPSS or CRS. Firms to the right of this point, like firm 3 are considered too big and therefore operating under DRS. Whereas those to left like firm 2 are deemed too small and operating under IRS. In either scenario, productivity as depicted by the slopes of lines 0T and 0S are less than that of the 0R (the CRS frontier and the MPSS). Returning to the firm under consideration (firm 4), under output and input orientation, its scale efficiencies are $X_4\,\mathrm{C}/X_4\mathrm{D} = Y_3/Y_4$ and $Y_1\mathrm{A}/Y_1\mathrm{B} = X_1/X_2$ respectively. This means that the firm 4 could increase its productivity just by trying to reach the MPSS or CRS frontier. This can be done by moving from the efficient point C on the VRS frontier to point D on the CRS frontier, under the output orientation. Alternatively, it could move from the efficient point B on the VRS frontier to point A on the CRS under input orientation. The relationship between CRS, VRS and scale efficiencies is also exploited by developing an equation which states that the ratio of CRS efficiency to that of VRS is scale efficiency. This relationship can be alternatively stated as; ['global' technical efficiency (CRS)] = ['pure' technical efficiency (VRS)]* [scale technical efficiency]. This can be proven from figure 3.1. As already indicated under output orientation, VRS efficiency =$Y_1/Y_3$ and CRS efficiency =$Y_1/Y_4$. Scale efficiency therefore is equal to $(Y_1/Y_4)/(Y_1/Y_3) = Y_3/Y_4$. For the input orientation, it is$(X_1/X_4)/(X_2/X_4) = X_1/X_2$. The two results are the same as earlier on presented.

**3.2.3.2. Allocative and Cost Efficiencies, and Slacks.**

Figure 3.2 and 3.3 would be used to explain the remaining concepts under input and output orientations respectively. These are allocative and cost efficiencies, and slacks. These two efficiencies cannot be explained in figure 3.1 because they require extra functions to be constructed; the isocost or the budget line for the input oriented and the isorevenue line for output orientation. When this

price information is available, the behavioral assumption of cost minimization and revenue maximization is automatically invoked (Coelli et al. 2005, p.5). By not relocating inputs and outputs with price information, the technically efficient DMU is likely to fall short of operating at a minimum cost or maximum revenue. The price information of output gives revenue efficiency estimates while that of inputs gives the allocative efficiency estimates (or price efficiency). These two estimates will then lead to profit efficiency. For the scope of this study, only the allocative efficiency would be considered (Coelli et al. 2005, p.5; Cooper et al. 2006, p.245). Technical efficiency is the prerequisite for these efficiencies; that is a firm has to be technically efficient before it can be allocatively or cost efficient. This is however not a sufficient condition for cost efficiency. Allocative efficiency assesses the ability of a firm to proportionally combine inputs and outputs in an optimal way given their prices. In the case of inputs, it is called input allocative efficiency (input orientation) which measures the part of increased cost resulting from the uneconomic mix of inputs, given their prices. In other words, the selected input mix produces the given quantity at the minimal cost possible. In the same vein, output allocative efficiency (output orientation) measures the component of revenue shortfall resulting from the inappropriate mix of outputs given their prices. This means that the resulting output mix gives the highest possible revenue given the input and the prevailing prices of outputs (Thanassoulis, 2002, p.81).

Cost efficiency as the name suggests measures the ability of the firm to produce a given output at the minimum cost. That is, given input prices and output quantity, it is the ratio of minimum feasible cost to observed cost. Because the behavioral assumption is cost minimization, it is estimated with an input orientation. Its output orientation counterpart is revenue efficiency, which is the ratio of the actual revenue to that of the maximum feasible revenue. However, whiles revenue efficiency is not considered in this thesis, its components such as revenue are used in the farm analysis. The cost efficient is variously referred to as ‘overall’ and ‘economic’ efficiency.

Cost and revenue efficiencies are considered products of technical and allocative efficiencies. Cost efficiency can be decomposed into input-oriented technical efficiency and input allocative efficiency. In the same vein, revenue efficiency is the product of output-oriented technical efficiency and output allocative efficiency (Kumbhakar and Lovell, 2000 p. 18). From this relationship, allocative efficiency is in most cases is residually derived from estimated technical and cost efficiencies.

The final concept is slacks. It is the input excess and output shortfall that is present at the optimal solution or the frontier. This means that it is possible for a firm on the frontier to be inefficient. It is widely associated with nonparametric techniques where the piece-wise frontiers or isoquants are used. That explain why it is hardly encountered in parametric efficiency analysis (Porcelli, 2009, p.7). The position of slacks has been a source of controversy since the dawn of modern efficiency measurement. Even though Farrell was well aware of the issue of slacks, his measure did not take it into account. This is why his measure is referred to as 'mix inefficiency' or 'weak efficiency' (Cooper et. al. 2007, p. 45). This is opposed to 'Pareto-Koopmans Efficiency' defined earlier which invoke the condition of zero slacks; that is, a firm is fully efficient if it is operating on the frontier and at the same time have zero slacks. This is the reason it is referred to as 'strong efficiency' (Coelli et al. 2005, p.164; Ramanathan, 2003 p.35). The other source of divergent views about slacks is about how to deal with it. Whiles others consider it a 'small sample problem' and should be ignored, others insist on reporting it with efficiency estimates. Ferrier, Lovell and Coelli belong to the former group who insist that it is captured as allocative inefficiency, hence should be ignored in the estimation of technical efficiency (Coelli et al. 2005, p.199). Despite admitting the fact that it is a 'small sample problem', the latter group insists, it must be pointed out, and it is the prerogative of the researcher to either correct or leave it (Daraio and Simar, 2007, p.32). Yet others like Ali and Seiford (1993) treated slacks as a source of technical inefficiency (Sharma et al. 1999). There is a technique of

efficiency estimation based solely on the values of slacks. It is called Slack-Based Measure (SBM). In the usage of this technique and in general literature, the input excess (input slacks) and the output shortfall (output slacks) are represented as $S_i^-$ and $S_i^+$ respectively (Mendes et al. 2013a, p.127).

The diagrammatic representations of these concepts are presented in figures 3.2 and 3.3 respectively. Whiles figure 3.2 represents input orientation with a single output two inputs scenario, figure 3.3 represents the output orientation with a two output single input scenario. In both figures, $QQ^1$ and $PP^1$ represent the frontier. $QQ^1$ is the isoquant which represents the minimum combination of inputs used in the production of a given quantity. $PP^1$ on the other hand is the production possibility frontier which depicts the maximum combination of outputs that can be produced with a given input. As mentioned earlier, technical efficiency estimation is a prerequisite for allocative and cost efficiency measures. Even though its estimation follows the same principle in the single output single input case, the radial expansion and contraction are done directly from the origin where all outputs and inputs are zero. However in the case of figure 3.1, the radial and expansion and contraction originates from the axis where output is zero on the x-axis and input is zero on the y-axis. In both figures firm 1 is considered technically inefficient because it is operating above $QQ^1$ in figure 3.2 and below $PP^1$ in figure 3.3. To be technically efficient, firm 1 has to radially reduce the quantities of inputs X1 and X2 along line 01 in figure 3.2. In figure 3.3 however, there has to be a radial expansion of outputs Y1 and Y2 along 01. The technical efficiencies from both figures are 0A/01 [1/(01/0A)] for figure 3.2 and 01/0A for figure 3.3. In the presence of price information for inputs and outputs, two different frontiers are constructed on both figures. With the knowledge of input prices, $CC^1$ in figure 3.2 is constructed. It is referred to as the isocost line, which represents the lowest feasible cost combination of inputs that produces the quantity associated with the isoquant. Output price information in figure 3.3 enables the construction of the isorevenue function ($RR^1$) that shows the maximum possible combination of

outputs that generate given revenue for the firm. With this information it is possible for firm 1 in figure 3.2 at its fully efficient point A, to reduce cost by AB just by moving downward the isoquant to point C. In this process more of input 1 ($X1_1X1_3$) is reallocated for reduction in input 2 ($X2_3X2_2$). This movement measures its allocative efficiency; that is 0B/0A. In the output oriented counterpart in figure 3.3, revenue can be increased by AB by moving from point A to point C. In this case firm 1 just have to allocate more production volume to output 1 ($Y1_4Y1_5$), whiles reducing the production of output 2 ($Y2_3Y2_2$). The allocative efficiency thereof is 0A/0B. Invoking the behavioral assumption of cost minimization and revenue maximization, this technically efficient point A on both figures has fell short of these new frontiers ($CC^1$ and $RR^1$); while point A in figure 3.2 is operating at a higher cost, it is generating less revenue relative to the $RR^1$ frontier in figure 3.3. This means they are both cost and revenue inefficient, and the only way to be efficient is moving towards $CC^1$ and $RR^1$ respectively. The cost efficiency is therefore 0B/01 in figure 3.2, while the revenue efficiency is 01/0B in figure 3.3.

Exploiting the relationship between cost, revenue, technical and allocative efficiencies, allocative efficiency can be estimated residually; TE * AE = CE and TE * AE = RE. From figure 3.2 (0A/01)*(AE) = (0B/01)

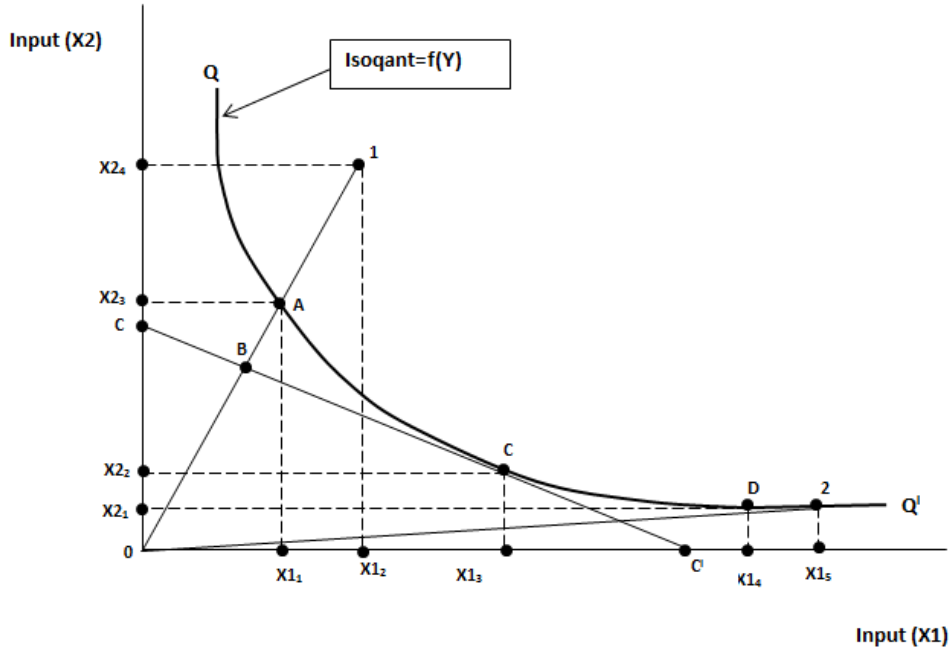
AE= (0B/01)*(01/0A) = 0B/0A

From figure 3.3

(01/0A)*AE = (01/0B)

AE= (01/0B)*(0A/01) = 0A/0B

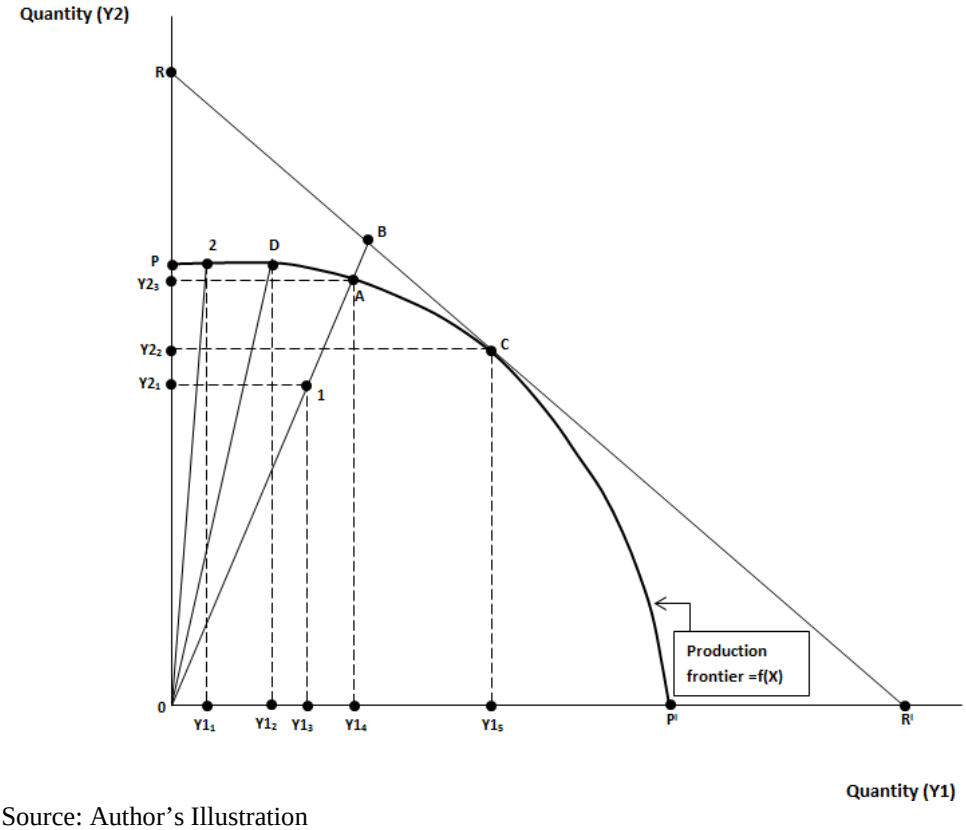
These correspond to the graphical estimation of allocative efficiency. This relationship would be employed in the study




Source: Author's Illustration

Figure 3.2. Input Oriented Efficiencies and Slacks

According to Coelli et al. (2005, p.54 and 56), both CE and RE will always be less than or equal to technical efficiency. This assertion is true from figures 3.2 and 3.3. This makes it possible for the residual AE above to take a positive score less than or equal to one. Furthermore, from the two diagrams, it can be observed firm 2 is technically inefficient even though it is on the frontier. These are the cases of input and output slacks. From figure 3.2, Even though firm 2 is on the technically efficient frontier, it is wasting $X1_4X1_5$ amount of input 1. In the case of output orientation in figure 3.3, firm 2 is losing $Y1_1Y1_2$ quantity of output 1, even though it is operating on the frontier.




Source: Author's Illustration

Figure 3.3. Output Oriented Efficiencies and Slacks

These could be eliminated by moving to point D on both figures. The presence of these slacks in both diagrams means firm 2 is experiencing 'weak efficiency' whiles that of firm 1 at point A is described as 'strong efficiency' because it has zero slacks.

For all these various concepts and efficiency types there are methods that underlines their estimation. The accurateness of the methods reflects the direction of the analysis and interpretation. Efficiency is a relative concept. Every measurement is done relative to a constructed frontier. How these frontiers are constructed determines the technique or method to use. Among the different and competing techniques used in the construction of the frontier, DEA and SFA are

going to be used in this thesis. Owing to the relative pros and cons of each method, the study employed both methods and compared their input oriented estimates. For other minor comparisons, output oriented was used. Under each technique, technical, allocative and cost efficiencies under CRS and VRS assumptions were estimated and compared.

#### 3.2.3.3. Selection of Orientation and Returns to Scale

The comparison of estimates between DEA and SFA should be consistent with orientations and scale of operation; i.e. input oriented DEA compared with input oriented SFA and output oriented DEA with output SFA. VRS and CRS estimates in DEA to VRS and CRS estimates in SFA. This informs the need to select the appropriate scale of operation and orientation.

According to Daraio and Simar (2007) the choice of input and output orientations are based strictly on the objective of the DMU; whether to conserved input or augmented output. The risky nature of agriculture makes it difficult for farmers to set reliable benchmarks on output, income and profit targets. However, farmers have more control over inputs they use in the production process. That is why most agriculturally related efficiency measurement literatures use the input orientation. There are however some exceptions. Government policies may assign quotas to the production of some crops, which would demand output orientation when the efficiencies of those farms are to be estimated. For example, Mendes et al. (2013b) in their study on dairy in the Azorean islands in Portugal were forced to use output-orientation because the Common Agricultural Policy of the European Union has assigned quotas to its production. Studies in the agricultural sector with similar techniques as this thesis have used the input orientation; Sharma et al. (1997, p.12), Sharma et al. (1999, p.8), Bravo-Ureta and Evenson (1994), Bravo-Ureta and Pinheiro (1997) and Singh et al. (2001), just to mention a few. Additionally, in the specific case of this thesis, output orientation would not be appropriate as a consistent comparison of all the efficiencies. That is, output

orientation is possible for technical efficiency in both techniques but not possible for allocative and cost efficiencies since they assume a cost minimization objective. However input orientation is capable of being applied to all efficiencies in both techniques, making comparison more consistent. Meanwhile, the output orientation for technical efficiencies in both techniques would be estimated for comparison purposes. The analyses in this study are not restricted to a particular RTS assumption. Both CRS and VRS efficiency scores would be estimated and compared.

### 3.2.4. Data Envelopment Analysis (DEA)

Drawing inspiration from Farrell's piece-wise linear convex hull proposal, Charnes, Cooper and Rhodes (CCR) developed the DEA technique in 1978. This method of constructing the frontier uses mathematical programming (linear and quadratic) and it is non-stochastic and non-parametric; meaning all deviation from the constructed frontier is considered as inefficiency (Coelli et al. 2005). It is estimated by assigning appropriate set of weights for all DMUs involved. These assigned weights maximize the efficiencies of each DMU relative to the efficiencies of other DMUs and subject to the condition that their efficiencies are restricted to positive and less than or equal to one. The DMU under consideration is called the reference or the base DMU (Ramanathan, 2003, p.39). This technique does not allow for statistical or white noise for which reason it does not envelope the data tightly. However, under some assumptions on the technology, it can envelope the data as tightly as possible (Lovell, 1993 p. 26).

In relation to this frontier, technical, allocative, cost, revenue and scale efficiencies can be estimated. However, technical efficiency has been the focus of this technique since its inception. This is partly due to the fact that DEA was originally developed as a performance measurement tool in a public sector environment where prices are not very well determined, hence the use of quantities

which only estimates technical efficiency. Others are of the view that technical efficiency is the best way to measure performance and that including price information will not be a level ground for comparison, especially between private and public entities (Lovell, 1993 p. 26).

Like Farrell, the CCR assumed input oriented, imposed a CRS on the production technology and suppressed slacks. They also imposed a strong input and output disposability, convexity of input-output combination as well as extending it to multiple output scenarios. Since then there has been a lot of modifications and extensions, mostly by the same originators of the technique. They followed it up with the multiplicative models in 1982 and 1983. These models sort to find interpretation to piecewise Cobb-Douglas as well as other log-linear frontiers. The most significant among the extension came in 1984 when Banker, Chames and Cooper (BCC) relaxed the CRS assumption. The relaxation of the CRS assumption made it possible for them to calculate 'pure' technical (VRS) and scale efficiencies. They could further identify the scale of operation; increasing, decreasing or constant returns to scale. The additive model and its extension were done in 1985 and 1987 respectively (Barros and Perrigot, 2007, p. 197; Charnes et al. 1994 p. 24; Coelli et al. 2005, p. 162). These modifications especially the BCC model opened up the applicability of DEA. In spite of the many advantages of DEA, the CRS assumption was responsible for its lack of widespread attention, as many researchers considered it over-restrictive (Ramanathan, 2003, p.69). The choice of any of the above models according to Nakanishi and Falcocchio (2004, p. 191) depends primarily on two major factors: 'the type of envelopment surface which can be either constant or variable returns-to-scale and the projection path leading to the envelopment surface which is analogous to the orientation type'. This thesis using the first factor focuses on the scale of operation, hence the choice of the CCR and BCC models.

As powerful and widely used this technique can be, it has advantages and disadvantages relative to other techniques that have been developed for the same

purpose. The main touted advantage of DEA is its objectivity and flexibility in accommodating the data under consideration (Pedraja-Chaparro et al. 1997 p.5). Few a priori assumptions are made about the data, making the frontier to fully reflect the shape dictated by the data. In other words, the functional form, the weights as well the distributions of error terms are not predetermined (Reig-Martinez and Picazo-Tadeo 2004, p. 21; Sharma et al.1999, p.2). The curvature conditions; monotonicity and convexity are the commonly used assumptions. These conditions only define the structure of the frontier or the production technology. Whiles the first assumes unwanted inputs and outputs can be freely disposed the latter forms a convex set to cater for variable returns to scale. The problems of functional misspecification and selection of inappropriate distribution are avoided. Aside being adoptable to any input output relationship, it has the ability to compute multiple outputs and inputs simultaneously. This makes it possible to be applied to production environment that are complex (Silva et al. 2013a p.7; Jacobs, 2001).

Furthermore, it also considered relatively computationally less difficult hence its wider application (Ramanathan, 2003, p.179). It is also known to finding relationships that otherwise could not be discovered by other techniques on the same data set. Seiford and Thrall (1990) observed studies that used different techniques on the same data set. They concluded DEA could establish a relationship in data which other methods could not. Example is the study by Banker, Conrad, and Strauss (1986) which established the presence of returns to scale in 144 North Carolina hospitals, when other econometric based techniques could not establish that (Charnes et al. 1994 p. 10). The technique is also considered very efficient in selecting the most efficient (set of best DMUs) for the construction of the frontier. That is, it compares each DMU with the most efficient ones (peers) and the best practice DMUs in the sample. Unlike in parametric analysis where an optimized regression represents all the DMUs, DEA optimizes for each DMU. This gives more information about each DMU in the sample (Bala

and Cook, 2003; Nakanishi and Falcocchio, 2004 p. 183). When only quantity data are involved, DEA is considered very effective in identifying and measuring efficiencies of DMUs. In the case of index numbers, price information must be included, while the econometric methods have problems with degrees of freedom (Diewert and Mendoza, 2007 p. 79). In the area of operations research especially, DEA offers a summary measure of each DMU's performance. The results of the technique are enough since its takes into consideration all the indicators deemed pertinent. This would avoid individual analysis of various indicators whose results may seem conflicting sometimes (Nakanishi and Falcocchio, 2004 p. 183).

The above mentioned advantages seem to a large extend responsible for the criticisms of DEA. The biggest criticism of DEA stems from its inability to separate statistical noise and inefficiency. Its deterministic nature implies all deviations from the frontier are considered as inefficiency. However, it is a known fact that deviation from the frontier is not caused by only inefficiency, but by uncontrollable environmental variables and measurement errors. This means that efficiency estimates by this technique is likely to be biased if the data is characterized by stochastic elements (Silva et al. 2013a p.7). Owing to the fact that DEA is non-stochastic, efficiency results are likely to be sensitive to measurement errors or other noise in data (Sharma et al. 1999). This means that, the most efficient DMUs used in the construction of the frontier could just be because an output or input value has been over or under stated. If these errors are not corrected, results can sometimes be abnormal. In the specific case of outliers, both the magnitude and the number of inefficient DMUs increase, resulting in some DMUs being "super-efficient" (Daraio and Simar, 2007 p. 38). Coelli et al. (2005, p.169) suggested that a proper checkup of the data should be done in order to remove any abnormality, especially outliers before using this technique. A sensitivity analysis is also advised on the post-DEA results (Ramanathan, 2003, p.179). As mentioned before, the technique in its original form does not consider statistical noise, hence less accommodating to statistical hypotheses tests.

Assumptions on the statistical noise, production frontier and other errors are prerequisite for hypotheses tests (Reinhard et al. 2000 p. 15). In explaining this point, attention must be paid to the phrase 'in its original form'. This is because attempts have been made till date to establish codified statistical testing in DEA. Progress has been made in this regard especially tests concerning efficiency comparisons of DMUs in different groups, presence of scale and allocative efficiencies, technical and productivity change etc. The stochastic characterization of DEA efficiency would open door to more statistical and hypotheses testing, hence the argument that classifying DEA as a non-statistical technique is a misrepresentation (Banker and Natarajan, 2011). DEA is also disadvantaged when it comes to the shadow prices. This is because of the non-parametric piecewise surface (or frontier), which is made up of intersecting planes. This makes it difficult to estimate shadow prices for the efficient points on the frontier since a range of price ratios can be gotten and not absolute points on the frontier (Coelli and Perelman, 1999 p. 2; Silva et al. 2013a, p 8). Furthermore, there is an argument that, since the technique considers only the most efficient DMUs in the shaping of the frontier, it is likely to exaggerate the number of efficient DMUs. That is, many DMUs may be efficient even if they are not. On the other hand, there may be a misrepresentation of the optimal frontier if all the DMUs in a particular sample are weak performers. In this case the sample has to be increased to include more efficient DMUs (Nakanishi and Falcocchio, 2004 p. 184). This problem is exacerbated in a small sample. The multi input and output applicability advantage of DEA turns to have a consequence of increased efficient firms with increased variables. That is, more variables automatically generate more efficient DMUs from the same sample (Reinhard et al. 2000, p.4). The issue of assigning weights is yet another limitation of DEA. The nonrestrictive nature of weights in DEA is considered among its advantages, that is its objectivity and flexibility. However, this advantage can be problematic when information on relative importance or prices of inputs and outputs are available to the researcher. In this case it would be

prudent for the researcher to restrict the weights in accordance with the information at hand. This will prevent high weights being assigned to relatively unimportant inputs and outputs or relatively lower weights assigned to relatively important quantities (Pedraja-Chaparro et al. 1997 p.5; Joro and Korhonen 2015, p. 127). Researchers have tried to find their way around this criticism by applying weight restrictions in DEA analysis. The first of which was Thompson and his colleagues in 1986. However, weight restriction has not received the much needed attention because the numerous weights selection techniques and their individual limitations (Nakanishi and Falcocchio, 2004, p. 184). Finally, DEA in certain circumstances gives strange and illogical efficiency estimates. For example, in a two output case, if two DMUs produce the same amount of output 1 but the second DMU produces more of output 2 than the first DMU, it is expected that the second DMU be considered more efficient than the first one. However according to Ramanathan (2003, p.180), these two DMUs are considered equally efficient.

**3.2.4.1. DEA Model Presentation**

Technical Efficiency: The model presentation in DEA is done by means of linear programming. There are basically two ways of presenting it, the multiplier form and the envelopment form (Coelli, 1996, p.10; Ramanathan, 2003, p.59). Even though they both measure efficiency, the envelopment form is more attractive in the sense that its presentation is simpler and has fewer constraints. In linear programming language, the multiplier form is the primal, whiles the envelopment form is the dual. The multiplier form assigns weight to inputs and outputs whiles the envelopment form assigns to DMUs involved. Also, the number of constraints in the multiplier form depends on the number of DMUs whiles that of the envelopment form is based on the number of inputs (Ramanathan, 2003, p.51, 59). Since agricultural economists have to deal with more number of DMUs than inputs in most times, the envelopment form is preferred. Hence, all the model presentations will be in the envelopment form.

*Definition of variables:* Assuming there are **N** DMUs, among whom efficiencies are to be compared, and **n** represents any DMU. Let **x** represent all inputs whiles **y** represents all outputs. It is further assumed that, at any point in time, a DMU utilizes varying amounts of **i** inputs to produce varying amounts of **j** outputs. For example, $\mathbf{y_{jn}}$ and $\mathbf{x_{in}}$ are $j^{th}$ output and $i^{th}$ input, respectively, of the nth DMU. $\mathbf{y_{jn}}$ and $\mathbf{x_{in}}$ are assumed to be greater than or equal to zero ($\mathbf{y_{jn}} \geq 0$, $\mathbf{x_{in}} \geq 0$), and finally each DMU has at least one positive input and one positive output value.

The model presentation will focus on the $m^{th}$ DMU (the reference DMU), and the variable definitions are as follows;

$\boldsymbol{\theta_m}$ is the technical efficiency of the $m^{th}$ DMU by input orientation

$\boldsymbol{\phi_m}$ is the technical efficiency of the $m^{th}$ DMU by output orientation

$\mathbf{y_{jm}}$ is $j^{th}$ output of the $m^{th}$ DMU,

$\mathbf{x_{im}}$ is $i^{th}$ input of the $m^{th}$ DMU,

$\mathbf{y_{jn}}$ is $j^{th}$ output of any DMU

$\mathbf{x_{in}}$ is $i^{th}$ input of any DMU

$\boldsymbol{\lambda_n}$ is the aggregated weight assigned to any firm in input approach

$\boldsymbol{\mu_n}$ is the aggregated weight assigned to any firm in output approach

DMU, n = 1, 2… N. Note that here **n** includes **m**.

Input oriented model;

$\min \ \theta_m$

Subject to;

$$\sum_{n=1}^{N} y_{jn}\lambda_n \geq y_{jm}; \quad j = 1, 2, 3, \ldots \ldots \ldots J \qquad (3.5)$$

$$\sum_{n=1}^{N} x_{in}\lambda_n \leq \theta_m x_{im}\,; \quad i = 1, 2, 3, \ldots . I \tag{3.6}$$

$$\sum_{n=1}^{N} \lambda_n = 1 \tag{3.7}$$

$\lambda_n \geq 0; \quad n = 1,2,3 \ldots \ldots \ldots . . N$

$\theta_m$ unrestricted (free)

When this model is optimized, the θ becomes the efficiency estimate while λ becomes the weight of DMUs involved. The left-hand side (LHS) of the constraint, (Eqn 3.5) is the weighted sum of the outputs of all the firms and the right-hand side (RHS) is the output of the reference firm **m**. It states that the weighted combination of all the outputs of all the firms should be at least equal to the outputs of the reference firm. Likewise, the LHS of Eqn 3.6 is the weighted combination of all inputs of all the firms, which should not be more than all inputs used by **m** DMU multiplied by its efficiency. Eqn 3.7 is the Variable Returns to Scale (VRS) restriction, which makes sure that firms are compared with firms of the same scale, without which the model automatically reflects a Constant Returns to Scale (CRS) situation (Coelli, 1996, p.174)

*Output oriented model;*

max $\phi_m$

Subject to;

$$\sum_{n=1}^{N} y_{jn}\mu_n \geq \phi_m y_{jm}\,; \quad j = 1, 2, 3, \ldots \ldots \ldots . J \tag{3.8}$$

$$\sum_{n=1}^{N} x_{in}\mu_n \leq x_{im}; \quad i = 1, 2, 3, \ldots . I \tag{3.9}$$

$$\sum_{n=1}^{N} \mu_n = 1 \tag{3.10}$$

$\mu_n \geq 0; \quad n = 1,2,3 \ldots \ldots \ldots . . N$

$\phi_m$ unrestricted (free)

In this second model $\phi$ and $\mu$ represent efficiency of the DMU and the weight of DMUs respectively. Eqn 3. 8 states the weighted combination of all the outputs of all the firms should be at least equal to the outputs of the reference DMU multiplied by its efficiency. Eqn 3.9 states that the weighted combination of all inputs of all the firms should not be more than all inputs used **m** DMU. Eqn 3.10 has the same explanation as Eqn 3.7.

As mentioned earlier the ratio of the CRS technical efficiency to the VRS technical efficiency is the scale efficiency. However, this scale efficiency estimates cannot indicate exactly on which scale a given DMU is operating, i.e. whether increasing, constant or decreasing returns scale (Ramanathan 2003, p.51, 59). To establish this, efficiencies of 3 RTS assumptions are estimated and compared. They are CRS, VRS and Non-Increasing Returns to Scale (NIRS). Since the first two have been discussed, attention is given to only NIRS. The NIRS restriction is imposed by substituting Eqn 3.7 and Eqn 3.10 with Eqn 3.11.

$$\sum_{n=1}^{N} \mu_n \leq 1 \tag{3.11}$$

Eqn 3.11 is referred to as the NIRS restriction. In order to determine the scale under which the reference DMU is operating, a comparison is made between

CRS, VRS and NIRS. When NIRS and VRS estimates are not equal, it means IRS. When they are equal but not equal to CRS, it reflects Decreasing Returns to Scale (DRS), and finally it is CRS when CRS and VRS are equal (Coelli et al. (2005, p.174; Ramanathan 2003, p.51, 84).

Allocative and Cost Efficiencies: The cost minimizing linear programming model will produce values to calculate cost efficiency (CE). Allocative efficiency is the ratio of cost efficiency to technical efficiency. The prevailing input prices put together with output quantities produce the cost equation.

*Definition of* variables: Let's add **c** as a new variable definition for unit cost of inputs employed, **k** represent total cost of production and **ψ** represents the aggregated weight to any DMU.

Then the total cost function therefore for any DMU is;

$$\sum_{n=1}^{N} c_i x_i = k \tag{3.12}$$

According to Linna and Hakkinen (1998, p. 178), there are two stage process for estimating cost efficiency in nonparametric approach. The first is to minimize the total cost equation in eqn 3.12. Since the DMUs do not have control over input prices ($c_i$) the only way to get the minimum possible total cost is using the minimum possible amount of inputs ($x_i^*$). Secondly, this feasible minimum cost (Eqn 3.13) is then compared to the observed cost Eqn 3.12 to estimate cost efficiency.

*The model;*

$$min \sum_{n=1}^{N} c_i x_i^* = k^* \tag{3.13}$$

Subject to;

$$\sum_{n=1}^{N} x_{in}^{*}\psi_n \leq x_{im}\,;\quad i = 1,2,3 \ldots\ldots I \tag{3.14}$$

$$\sum_{n=1}^{N} y_{jn}\psi_n \geq y_{jm}\,;\quad j = 1,2,3 \ldots\ldots J \tag{3.15}$$

$$\sum_{n=1}^{N} \psi_n = 1 \tag{3.16}$$

$\psi_n \geq 0; \quad n = 1,2,3 \ldots\ldots N$

The constraints reflect the same interpretation as the input oriented model, since it is a minimization problem. The striking difference however is the absence of inefficiency term.

It has to be noted that since this is an input orientation, there is a target output and a given unit cost of input. When this model is optimized, it produces the optimal input bundle of $x_i^*$ and $k^*$ as minimum total cost. The difference between the observed k and the optimized $k^*$ represent how much cost can be reduced so as to be both technically and allocatively efficient. Their ratio gives the cost efficiency.

$$CE = \sum_{n=1}^{N} c_i x_i^* \Big/ \sum_{n=1}^{N} c_i x_i = \frac{k^*}{k} \tag{3.17}$$

Allocative efficiency is residually obtained from this relation;

$$AE = \frac{CE}{TE} \tag{3.18}$$

Both CE and AE, like TE, have their values ranging between 0 and 1, where 1 means full efficiency.

### 3.2.5. Stochastic Frontier Analysis (SFA)

As mentioned earlier, Aigner et al. (1977) and Meeusen and Van den Broeck (1977) independently proposed this technique (Silva et al. 2013a, p.5; Darku et al. (2013, p.2). Just as agricultural data were used in Farrell's 1957 seminal paper, the farm-level application of the stochastic frontier analysis was done in the same year it was developed, by Battese and Corra (1977) (Battese, 1992). The deviation from the frontier is divided into two; a two-sided symmetric random error that accounts for statistical noise (v) and the one-sided inefficiency (u) term. Statistical noise (v) represents the effects of factors that are outside the control of the firm, such as measurement errors, omission of relevant variables, trade union effects, government regulatory policies, environmental and natural shocks, etc (Coelli et al. 2005, p.261). The inefficiency component (u) however reflects factors that can be controlled by the firm, and it is nonnegative bounded by zero and one. The combination of these two error components gives the composed error term $\varepsilon_i = v_i - u_i$. That is why it is alternatively referred to as a "composed error" model (Kumbhakar and Lovell, 2000, p. 8). Estimates are estimated using regression and maximum likelihood techniques. It imposes strict functional and distributional restrictions on the data, which preempts the shape of the frontier. These restrictions enable it to formally test hypotheses and construct confidence intervals (Daraio and Simar, 2007, p.30; Silva et al. 2013a, p.8). The functional forms include Cobb-Douglas production functions (Hannesson 1983), CES production functions (Campbell and Lindner 1990), and translog production functions (Squires 1987, Pascoe and Robinson 1998) (Pascoe et al. 2003, p. 4). The commonly used functional forms are Cobb-Douglas and transcendental-logarithmic (translog) production functions. The distributional restrictions are normal for the statistical noise component (v), and either half-normal, truncated normal,

exponential or gamma distribution for the inefficiency (u) term. Scale restrictions are also possible. Like the coining of the DEA term, they also coined the term Stochastic Frontier Analysis (SFA).

The principal advantage of this technique is its ability to separate deviations from the frontier into statistical noise and inefficiency. Practically, deviation from the frontier cannot not solely be attributed to the mismanagement of the DMU but also to the stochastic factors outside their control. Especially in the area of agriculture these stochastic factors are inevitable and very significant (Silva et al. 2013a p.8). Another importance attached to SFA is its ability to statistically test hypothesis as well as construct confidence intervals for the purposes of statistical inference. These tests include significance or otherwise of efficiency and coefficient estimates, the determination of returns to scale, goodness of fit measures etc. (Hjalmarsson et al. 1996 p. 2). The technique has also been highly praised for its allowance for a richer specification when applied to panel data (Reinhard et al. 2000, p. 4). Technically, the fact that panel data has more data than cross sectional data means that it has more advantages when SFA is applied. In addition to the fact that DMU specific efficiencies are more consistently estimated with panel data, they also require less strong assumptions (Zhang, 2012, p. 33; Farsi, et al. 2006). Furthermore, unlike DEA, SFA is not sensitive to the presence of outliers in the data, even though it is less robust. It identifies these outliers as a form of noise and treats it as such (Sharma et al. 1999).

The limitation of SFA lies in the fact that data is forced to fit into an a priori assumption. Just like most of the advantages related to the use of SFA emanate from the imposition of these restrictions, so are the limitations. On the functional restrictions, there is a chance of misspecification which often translates into confounding inefficiency estimates. Aside that, the functional forms especially the flexible ones have a greater tendency of exhibiting multicollinearity problems as well as violating certain theoretical conditions. The curvature conditions like the concavity in inputs in translog production function in particular are not globally

satisfied (Reinhard et al. 2000, p. 4; Lansink and Reinhard, 2004, p. 6). These distributions which most often do not have a theoretical justification are capable of altering the inefficiency estimates (Murillo-Zamorano, 2004). Whiles some distributions are more restrictive and generate more efficient firms, others are less restrictive. Sharma et al. (1999) summarizes this issue by stating that 'The need for imposing an explicit parametric form for the underlying technology and an explicit distributional assumption for the inefficiency term are the main weaknesses of the parametric approach'. In the most common form of SFA, it cannot handle multiple outputs. Modern production units use multiple inputs to produce multiple outputs, and efficiency estimation would be more accurate if all can be incorporated. Even though the multiple outputs have been developed, their application is complex and limited (Pascoe et al. 2003 p. 3). As mentioned earlier, the issue of outliers is a plus to SFA in the sense that it is less sensitive to outliers. This is because it amalgamates it with the noise term. However this avoidance means that, some inefficient DMUs would not be identified. On the other hand, DEA in the presence of outliers will estimate very large inefficiencies in the sample. This therefore means that the problem of outliers is a problem for both techniques, but for different reasons (Sarafidis, 2002).

It can be seen that the issue of outliers is very important in both DEA and SFA. It therefore calls for the investigation in the study data for their possible presence or otherwise. The study would also analyze, to what extent is it present in each of the variables to be used in the estimation of the production functions. For comparison's sake two competing methods would be used: the Interquartile Range (IQR) method and the Z score method (Anderson, 2014).

For whatever functional form and distributional assumption taken, the generalized stochastic production function is

$$Y_i = f\ (\ X_i;\ \beta_i) + \ \varepsilon_i \qquad (3.19)$$

Where $\varepsilon_i = v_i - u_i$ (3.20)

$Y_i$ is the quantity of maize output, $X_i$ are inputs, $\beta_i$ is the parameters which represent output elasticities of inputs employed, and $\varepsilon_i$ is the composed error term already defined.

Unlike other production functions which has a composed error term ($\varepsilon_i$), the stochastic production frontier segregates it as in eqn 3.20. Whiles the others are made up the deterministic and the error term component, the stochastic production function is made up of the deterministic, noise and the inefficiency terms. To illustrate this, a specific functional form like Cobb-Douglas is assumed.

$$Y_i = A\prod_{k=1}^{k=K} {X_k}^{\beta_k} e^{v_i - u_i} \quad \sum_{k=1}^{k=K} \beta_k = rts \quad lnA = \beta_0 \quad \varepsilon = v_i - u_i \qquad (3.21)$$

k is the number of inputs

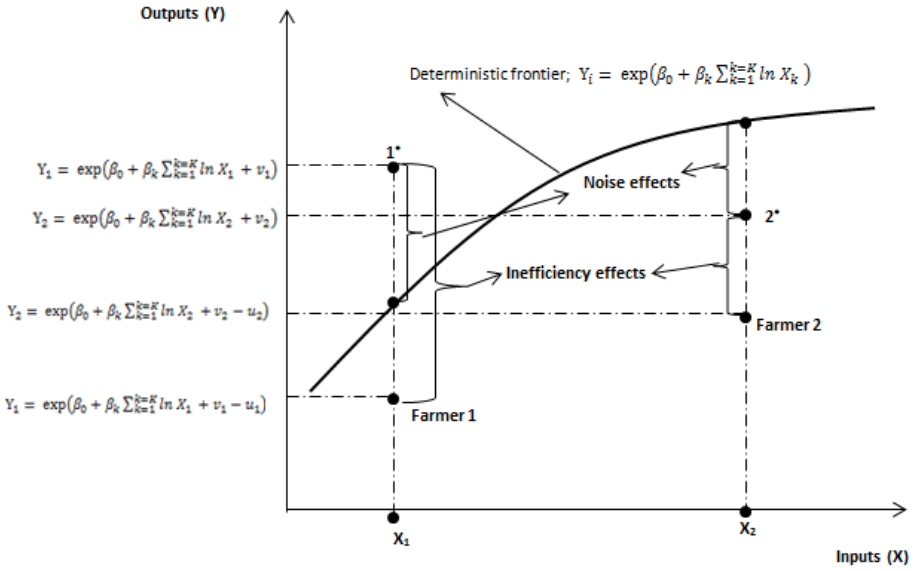
Linearizing;

$$\ln Y_i = \beta_0 + \beta_k \sum_{k=1}^{k=K} ln\, X_k + v_i - u_i \qquad (3.22)$$

For the sake of illustration, it can be put in another way;

$$Y_i = \underbrace{\exp\left(\beta_0 + \beta_k \textstyle\sum_{k=1}^{k=K} ln\, X_k\right)}_{\text{Deterministic component}} * \underbrace{\exp(v_i)}_{\text{Noise}} * \underbrace{exp(-u_i)}_{\text{Inefficiency}} \qquad (3.23)$$

The output values of the production function are bounded from above by the noise or random error component ($v_i$). Since this component can be positive or negative, the stochastic frontier varies about its deterministic component (Coelli et al. 2005). This could alternatively be explained in the figure 3.4. Output values are measured on the vertical axis whiles that of inputs are on the horizontal axis. Considering the case of one input-one output for two hypothetical farmers 1 and 2. As characteristic of a Cobb-Douglas production function, the deterministic frontier in the diagram exhibits diminishing returns to scale. Farmer 1 employs input $X_1$ to produce output $Y_1$ and likewise farmer 2 using input $X_2$ to produce Output $Y_2$. These points are indicated as farmer 1 and 2 respectively. However in the absence of inefficiency both will be producing at points 1* and 2* respectively. This demonstrates why the inefficiency term (u) has a negative sign; that is, without inefficiency, output is always higher in both cases. However the case of the noise term, it is either be positive or negative. As seen from the diagram, the noise term is positive for farmer 1 and negative for farmer 2. This is indicated by their location on the opposite of the deterministic frontier; farmer 1 above and farmer 2 below.




Source: Author's illustration
Figure 3.4. Stochastic Production Frontier

It must be made clear that the individual error terms do not determine the location of the farmer around the deterministic frontier, but rather its combined effect. For example, farmer 1 is located below the deterministic frontier because the combined effect of the positive noise term and the negative inefficiency term is negative. That is $\varepsilon_1 = v_1 - u_1$= negative

### 3.2.5.1. Efficiency Measurement

The technical definition of technical efficiency or inefficiency does not change with methods. As it has been defined and demonstrated previously, efficiency in the output context is the ratio of the observed output to the output on the stochastic frontier (the most efficient frontier). The most efficient frontier in this case is that part of the stochastic frontier where the inefficiency term is zero, that is $Y_i = \exp(\beta_0 + \beta_k \sum_{k=1}^{k=K} ln\, X_k) * \exp(v_i)$. This is clearly represented as points 1* and 2* for farmer 1 and 2 respectively in figure 3.4. The observed output, which incorporate the inefficiency term is $Y_i = \exp(\beta_0 + \beta_k \sum_{k=1}^{k=K} ln\, X_k) *$

$\exp(v_i) * exp(-u_i)$. These are farm 1 and farm 2 on the diagram. These are alternatively expressed on the output axis in the diagram. Technical Efficiency (TE) therefore;

$$\mathrm{TE}_i = \frac{\exp(\beta_0+\beta_k \sum_{k=1}^{k=K} ln\, X_k) * \exp(v_i) * exp(-u_i)}{\exp(\beta_0+\beta_k \sum_{k=1}^{k=K} ln\, X_k) * \exp(v_i)} = exp(-u_i) \qquad (3.24)$$

This equation looks very simply only under the condition that all the parameters involved are known. The much known Ordinary Least Square (OLS) method can be used, but the intercept parameter ($\beta_0$) will be biased downwards making it inappropriate for the estimation of technical efficiency. However, it is capable of determining the presence or otherwise of technical efficiency. That is if $u_i = 0$ then the composed error term collapses to the noise term ($\varepsilon_i = v_i$), which is symmetric. It therefore means that in the presence of inefficiency ($u_i$), the error term would be negatively skewed. That is, the skewness of the error term in an OLS estimation can determine the presence or otherwise of technical inefficiency (Kumbhakar and Lovell, 2000). Other estimation methods have been developed in the context of deterministic frontiers; they are Corrected Ordinary Least Squares (COLS), Modified Ordinary Least Squares (MOLS) and Goal programming by Winsten (1957), Afriat (1972) and Richmond (1974), and Aigner and Chu (1968) respectively (Kumbhakar and Lovell, 2000). In the case of stochastic frontier analysis, the composed asymmetric error term makes the above methods impotent. The maximum likelihood (ML) method and the Bayesian approach take this into consideration. However, the former has the edge in empirical application than the latter. The evidence of this according to Mastromarco (2008), is found in the studies of Koop et al. (1999, 2000a, b) and Koop (2001). The ML has therefore been selected as the estimation technique for the stochastic production frontier. Even though it requires some distributional assumptions, it is capable of estimating all the parameters consistently, as well as the farm specific noises and

inefficiencies at the same time. Aside these parameters, it also estimates the variances and the standard deviations of the noise and inefficiency components. That is $\sigma_v^2$, $\sigma_u^2$ , $\sigma_u$, $\sigma_v$ and $\sigma^2$. From these, important statistics like the lambda ($\lambda = \sigma_u/\sigma_v$), gamma ($\gamma = \sigma_u^2/\sigma^2$), $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and Log likelihood functions are estimated. Bravo-Ureta and Pinheiro (1997). The importance of these will come to light in the results section of this thesis. The ML technique is a two-step procedure; the first being the estimation of the slope parameters using the OLS and the second being the estimation of the intercepts and the variances of the two error components, $v_i$ and $u_i$. In the second step, the ML is used with a specified distributional assumption. With these estimates, farmer specific efficiencies and noises can be estimated (Kumbhakar and Lovell, 2000). Furthermore the ML estimators have many asymptotic properties, which makes it more preferable to COLS. Coelli (1995) proved this in a Monte Carlo study, but quick to admit that the finite sample properties of the two estimators are unknown (Coelli et al. 2005). There are three main estimation challenges to the application of the above simplified procedure in estimating the parameters and the inefficiencies. First is the segregation of the composed error term ( $\varepsilon_i$ ) in to $v_i$ and $u_i$ estimates, second is the specification of the distribution and finally estimation technique selection. These are treated separately under separate heading below.

**3.2.5.2. Decomposition of Composed Error**

The solution to this lies in the famous work of Jondrow et al. (JLMS) (1982). They were of the view that, in as much as the composed error term ( $\varepsilon_1$ ) can be estimated, inefficiency can be estimated since the error term contains information on $u_i$, that is $\varepsilon_1 = v_1 - u_1$. They did this by estimating both the mean and the mode of the conditional distribution of $u_i$ given $\varepsilon_1$. For the distributional assumption, half-normal and exponential were assumed for $u_i$. Employing the half-

normal distribution and using only the mean, the conditional mean of $u_i$ given $\varepsilon_i$ is;

$$E(u_i/\varepsilon_i) = \sigma_* \left[ \frac{f(\varepsilon_i\lambda/\sigma)}{1 - F(\varepsilon_i\lambda/\sigma)} - \left(\frac{\varepsilon\lambda}{\sigma}\right) \right] \quad (3.25)$$

Where $\sigma_*^2 = \sigma_u^2\sigma_v^2/\sigma^2$, $\lambda = \sigma_u/\sigma_v$, f is the standard normal density function, and F is the cumulative distribution function. F and f are all evaluated at $\varepsilon\lambda/\sigma$.

And for the exponential case;

$$E(u_i/\varepsilon_i) = \sigma_v \left[ \frac{f(A)}{1 - F(A)} - (A) \right] \quad (3.26)$$

Where $A = \varepsilon/\sigma_v + \sigma_v/\sigma_u$

The work of Jondrow et al. (1982) has informed the discovery of other point estimators like Battese and Coelli (1988), which according to Kumbhakar and Lovell, (2000) is preferred to JLMS (1982).

**3.2.5.3. Distributional Assumptions**

The second issue has to do with distributional assumptions. As mentioned earlier, specification of a distributional assumption of $u_i$ is a requirement in the estimation of efficiencies in stochastic frontier analysis. However, there are a lot of these distributional assumptions, which have all been applied to empirical data. The most common of them are half-normal (Aigner, Lovell and Schmidt, 1977), exponential (Meeusen and van den Broeck, 1977 and Aigner et al. 1977), truncated normal (Stevenson, 1980), and gamma (Greene, 1990) (Coelli et al. 2005). The first two distributions are restrictive and single-parameter, whiles the last two are

more flexible, two-parameter, and respectively derived from the first two distributions (Fried et al. 2008).

Before proceeding to outline how the distributions were selected, it is better to answer the question: does the distribution matter? Not all researchers in this field pay attention to the answer of this question, as they feel it is irrelevant. Their argument stems from the fact that efficiency estimates are relatively robust to distribution of the inefficiency term (Greene, 2008). This line of argument may not be entirely correct. It has been empirically proven that the argument is true when the research is focused on only efficiency rankings (Coelli et al. 2005). However, there is evidence that estimated stochastic frontiers and firm specific efficiencies are actually very sensitive to distributional assumptions (Kumbhakar and Lovell, 2000; Greene, 2008). For this research, the answer to the question is 'yes'. This is because the research would be interested both in the efficiency estimates and their rankings. Two procedures would be used in the selection of a distribution for the study; the first would be elimination of distributions that are incapacitated in the context of the study and the data. Secondly, a series of likelihood ratio tests would be conducted on the rest finally choose one for the analyses.

In the context of this research, the gamma distribution is the first to be eliminated for one major and one minor reason. The major reason being the fact that, it is not appropriate for small sample estimation like this study. Ritter and Simar (1997a) argued that the estimation of a normal gamma stochastic frontier model is in a serious doubt if the sample size is not in several hundreds. This has a direct bearing on the estimation of the inefficiency term. Their reason is that, in a fewer sample normal gamma stochastic frontier is not distinguishable from an ordinary least squares model. They further argued that, even with a sample in several of hundreds, it is sometimes not distinguishable from normal-exponential stochastic frontier model and other normal-gamma models. Their argument was so convincing that the originator of the gamma distribution model, William Greene had to acknowledge and admit it in Greene (2008). To quote their concluding

sentence 'We fear that the normal-gamma model and probably other free-shape models aimed at estimating frontiers and inefficiencies from small to medium sized samples may not form the basis of valid measurement processes'. With a sample size of 121 farmers, I also share their fear. In essence this study falls short of the sample size needed by a gamma distribution for proper estimation of the stochastic frontier. The other reason has to do with its applicability. Estimation of the gamma distribution is exceedingly difficult, and by the admission of Greene (2008) himself, it inhibits it application. This was also confirmed by Ritter and Simar (1997a).

The second elimination method is the restrictiveness of the distribution. Leading researchers in this field like (Coelli et al. 2005), (Kumbhakar and Lovell, 2000), (Greene, 2008) and (Ritter and Simar, 1997a and 1997b) have often encouraged the use of simpler restrictive half-normal and exponent distributions to that of less restrictive truncated normal and gamma distributions. Whiles some have reached this conclusion based on empirical application on data, others did so by reviewing literature. Coelli et al. (2005) admitted that, even though theoretical considerations can suggest the use of the less restrictive distributions because of their non-zero modes, the computational complexities are too much a cost to bear. They also added that, in instances where the $u_1$ and $v_1$ have similar Probability Density Functions (PDFs), the inefficiency and the noise effects are difficult to distinguish. Further acknowledging the robustness of efficiency rankings and the sensitivity of efficiency estimates, they concluded on the principle of parsimony, that the restrictive half-normal and exponential distributions are preferred. Kumbhakar and Lovell, (2000) also arrived at this conclusion using Greene's 1990 estimation of the stochastic cost frontier on US electric utilities. Greene (1990) applied all the four distributional assumption in this study and reported the mean efficiencies as follows; 0.877 (half normal), 0.901 (exponential), 0.896 (truncated normal), and 0.895 (gamma). Further analyzing this results, Kumbhakar and Lovell, (2000) concluded that the restrictive half-normal and exponential models

are enough. Following this findings Greene, (2008) returned with a similar analysis, casting doubt over the techniques used by Kumbhakar and Lovell, (2000). He posited that, for such an analysis, the data should have been fitted into a full translog model and estimated as a production rather than the cost function. Despite these disagreements, he arrived at very similar conclusions with former. Finally the studies of Ritter and Simar, (1997a and 1997b) which focused on the application of the normal gamma distribution, suggested the use of half normal or exponential rather than more flexible ones; truncated normal and gamma distributions. They further suggested the choice between one-parameter half normal and exponential distributions is inconsequential. By this, the study would eliminate truncated normal and gamma (already eliminated) distributions leaving half normal and exponential as the candidates.

The conclusion that the choice between these two remaining candidates is immaterial is enough for us to arbitrarily use one of them. However, a combination of maximum likelihood ratio test and a sequential analysis test would ultimately leave us with one distribution. The sequential analysis test was also adopted in the selection of the model for the study of Bhattacharyya et al. (1995). Using likelihood ratio test and half normal distribution as the reference; if between half normal and truncated normal, the latter is found to be adequate, the exponential distribution would be used. But if half normal is adequate, then that is what would be employed.

**3.2.5.4. Selection of Estimation Technique**

Like in the case of DEA, the estimation of efficiencies in stochastic frontier can be input oriented or output oriented. Furthermore, in the same way, technical efficiency forms the basis for the estimation of cost and allocative efficiencies. However in this case, regardless of the orientation the output oriented technical efficiency or inefficiency is a prerequisite for the estimation of all other efficiencies. That is, the technical efficiency estimate ($TE_i = exp(-u_i)$ ) in eqn

3.24. As explained earlier, input orientation has been chosen for the analysis and for comparison's sake, all the techniques must be input oriented. However, just like in the DEA the output orientation would be estimated to examine the extent to which the two techniques agree. Since the output oriented technical efficiency has been presented already in eqn 3.24, the concept of Cost and Allocative efficiencies are presented below.

Total cost of a DMU is generally is the summation of the product of each input quantity and per-unit input price. That is

$$C_i = \sum_{k=1}^{k=K} X_{ik} * P_{ik} \tag{3.27}$$

Dealing with a stochastic production frontier, means the cost frontier should also be stochastic.

The general stochastic cost frontier can be expressed as;

$$C_i = f\,(Y_i, P_i;\ \beta_i) + \varepsilon_i \tag{3.28}$$

Where $\varepsilon_i = v_i + u_i$

In Cobb-Douglas form is;

$$C_i = A^* \prod_{K=1}^{K=K} {P_{ik}}^{a_i}\ Y_i^{b_i}\ e^{v_i+u_i} \qquad lnA^* = a_0 \tag{3.29}$$

C is total cost, P is the unit price of each input, Y is the total output of maize produced, k is the number of inputs $a_i$ and $b_i$ are coefficients of unit prices

and output respectively. Cost efficiency by definition is the ratio of the minimum cost to the observed cost of the DMU (Coelli et al. 2005).

Linearizing the Cobb-Douglas cost function, the observed and the minimum costs are;

*The observe cost;*

$$lnC_i^o = a_0 + \sum_{k=1}^{k=K} a_i lnP_{ik} + b_i lnY_i + (v_i + u_i); \quad i = 1,2,3 \ldots . k \quad (3.30)$$

*Minimum cost*

$$lnC_i = a_0 + \sum_{k=1}^{k=K} a_i lnP_{ix} + b_i lnY_i + (v_i); \quad i = 1,2,3 \ldots k \quad (3.31)$$

Where $\boldsymbol{c_i^o}$ and $c_i$ means observed cost and minimum cost respectively. $a_0$, $a_i$ and $b_i$ are parameters to be estimated. $v_i$ and $u_i$ still have the same interpretation just that **u** is now adding instead of subtracting to indicate that inefficiency have a positive effect on total cost of production. Cost efficiency by definition is the ratio of $c_m$ to the $c_m^o$;

$$\text{CE} = \frac{c_m}{c_m^o} = exp(-u_i) \quad (3.32)$$

Exploiting the relationship between economic, allocative and technical efficiencies, allocative efficiency can be calculated.

According to Singh et al. (2001), there are basically two main ways of estimating this; either the cost function is estimated directly or indirectly from an already estimated production function. Schmidt and Lovell (1979) propounded the former, where they were able to estimate thereof input oriented technical, allocative and cost efficiencies. This method does not only require accurate information on total cost, input prices and output data, but that there must be

considerable variations in the price data (Jiang and Sharp, 2014). It requires the specification of both the production function and distributional assumption. This condition is necessary because the procedure involves the use of regression. Even though the Cobb-Douglas production function was used, there has been extension of their procedure to accommodate other production functions like the translog. Examples of these given by Singh et al. (2001) are; Greene (1980), Kopp and Diewert (1982), Zeischang (1983), Schmidt and Sickles (1984), Bauer (1990), Ferrier and Lovell (1990), Atkinson and Cornwell (1994), Mensah (1994), Oum and Zhang (1995), Balk (1996) and Kumbhakar (1997). The estimation method by Schmidt and Lovell (1979) could only produce producer-specific estimates of cost efficiency, hence the use of single-equation models. However, this thesis requires input oriented technical and allocative in addition to this cost efficiency. The product of these additional efficiencies (technical and allocative) by definition is cost efficiency; hence the decomposition of their cost efficiency is necessary. Building on this method, Kopp and Diewert (1982) and Zieschang (1983) developed the simultaneous-equation cost frontier models to decompose the cost efficiency into technical and allocative efficiencies. This method however requires further data on either input quantity or input cost share (Kumbhakar and Lovell, 2000). For the estimation of the parameters involve in this procedure either the method of moments or maximum likelihood approaches can be employed (Schmidt and Lovell, 1979). As in the technical efficiency case, JLMS or the Battese, and Coelli decomposition is required to separate the noise component from cost inefficiency.

The procedure that involves the indirect estimation of the cost function exploits the duality principle between the cost and production functions. The parameters of the cost functions, optimal input vectors as well input oriented technical, allocative and cost efficiencies are estimated from this relationship. This procedure however is restrictive in terms of the production function to be used since not all production function functions are self-dual. For this reason, the Cobb-

Douglas production function is used in studies using this procedure (Schmidt and Lovell, 1979). This procedure is not econometric as the first and does not need considerable variation in the data especially the price data.

The study is adopting the latter procedure for one particular reason; non variability of some input prices. As discussed already under input and output prices, there are inputs with fixed prices, whiles other do not vary considerably. Choosing this procedure is by extension employing the Cobb-Douglas production and the distributional assumption would be decided between half normal and exponential models. However, a hypothesis test would still be conducted to find out the appropriateness of the chosen Cobb-Douglas production function in respect to the sample. This chosen procedure would be further expatiation in a new subtitle.

**3.2.5.5. Analytical Framework and Model Presentation**

As mentioned this procedure begins with the estimation of a Cobb-Douglas production function in eqn 3.21, and linearizing it to form eqn 3.22. The parameters (β's) as well as $v_i$ and $u_i$ are estimated using maximum likelihood estimation, with a defined distributional assumption. The model in eqn 3.22 is estimated using the NLOGIT 5.0 program. Unlike other efficiency analyses software, NLOGIT 5.0 in addition to the parameters and the inefficiencies estimates, gives the individual deterministic predicted values, noise and composed error terms. To proceed with the standard cost efficiency decomposition techniques, the output must be adjusted for the noise component in the model, leaving it in the deterministic framework (Singh et al. 2001). That is the noise component is subtracted from both sides of the model.

$$\ln Y_i - v_i = \ln \widehat{Y}_i = \beta_0 + \beta_k \sum_{k=1}^{k=5} ln\, X_k - u_i \quad (3.33)$$

or in a nonlinear form as;

$$Y_i * e^{-v_i} = \hat{Y}_i = A \prod_{k=1}^{k=5} {X_k}^{\beta_k} e^{-u_i} \quad (3.34)$$

Where $\beta_1$, $\beta_2$, $\beta_3$, $\beta_4$ and $\beta_5$ represent the coefficients of labor, machinery, nitrogen, phosphorous and pesticide respectively. $\hat{Y}_i$ is the output adjusted for statistical noise

As mentioned earlier, the input oriented technical efficiency is the starting point. This is done by first finding the input combinations at which the production function ($\hat{Y}_i$) is equal to the observed input ratios ($X_1/X_k = R_{1k} \quad (k > 1)$), that is the technically efficient input vector ($X^t$). This requires solving them simultaneously. Before that, the results from the parameter and inefficiency estimates must be substituted into the equation to estimate $\hat{Y}_i$ (Bravo-Ureta and Evenson, 1994).

Each of the technically efficient input vector ($X^t$) from this solution is then multiplied by it corresponding observed input price for each farmer, and summed. This gives technically efficient total cost of production for each farmer (eqn 3.37). The difference between this total cost and observed total cost of production is accounted for by technical inefficiency. Therefore the ratio of this cost to the observed total cost gives technical efficiency.

In the specific case of this thesis with one output, five inputs and an assumed Cobb-Douglas production function, the presentation of the simultaneous equation is

$$\hat{Y}_i = \beta_0 X_1^{\beta_1} X_2^{\beta_2} X_3^{\beta_3} X_4^{\beta_4} X_5^{\beta_5} e^{-u_i} \quad (3.35)$$

$$\frac{X_1}{X_2} = R_{12}, \quad \frac{X_1}{X_3} = R_{13}, \quad \frac{X_1}{X_4} = R_{14} \quad \text{and} \quad \frac{X_1}{X_5} = R_{15} \tag{3.36}$$

The technically efficient cost is;

$$C_i = \sum_{k=1}^{k=K} X_{ik}^{t} * P_{ik} \tag{3.37}$$

$$\sum_{k=1}^{k=K} X_{ik}^{t} * P_{ik} \Big/ \sum_{k=1}^{k=K} X_{ik} * P_{ik} = TE_i \tag{3.38}$$

Assuming the production function in eqn 3.34 is dual, the corresponding cost frontier would be

$$C_i = A^* \prod_{k=1}^{k=5} {P_{ik}}^{a_i} \hat{Y}_i^{b_i} \qquad lnA^* = a_0 \tag{3.39}$$

The formulation for transforming the production function into a cost function is given below;

$$C_i = rst * \left( A * \prod_{k=1}^{k=5} {\beta_k}^{\beta_k} \right)^{-1/rst} \left( \prod_{k=1}^{k=5} {P_k}^{\beta_k} \right)^{1/rst} \hat{Y}^{1/rst} \tag{3.40}$$

Where;

$$A^* = rst * \left( A * \prod_{k=1}^{k=5} {\beta_k}^{\beta_k} \right)^{-1/rst} \qquad a_i = {\beta_k}/{rst} \qquad b_i = {1}/{rst}$$

Where $P_1$, $P_2$, $P_3$, $P_4$ and $P_5$ represent the per-unit prices of labor, machinery, nitrogen, phosphorous and pesticide respectively.

From here, Shephard's lemma is applied on the estimated cost frontier to yield the conditional input demand or the cost efficient input vectors ($X^c$) (Sharma, Leung and Zaleski, 1999). That is, differentiating the cost function with respect to individual input prices.

$$\partial C_i / \partial P_k = X_{dk} = X_k^c \left(P_k, \hat{Y}_i, \delta\right) \quad (3.41)$$

$X_{dk}$ = conditional input demand function, $X_k^c$ = cost/economically efficient input quantity

In order to calculate the cost or economically efficient input combinations, the observed input prices ( $P_k$ ) and adjusted output ($\widehat{Y_i}$) should be substituted into each input demand function.

When these economically efficient input combinations are multiplied by their respective observed prices ( $P_k$ ) and summed, the results is economically efficient cost of production for that particular farmer (eqn 3.42). It is therefore logical that the difference between this and the observed cost of production is the results of inefficiency in cost of production.

Therefore input oriented cost efficiency is the ratio of the economically efficient cost of production to the observed cost of production.

The cost efficient cost is;

$$C_i = \sum_{k=1}^{k=K} X_{ik}^c * P_{ik} \quad (3.42)$$

$$\sum_{k=1}^{k=K} X_{ik}^c * P_{ik} \Big/ \sum_{k=1}^{k=K} X_{ik} * P_{ik} = CE_i \quad (3.43)$$

Input oriented allocative efficiency ( $AE_i$) is derived from the results of the input oriented technical efficiency and cost efficiency. As explained earlier, cost efficiency is the product of technical and allocative efficiencies. Therefore;

$$AE_i = \frac{CE_i}{TE_i} = \left(\sum_{k=1}^{k=K} \mathrm{X}_{\mathrm{ik}}^{\mathrm{c}} * P_{ik} \Big/ \sum_{k=1}^{k=K} X_{ik} * P_{ik}\right) \Big/ \left(\sum_{k=1}^{k=K} \mathrm{X}_{\mathrm{ik}}^{\mathrm{t}} * P_{ik} \Big/ \sum_{k=1}^{k=K} X_{ik} * P_{ik}\right) \quad (3.44)$$

$$AE_i = \sum_{k=1}^{k=K} \mathrm{X}_{\mathrm{ik}}^{\mathrm{c}} * P_{ik} \Big/ \sum_{k=1}^{k=K} \mathrm{X}_{\mathrm{ik}}^{\mathrm{t}} * P_{ik} \quad (3.45)$$

*Diagrammatical Presentation*

It can be observed from the estimation of the various efficiencies that, each of them is an extra cost relative to a particular cost frontier. Those cost frontiers are as follows;

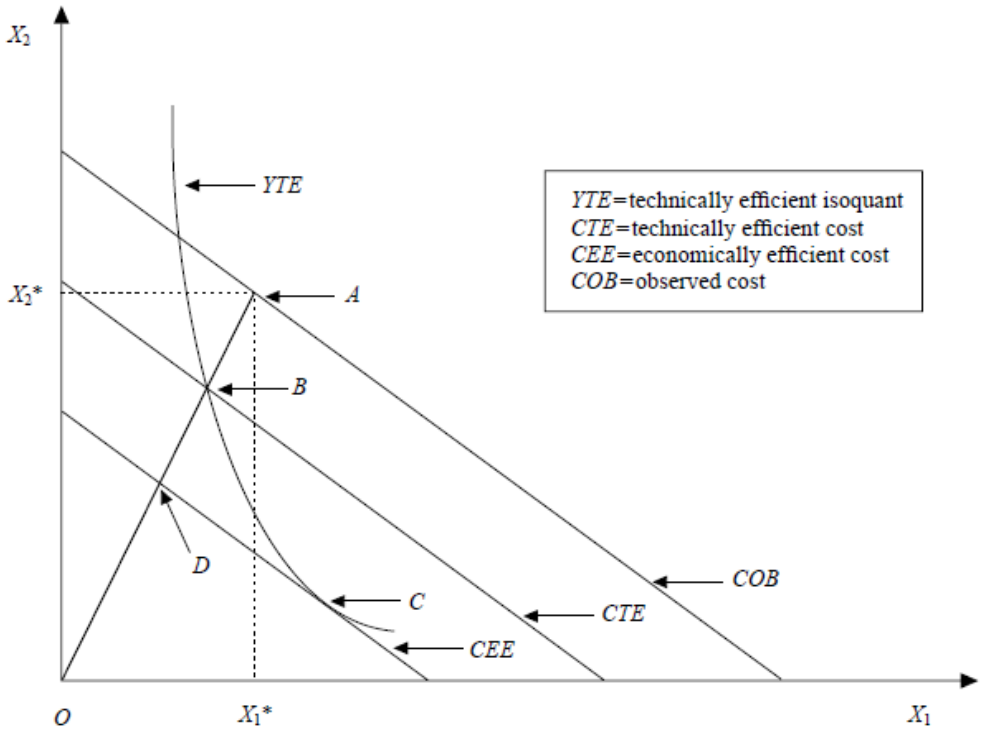
Observed or total cost (COB) as in eqn 3.27 $= \; C_i = \sum_{k=1}^{k=K} X_{ik} * P_{ik}$

Technically Efficient cost (CTE) as in eqn 3.37 $= \; C_i = \sum_{k=1}^{k=K} \mathrm{X}_{\mathrm{ik}}^{\mathrm{t}} * P_{ik}$

Cost or Economically Efficient cost (CEE) as in eqn 3.42 $= \; C_i = \sum_{k=1}^{k=K} \mathrm{X}_{\mathrm{ik}}^{\mathrm{c}} * P_{ik}$

The other important frontier is the technically efficient isoquant (YTE), which as mentioned earlier is the prerequisite for the estimation of all other efficiencies. This is expressed clearly diagrammatically in Bravo-Ureta and Pinheiro (1997); figure 3.5. Point B in the diagram represents the solution for the simultaneous equations in eqn 3.35 and 3.36. Therefore technical efficiency or inefficiency measures the

cost incurred for producing on the observe cost frontier (COB) instead of the technically efficient cost frontier (CTE). In the same vein, allocative inefficiency is the cost incurred for producing on the technically efficient cost frontier (CTE) instead of the cost efficient frontier (CEE), and finally Cost inefficiency is incurred when a DMU produces on the observed cost frontier (COB) instead of the cost efficient one (CEE). These clarifications would be very important in the results discussion section.




Notes: 1. According to equation (2) $k_2$, ($i$=2) in this figure, is equal to $OX_1^*/OX_2^*$.
2. According to equations (5), (6), and (7) $TE$, $EE$, and $AE$ are equal to: $TE=OB/OA=CTE/COB$, $AE=OD/OB=CEE/CTE$, and $EE=TE \cdot AE=OD/OA=CEE/COB$.

Sorce: Bravo-Ureta and Pinheiro (1997).

Figure 3.5. Graphical Representation of Observed Cost, Technical and Economically Efficient Cost Measures.

**3.2.5.6. Statements of Hypotheses**

The stochastic frontier analysis as mentioned earlier, allows for the testing of hypotheses based on certain assumptions. The null hypotheses to be tested are; 1. No stochastic inefficiency in the model. 2. The function is exhibiting constant returns to scale. 3. A simpler half-normal distribution is adequate. 4. The Cobb-Douglas production function is appropriate (Battese and Coelli, 1993; Mugisha, 2007; Baten et al. 2009; Dudu and Kilicaslan , 2008). The first hypothesis, which concerns the inefficiency, is referring to output orientation technical inefficiency term in eqn 3.21. Even though that is not what the thesis sets out to measure, it is a means to an end. That is, the estimation of all input oriented efficiencies depends on the value of that inefficiency term. This makes hypothesis test relating to the output oriented inefficiency term very relevant to this thesis. The hypothesis seeks to state that the inefficiency term in eqn 3.21, does not exist and that the average deterministic frontier is enough. If this hypothesis is true, the OLS estimation would be appropriate. This hypothesis is very relevant to the estimation technique selected. It is an important component in the estimation of all the other input oriented efficiencies, hence its statistical existence or otherwise is very relevant. The existence of a CRS in the production function is tested by the second hypothesis. The third and the fourth hypotheses are self-explanatory.

All the hypotheses tests require the Log likelihood functions (LLF) of both the restricted and the unrestricted functions. From these, the likelihood ratio (LR), which represents the test statistic, can be calculated. This is then compared with the chi-squared statistic to make a decision. The generalized likelihood ratio statistic is given as;

$$LR(\lambda) = -2\left\{ln\left(\frac{LW}{LU}\right)\right\} = -2\{ln(LW - LU)\} = -2\{ln[L(H0) - L(H1)]\} \qquad (3.46)$$

Where ln (LW) is the value of the log likelihood function for the restricted stochastic frontier model and ln (LU) being the value of log likelihood functions

for the unrestricted stochastic frontier model. The null hypothesis (H0) is for the restricted stochastic frontier whiles alternative hypothesis (H1) for the unrestricted stochastic frontier model. The LR (test statistic) is assumed to be mixed chi-squared distributed. Different testing techniques can produce different results on the same data (Coelli et al. 2005, p.259). For this reason, other alternative testing procedures on these hypotheses would be conducted alongside where possible.

### 3.2.6. Post Efficiency Analyses

After the estimation of the various efficiency estimates from DEA and SFA, the agreement between these two techniques would be tested through the selected post efficiency analyses.

#### 3.2.6.1. The Paired T Test

The first thing one would sort to find out is whether the means from both techniques are equal.

No procedure answers this better than the paired t-test as efficiency estimates from DEA and SFA are correlated or paired with other. This test is used to compare before and after sample observations on the same data, and for comparison between two different techniques used in the measurement of the same variable or statistic (Shier, 2004; Kim, 2015). This thesis falls in the latter case. The test does not require both variables to have the same variance and at the same time they should be dependent (Sharma et al. 1999). It tests the null hypothesis that the mean difference of the two sample estimates is equal as against the alternative that they are not equal. This gives the statistical significance to discussions that involve the comparison between the estimates from both techniques. For example, we cannot statistically conclude that an estimate in DEA is greater or lesser than another in SFA if this test accepts the hypothesis that the two estimates are equal. The statistic according to Anderson (2014) is calculated by the formula:

$$t = \frac{\bar{d}}{s_d/\sqrt{n}} \tag{3.47}$$

Where;

$$\bar{d} = \frac{\sum_{i=1}^{n} d_i}{n} \qquad and \quad s_d = \sqrt{\frac{\sum_{i=1}^{n}(d_i - \bar{d})^2}{n-1}}$$

$\bar{d}$ is the average difference between the paired samples and $s_d$ is the sample standard deviation. The critical values are found using the student's t-distribution table with n-1 degrees of freedom.

**3.2.6.2. The Spearman Rank Correlation Coefficient**

The spearman rank correlation coefficient ($rho = \rho$) for various efficiencies from the two techniques would be estimated. That is between $TE_{DEAVRS}$ and $TE_{SFAVRS}$, $TE_{DEACRS}$ and $TE_{SFACRS}$, $AE_{DEAVRS}$ and $AE_{SFAVRS}$, $AE_{DEACRS}$ and $AE_{SFACRS,}$ $CE_{DEAVRS}$ and $CE_{SFAVRS}$, $CE_{DEACRS}$ and $CE_{SFACRS}$. The same correlation coefficient of other possible combinations of estimates like the output oriented technical efficiencies would also be examined. Like all correlation coefficients, the strength and the direction of the relationship between the variables involved are examined (Rumsey, 2009). However, the choice of correlation coefficients depends largely on the variables to be dealt with. Most commonly used is the Pearson's correlation which according to Rumsey (2009) is applicable under certain conditions. If any of those conditions is not met than the spearman rank correlation coefficient should be applied instead. Among the conditions are that both variables must be numerical but not ordinal, should have a linear relationship and finally, they should be normally distributed.

The use of efficiency estimates from both DEA and SFA would have meant the fulfilment of the first condition. However, efficiency estimates would be presented in a ranked order form. That is < 10, ≥ 10 < 20, ≥ 20 < 30, ≥ 30 < 40, ≥ 40 < 50, ≥ 50 < 60, ≥ 60 < 70, ≥ 70 < 80, ≥ 80 < 90, ≥ 90 < 100 and 100. These efficiency estimate ranking become ordinal, hence violating the first condition. The second condition can be revealed via a scatterplot. If the relationship is not linear and monotonic or both, a spearman rank correlation is appropriate. The normality condition can also be tested. It is therefore obvious the choice is the nonparametric spearman rank correlation coefficient. The Spearman's rho is given by the formula;

$$\rho = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n^3 - n} \tag{3.48}$$

Where $d_i$ is the difference between the ranks for each farmer and n is the sample size.

**3.2.6.3. Best and Worst Performing Farmers**

This procedure reinforces the comparison between the two techniques. The idea is if the two techniques agree, then they should be able to fairly identify the same number of farmers who performed very well and those that performed poorly. The performance in this case is solely based on the various efficiency estimates. The estimates from each technique are first arranged in descending order and divided into four equal parts. The quartiles or the percentiles technique is used here to identify worst performing farmers (that is from the minimum to the 25$^{th}$ percentile or first quartile) and the best performers (that is from the 75$^{th}$ percentile or third quartile to the maximum). These categories from each technique are then compared to find out the percentage of the farmers in each category they both identified.

### 3.2.7. Causes of Inefficiency

The thesis not only intends estimating and comparing efficiency estimates but to investigate what social factors within the region affect those efficiencies. These factors are alternatively referred to as environmental factors (Coelli et al. 2005). These factors are normally considered to be beyond the discretionary control of the farmer. There are so many techniques in analyzing efficiency effects. However, each technique is based on the specific requirement of the available data. Coelli et al. (2005) outline 4 of them in the case of DEA. Firstly, the Banker and Morey (1986) approach is used when the environmental variables are ordinal or categorical. In situations where there is no natural ordering of those variables demands the use of Charnes, Cooper and Rhodes (1981) approach, where the sample is divided into sub samples for each variable category. These two techniques were criticized for not being tolerant of other types of variables, requiring an a priori assumption between the variables and efficiency, and their inability to consider more than one environmental variable in the analysis. Another method according to Coelli et al. (2005) is to incorporate those variables directly into the linear programming as a non-discretionary variable. This method like the first two has some serious limitations. It requires that environmental variables must be continuous not categorical, and at the same time the direction between the variable and efficiency must be known. The fourth and final method is the two-stage method. This method involves first estimating the efficiencies using the traditional outputs and inputs, and then regress the efficiencies against the identified environmental variables. The tobit regression is recommended in this case since OLS can predict efficiency scores greater than one. The signs of the corresponding coefficients give the relationship between the environmental variables and the efficiency estimates. The method has an advantage augmenting for the disadvantages of the first, second and third methods; that is, it is able to

accommodate both continuous and categorical variables, and at the same time doesn't need an a priori assumptions regarding the direction of the influence of the environmental variable. In instances where there is a strong need to use any of the first three techniques, this method can be used first to determine the direction between the efficiency estimates and the environmental variables. However, one main disadvantage of this method is the possibility of correlation between the traditional input variables and the environmental ones. In this instance, the result is likely to be biased. In the light of these advantages, Coelli et al. (2005) and most researchers in this field have considered the use of the two stage technique in most cases. This thesis therefore will also adopt this method.

There are two main methods in the case of SFA, the inefficiency effect approached and the chosen two stage method discussed already under DEA. The latter method is the same as explained earlier. The difference lies in the first stage, where the efficiency estimates are done by DEA technique and the other by SFA. The inefficiency effect method involve the modification of the stochastic production frontier by expressing inefficiency term ( $u_i$) as a function of the environmental variables, as in eqn 3.49. Unlike the two stage tobit approach, the existence or otherwise of technical efficiency can be tested before this step is taken to estimate its factors.

$$\ln Y_i = \beta_0 + \beta_k \sum_{k=1}^{k=K} ln\, X_{ik} + v_i - u_i(\partial_0 + \partial_z F_{iz} + W_{iz}) \qquad (3.49)$$

Where $F_{iz}$ are the environmental factors, $\partial_z$ are their coefficients and $W_{iz}$ is the truncation of the normal distribution with zero mean and variance $\sigma^2$, and at the point $-\partial_z F_{iz}$. That is, $W_{iz} \geq -\partial_z F_{iz}$. This assumption makes it possible for consistency of a non-negative truncation of the N($\partial_z F_{iz}, \sigma^2$) (Battese and Coelli, 1995). In stochastic frontier, this method is preferred over the two stage tobit

approach. However, the thesis is adopting the two stage tobit approach for two reasons; 1. The estimation techniques used under the SFA is not coherent with the efficiency effect model; that is, the duality approach used in the estimation of technical, allocative and cost efficiencies through the stochastic cost frontier. 2. For consistency of the comparison of the results of the DEA and SFA. This method is common to both estimation techniques. In order to avoid the Coelli's fear of a possible correlation between the traditional inputs and the environmental variables, the study would conduct some analyses in respect of the SFA. Firstly, correlation coefficients between the traditional inputs and the environmental variables would be conducted. Those with correlation coefficient above 80% would be dropped. The point-biserial correlation coefficient would be used in the case of the environmental variables that are measured as dummy variables. Secondly, an inefficiency effect model would be applied, after the results of the tobit regression. Even though, the output oriented efficiency is not the concern of this paper, the method combines both the traditional inputs and the environmental variables into one model. If such correlation exists, then it would render the said variable insignificant. That is any variable that is significant in the tobit analysis, but insignificant under the inefficiency effect model is rendered insignificant, and hence dropped. The remaining variables would then be used in the tobit regression analysis for all the other efficiencies.

### 3.2.8. Input Allocative Efficiency Coefficient (IAEC)

Not all research findings are feasible. Economic, social and environmental factors can inhibit the implementation of findings. Data available for this study can only allow for the economic feasibility of the findings in the estimated production function. For the production function, an input is allocatively efficient when the cost of increasing that input is equal to the amount of revenue or the value the corresponding output increase would produce (Grazhdaninova and Lerman 2005;

Sienso et al. 2014). This represents the first order condition for profit maximization or the economic optimum of any firm, even though this is input specific. That is why the allocatively efficient point is also the point of maximum profit. The values of the corresponding increase in output is remotely derived from marginal product (MP) of the input in question; that is, $MP_i * P_Y = VMP_i$. Where $P_Y$ is the unit price of maize output. MP for a Cobb-Douglas production is given as;

$$MP_i = \beta_i * \frac{\overline{Y}}{\overline{X}_i} \qquad (3.50)$$

Therefore VMP;

$$VMP_i = \left(\beta_i * \frac{\overline{Y}}{\overline{X}_i}\right) * P_Y \qquad (3.51)$$

$\beta_i$ is the output elasticity of the input in question; $\overline{Y}$ and $\overline{X}_i$ are geometric means of the maize output and the input respectively. The logarithmic nature of the production function and the data necessitates the use of geometric means, that is, the mean of natural logarithms. On the other hand, since farmers are price takers, the cost of increasing an additional input is the per-unit price of that input ($P_i$), which is approximated as the Marginal Factor Cost (MFC) (Grazhdaninova and Lerman 2005). That is $MCF_i = P_i$

This therefore means that an input 'i' is allocatively efficient when;

$$\left(\beta_i * \frac{\overline{Y}}{\overline{X}_i}\right) * P_Y = P_i \qquad or \qquad VMP_i = P_i \qquad (3.52)$$

Whiles some researchers make the allocative efficiency analysis directly from this equation, others rearrange it to form a coefficient or an index. The works of Grazhdaninova and Lerman (2005) and Sarris et al., (2006) are examples of the former. If $VMP_i > P_i$ then the input is question is underutilized, and it overused if $VMP_i < P_i$. Some of the examples of the latter group are Inoni (2007), Sienso et al.

(2014), Akçay et al. (1996) and Dilmen, (1976). The coefficient or index from the rearranged eqn 3.51 is written as;

$$\text{IAEC} = \frac{\beta_i * (\bar{Y}/\bar{X}_i) * P_Y}{P_i} \quad or \quad MP_i * \frac{P_Y}{P_i} \tag{3.53}$$

At an economic optimum or maximum profit, this coefficient should be equal to 1, implying the input is allocatively efficient. It does not require any change to its current quantity. If it is less than 1, the input is excessively used and should be reduced. If it is greater than 1, the said input is less utilized and should be increased (Dilmen, 1976; Akçay et al. 1996).

The IAEC is quite different from the allocative efficiency the study intends estimating from DEA and SFA. Whiles the IAEC is input specific, the latter measures for the entire inputs used in the production process. The IAEC is also output oriented (profit maximization) whiles the latter is input oriented (cost minimization). These make a direct comparison between them impossible. However, since the latter cannot point out the contribution of various inputs to the allocative inefficiency, the IAEC would help further in the discussion of its estimates.

### 3.2.9. Marginal Rate of Technical Substitution (MRTS)

The MRTS is basically defined as the slope of an isoquant. It is also seen as the ratio of the marginal products of the two input involved. However, in technical terms, it measures the additional amount of an input that needed to replace a unit reduction in another input, and still produce the same quantity of output (Rasmussen, 2013). Put differently, it also measures the amount of an input reduced as the results of a unit increase in the other. For example a MRTS, labor for machinery ($MRTS_{LM}$) is interpreted as how much labor is needed to

compensate for a unit reduction in machinery use for all the inputs in this study, there are a total of 10 of this ratio that can be estimated. However, of interest is the technical substitution between labor and machinery ($MRTS_{LM}$), nitrogen and phosphorous ($MRTS_{NPH}$), nitrogen and pesticide ($MRTS_{NP}$), and finally phosphorus and pesticide use ($MRTS_{PHP}$). The arrangement of the subscript is important in the interpretation of this ratio. Assume two inputs X1 and X2; the former on x axis and the latter on y, as depicted in figure 3.2. The $MRTS_{12}$ (input 2 for 1) represents how much of input should be reduced ($X_{23}$-$X_{22}$) for a unit increase in input 1 ($X_{13}$-$X_{11}$). The formula is therefore given as

$$MRTS_{12} = \frac{\Delta\bar{X}_2}{\Delta\bar{X}_1} = \frac{MP_1}{MP_2} = \frac{\alpha\bar{X}_2}{\beta\bar{X}_1} \tag{3.54}$$

$$MRTS_{12} = \frac{P_1}{P_2} \tag{3.55}$$

MP represents marginal productivities of inputs; $\alpha$ and $\beta$ represent the coefficients of input 1 and 2 respectively; P is the unit prices of inputs; the geometric means of the inputs are used in the estimation.(Engiz, 2007, p. 36)

At equilibrium, the farmers MRTS must be equal to the ratio of the prices of the two inputs involved. Given in eqn 3.55. This can be located at point C in figure 3.2. Just as the MRTS represents the slope of the isoquant ($QQ^1$) in figure 3.2, the ratio of the unit prices represents the slope of the isocost function ($CC^1$). The MRTS itself does not give much information unless it is compared with the ratio of prices. From this equilibrium, decisions are made as to whether to increase or decrease one input relative to the other. When $MRTS_{12} > P_1/P_2$ , it means that relative to input 1, input 2 is excessively used resulting in an expensive cost of production. This scenario means that the farmer is operating at a point above point C on the isoquant line $QQ^1$. The solution therefore is to decrease the use of input 2

and increase that of 1. That is, technically substitute input 2 for 1. On the other hand, if $MRTS_{12} < P_1/P_2$ , the point of operation is below point C on the isoquant, hence the need to decrease the use of input 1 for more of 2 (Engiz, 2007, p. 36)

### 3.3. Farm Analyses

#### 3.3.1. Gross Profit

The gross profit estimation was meant for the whole agricultural business of farmers, but information were lacking on other agricultural production. The study therefore focuses on maize production.

Gross profit which is also referred to as net income is basically the difference between revenue and expenses or cost of production (Kay et al. 2008, p.43). Under the assumption of revenue maximization and cost minimization, the gross profit helps farmers in making decisions concerning production, as well as measure of performance. The need for this estimation is summed up the words of Boehlje and Eidman (1984, p. 23); ‘‘to maximize income or even to survive, farmers must not only produce the crop or livestock product efficiently, but they must also buy the inputs and sell the product at prices that result in a profit.’’ In the estimation of the gross profit, output quantity, input quantities as well as their unit prices are need. In the specific case of this study, the maize output quantity used in the estimation of the efficiencies includes those consumed and those stored as seed. The unit price ($P_Y$) however would be estimated as an average retail price over the period of October 2014 to June 2015. In terms of the cost of production, the estimation is already a component of the input oriented efficiency estimation process. That is, in eqn 3.27

### 3.3.2. Cost of Inefficiency (COI)

Inefficiency in itself is a cost, however efficiency measures do not normally quantify that aspect of it. Just as there exist two ways of achieving efficiency objective, so its cost. The cost of being inefficient can be revealed in the monetary value (revenue) of the amount of output lost by being inefficient. It can also be seen as the cost of additional inputs used, which could have been eliminated by being efficient. The former is the output approach and the latter the input approach. These are to be expressed per acre and for the whole maize acreage in the region; that is, the per-unit values would be multiplied by the total maize acreage in region. This analysis helps policy makers and farmers to decide on improving inefficiency or not. If the cost of improving efficiency in the region like, provision of agricultural logistics and policies are more than the cost of inefficiency, it would make sense for farmers to remain inefficient. The same goes for the revenue lost to inefficiency. Even though the results of the analysis are largely based on the input oriented, both would be reported in this case. Furthermore, with the employment of DEA and SFA, each would have separate estimates of the cost of inefficiency. In the case of input oriented DEA estimates, the target inputs for each farmer is multiplied by the per-unit prices and summed. This is then subtracted from the observed total cost of production. These target inputs are the technically efficient input quantities adjusted for slacks. This is represented in eqn 3.56. For the output orientation, the per-unit price of maize ($P_Y$) is multiplied by the target output quantities and summed. The observed revenue is then subtracted from it to give the revenue lost as the results of inefficiency. Eqn 3.57. The input oriented SFA estimation has provided all information needed in the estimation of cost efficiency. Eqn 3.37, which represents the technically efficient cost of production, is subtracted from the observed cost of production in eqn 3.27. This gives the additional cost resulting from being inefficient. The case of the output orientation under SFA is quite different. When the observed data is fitted into the estimated deterministic stochastic frontier and adjusted for statistical noise,

the estimated output level is the maximum amount possible for each farmer. That is, they are all technically efficient. This represents the denominator in eqn 3.24. When this output is multiplied by the unit price of maize ($P_Y$), the resulting is the amount of revenue they would have earned if they were technically efficient. The actual revenue is the product of the observed output and the unit price. Their difference therefore gives the revue lost from being inefficient. Eqn 3.57

$$\text{COI} = \text{Total cost per farmer} - \left(\sum_{i=1}^{5} \text{Input targets}_i\right) * \text{unit price}_i \quad (3.56)$$

$$\text{COI} = \text{unit price}_i * \left(\sum_{i=1}^{5} \text{Output targets}_i\right) * \text{Total revenue} \quad (3.57)$$

### 3.4. Sample and Sampling Techniques

The sample was selected from the maize farmers in the Northern Region using a multi-staged stratified mixed sampling technique; probability and non-probability sampling techniques. The sample was informed by two documents; one from the regional agricultural office of the Ministry of Food and Agriculture (MoFA), and the other one from various district agricultural offices. The first document contained data on maize cropping area, average yield and total production for each of the 20 administrative districts for 2013 cropping season in the Northern Region. This document was the starting point for the sampling process. Figures for area cropped were used. There was a need to stratify this maize cropping area in order that districts with high, medium and small cropping area have equal chance of being represented in the sample. The first task was to find out how many of the 20 districts would be enough for the precision of the estimates in the sense that standard errors are minimal. This requires a stratified random sampling. In this case, the optimal sample allocation is used instead of the proportional one (Lee, et al. 2013, p. 1035).

The optimal stratified sample allocation formula;

$$n = \frac{(\sum N_h * S_h)^2}{N^2 * D^2 + \sum N_h * S_h^2} \quad (3.58)$$

n= sample size, $N_h$=h'th stratum, $S_h$= standard deviation of then h'th stratum, $S_h^2$

=variance of the h'th stratum, N=total number of the population, μ = mean, d=standard error= μ/ α, t value at 90% confidence level= 1.65, α =significance level=0.10, D=population standard deviation=d/1.65

Table 3.3. Stratification of Maize Acreage in the Region

| Stratum | Stratum (lower and upper limits) (Ha) | Average maize cropping area (Ha) | Number of districts in each stratum ($N_h$ ) | Std Dev. for each stratum ($S_h$ ) | $N_h*S_h$ | $N_h*(S_h)^2$ |
|---|---|---|---|---|---|---|
| A | 798-5000 | 3201.40 | 10 | 1495.82 | 14958.2 | 22374720.44 |
| B | 5001-10000 | 6936.00 | 6 | 1687.96 | 10127.8 | 17095310.40 |
| C | > 10001 | 11485.25 | 4 | 1693.76 | 6775.03 | 11475246.33 |
| **Total(∑)** | | | 20 | | 31861.03 | 50945277.18 |

μ = 5978.55

d=597.86

D= 597.86/1.65=362.34

$$\sum (N_h * S_h)^2 = 1015122379.43427$$

$$\sum N_h * (S_h)^2 = 50945277.18$$

$$n = \frac{1015122379.43427}{20^2 * 362.34^2 + 50945277.18} = 9.8 = 10 \quad (3.59)$$

This value represents the number of districts from which the final sample can be taken. However, it does not provide information on how much each stratum should contribute to make up this value 10. The Neyman allocation techniques can be used to distribute the sample size among the three strata such that the variance of the stratified estimator is minimized (Benedetti, et al. 2010).

Neyman's rule:

$$n_h = \frac{N_h * S_h}{\sum(N_h * S_h)} * n \quad (3.60)$$

All definition of variables remain the same except $n_h$ which denotes the allocated sample from the h'th stratum. This formula assigns five (5) districts to the stratum A, three (3) to B and 2 to C.

The next step is selecting these allocations from the various strata. Before that, some purposive considerations were made regarding some districts. Maize is grown in all the districts in the region. However, some districts are known to earn more income from a particular crop, even though their maize output and area may be higher than other districts. In this case, it would be difficult to find farmers who earn most of their income from maize in those districts. For example, Kpandai, Nanumba North and Nanumba South are known for yam and cassava production. In the light of this, the yam producing districts would be excluded in the random sampling of each stratum. Coincidentally all the yam producing districts to be excluded are in stratum A. This means that random sampling is used in the selection from B and C strata, whiles that of stratum A is done excluding the three yam producing districts. This resulted in the selection of East Gonja, East

Mamprusi, Saboba, Central Gonja and Bunkpurugu/Yunyoo Districts for stratum A, Savelugu/Nanton, Tamale Metro and Gushegu for B stratum, finally Tolon/Kumbungu and Yendi Districts for stratum C.

The next important question to be answered is what is the total sample size that would be selected from these ten (10) districts to be used for the study? According to Israel (1992), approaches used in determining the sample size are, using a census for small populations, imitating a sample size of similar studies, using published tables, and applying formulas to calculate a sample size. The thesis cannot use the first approach because it involves using the whole population as the sample. The second has the tendency of adopting the sampling mistakes of the previous studies. The use of the formulas requires more information about the population which is not available. The thesis therefore sort refuge in the use of Yamane (1967)'s published tables. For a 5% and 10% significance for a population of more than 100,000, a sample of 400 and 100 are required respectively. Using the 10% significance level, a sample of 100 farmers is adopted for the study. Israel (1992) cautioned that this number represents the obtained responses and that more sample should be targeted in order to compensate for nonresponses. In the light of this, 130 farmers were interviewed and after expunging farmers with incomplete records, a total of 121 responses were finally used for onward analysis. The required sample (100 farmers) was divided equally among the ten (10) selected districts. This means that response from each selected district should be at least ten (10) farmers. This selected sample is within the range of many other related studies; Sharma, Leung and Zaleski, (1997) - 60 swine producers; Kalaitzandonakes and Dunn (1995) - 82 maize producers; Singh, Coelli and Fleming (2000) - 23 dairy firms; Bravo-Ureta and Pinheiro, (1997) – 60 farms; Parlakay and Alemdar (2011) – 90 peanut farmers; Alemdar and Ören (2006a); 75 wheat farmers; Ören and Alemdar (2006b) – 149 tobacco farmers; Koc, Gul and Parlakay (2011) – 89 maize farmers; Xu and Jeffrey (1995) - 90 hybrid rice farmers and 100 conventional rice farmers; Erdal (2010) – 103 farmers; Kalirajan (1981) –

70 rice farmers; Kalirajan (1982) – 91 rice farmers; Bagi (1982) – 34 cropping farms; Bagi, (1984) – 193 farmers; Kalirajan and Flinn (1983) - 79 rice farmers; Bailey et al. (1989)- 68 dairy farms.

Finally, in order to obtain the specific farmers that would be interviewed, visits were made to selected district agricultural offices for the second document previously mentioned. This document contained basic information about maize farmers in the district. This information included their names, villages, sex and maize acreage. Simple random sampling was used to select the appropriate number of farmers from this list.

### 3.5. Data Collection Techniques

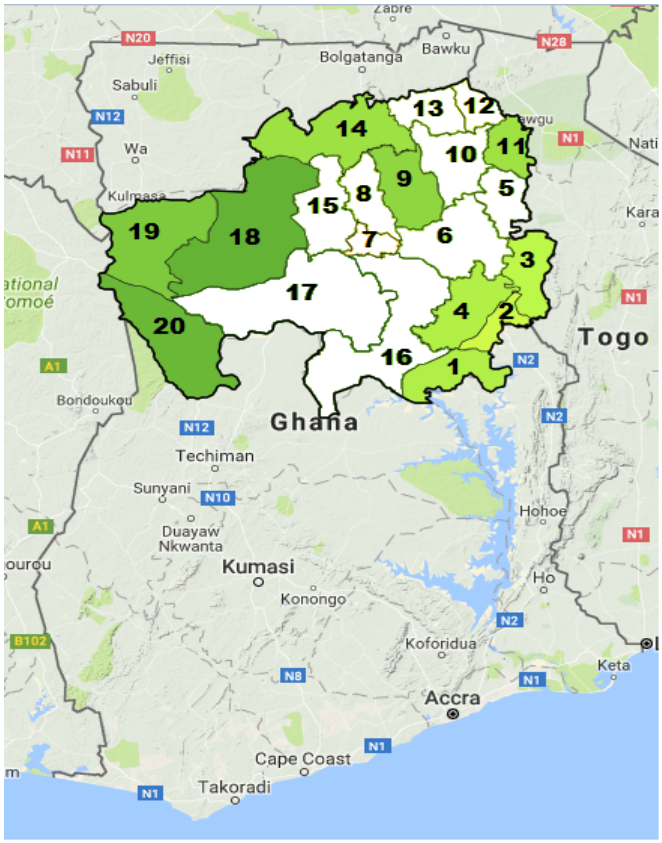
The data sorted were for 2014/2015 farming season. I personally administered the questionnaire with the help of the district extension officers or any appointed person. It was all face-to-face interviews with structured questionnaires. This technique was necessary because of the technical nature of this study. With most of the farmers being illiterates, any other method could not have been more efficient for this type of study.

# 4. RESEARCH RESULTS AND DISCUSSIONS

## 4.1. Study Area and Sampled Data

### 4.1.1. Study Area

The administrative landscape of the study region has been changing due to the creation of new administrative districts by successive governments.




1. Kpandai District
2. Nanumba South District
3. Zabzugu-Tatale District
4. Nanumba North District
5. Saboba District
6. Yendi Municipal
7. Tamale Metropolis
8. Savelugu-Nanton District
9. Karaga District
10. Gushegu District
11. Chereponi District
12. Bunkprugu-Yunyoo District
13. East Mamprusi District
14. West Mamprusi District
15. Tolon-Kumbungu
16. East Gonja District
17. Central Gonja District
18. West Gonja District
19. Sawla-Tuna-Kalba District
20. Bole District

Source: Google maps with author's artistic editing.

Figure 4.1. Map of Northern Region and Its Districts

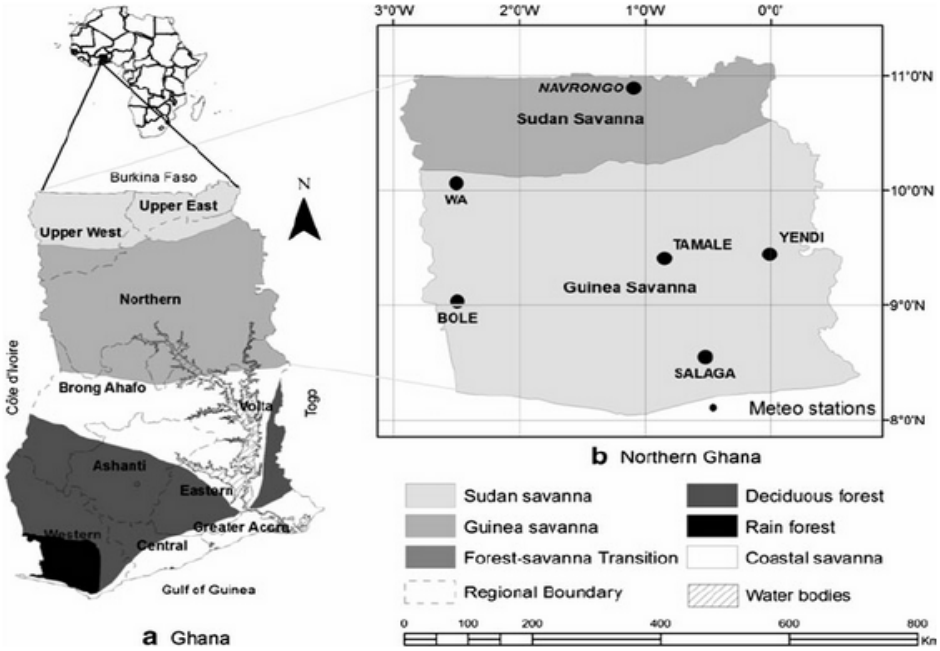
The current number of districts in the Northern Region is 6 more than what was used in the study. This is because these newly created districts were not properly functioning, and had no District Agricultural Offices. The few that had

their temporal agricultural offices did not have any information and would rely on the districts from which it was curved out. Figure 4.1 shows the map of Ghana, the Northern Region and its administrative districts.

#### 4.1.1.1. Climatic Conditions

Ghana's climate and soil conditions are often discussed in the light of the demarcated agro-ecological zones. By definition, an agro-ecological zone refers to "a biological and natural resource system managed by humans for the primary purpose of producing food as well as other socially valuable nonfood goods and environmental services." (Wood et al. 2000). Based on climate, vegetation and soil type, Ghana's agro-ecological zones have been classified into six (6); Sudan Savannah, Guinea Savannah, Transition, Deciduous Rain Forest, Rain Forest and the Coastal Savannah Zones. The figure 4.2 below represents these zones. Though they share some environmental conditions in common, there is always a distinction between them by climates, soil or rainfall patterns, or all of the three. These also determine the type of agricultural activities and food crops that are grown. Table 4.1 and 4.2 present both the climatic conditions and the food crops grown in various zones.

From the map, the regional boundaries of the study area (Northern Region) lie in the Guinea-Savannah agro-ecological zone. A small part of it however is intertwined with the Sudan-Savannah in its upper part. Nonetheless the two ecological zones share a lot in common. It can be observed from figure 4.1 that districts 12, 13 and 14 are located in the Sudan-Savannah. The similarities are further seen from the comparisons of table 4.1 and 4.2.




Source: Yengoh et al. ( 2010, p. 14)
Figure 4.2. Agro-Ecological Zone in Ghana

Table 4.1. Climates of the Agro-Ecological Zones of Ghana

| Agro-ecological zone | Area ($km^2$) | Mean Annual Rainfall(mm) | Mode | Major Rainy Season | Minor Rainy Season |
|---|---|---|---|---|---|
| Rain Forest | 9,500 | 2,200 | Bi-modal | March-July | Sept.-Nov. |
| Deciduous Rain Forest | 66,000 | 1,500 | Bi-modal | March-July | Sept.-Nov. |
| Transitional Zone | 8,400 | 1,300 | Bi-modal | March-July | Sept.-Oct. |
| Coastal Savannah | 4,500 | 800 | Bi-modal | March-July | Sept.-Oct. |
| Guinea Savannah | 147,900 | 1,000 | Uni-modal | May-Sept. | |
| Sudan Savannah | 2,200 | 1,000 | Uni-modal | May-Sept. | |

Source: FAO (2005), Adapted from data from the Meteorological Department, Legon, Accra, Ghana.

They all record the same amount of mean annual rainfall, they have the same uni-modal rainfall pattern, they experience rains in the same time of the year, and they grow almost the same type of food crops. It can further be seen that maize is grown in all ecological zones. The rainfall pattern limits agriculture in the Northern Regions to once in a year, compared with the other regions with minor rainy seasons.

Table 4.2. Major Crops Grown in the Agro-Ecological Zones

| Zone | Cereals | Starchy Crops | Legume | Vegetables | Tree crops |
|---|---|---|---|---|---|
| Rain Forest | Maize (4%), rice (15%) | Cassava (10%), cocoyam, plantain | | Pepper, okra, eggplant | Citrus, coconut, oil-palm, rubber |
| Deciduous Rain Forest | Maize (20%), rice (10%) | Cassava (50%), cocoyam, plantain | Cowpea | Pepper, okra, eggplant, tomato | Citrus, oil-palm, coffee, cocoa |
| Transition Zone | Maize (50%), rice (10%), sorghum (10%) | Yam, cocoyam, plantain, cassava (20%) | Cowpea, groundnut | Tomato, pepper, eggplant, okra | Citrus, coffee, cashew |
| Guinea Savannah | Maize (15%), rice (40%), sorghum (50%), millet (30%) | Yam, cassava (10) | Cowpea, groundnut, bambara | Tomato, pepper | Sheanuts, cashew |
| Sudan Savannah | Maize (5%), rice (10%), sorghum (40%), millet (70%) | Sweet potato | Cowpea, groundnut, bambara | Tomato, onion | |
| Coastal Savannah | Maize (6%), rice (15%) | Cassava (10%) | Cowpea | Tomato, shallot | Coconut |

Source: Source, FAO (2005), extracted from Gerken et al. (2001). The percentages in the parenthesis are the proportions to total production in the country.

The study considers the year under consideration (2014) as a normal year for agriculture based on productivity and rainfall pattern. There has been a

declining pattern rainfall since 2008, and even though, rainfall was lower compared to 2013, it provided favorable condition for early land preparation for maize (MoFA, 2015). Improvement in the irrigation infrastructure for food crops, which is virtually non-existent, would increase agricultural activities in the region. The Northern Region which largely lies in the Guinea savannah produces 15% of Ghana's total maize production.

#### 4.1.1.2. Soil Conditions

With the exception of the Coastal Savannah, the soil conditions in the northern regions (Upper East, Upper West and Northern Region) which comprise the Sudan and the Guinea savannah are known to be the poorest in the country. Table 4.3 represents the soil fertility conditions of seven regions in Ghana. Potassium, according to the authors, is not included because of its abundance in Ghanaian soils.

Table 4.3. Average Soil Fertility Status of Some Regions

| Region | Soil pH | Organic matter (%) | Total nitrogen (%) | Available P (mg/kg soil) | Available Ca (mg/kg soil) |
|---|---|---|---|---|---|
| Ashanti | 4.3 - 7.8 | 1.5 - 3.0 | 0.1 - 0.3 | 0.1 - 12.0 | 50 - 100 |
| Brong Ahafo | 3.5 - 6.7 | 0.3 - 1.7 | - | 0.1 - 64.3 | 16 - 140 |
| Greater Accra | 5.4 - 8.2 | 0.1 - 1.7 | 0.05 - 0.9 | 0.8 - 144.0 | 14 - 470 |
| Northern | 4.5 - 6.7 | 0.6 - 2.0 | 0.02 - 0.05 | 2.5 - 10.0 | 45 - 90 |
| Upper East | 5.1 - 6.8 | 1.1 - 2.5 | 0.06 - 0.14 | 1.8 - 14.8 | 44 - 152 |
| Upper West | 6.0 - 6.8 | 0.5 - 1.3 | 0.01 - 0.07 | 2.0 - 7.4 | 52 - 152 |
| Western | 3.8 - 7.1 | 1.0 - 5.7 | 0.06 - 5.4 | 0.4 - 11.3 | 28 - 420 |

Source: FAO (2005), extracted from Soil Research Institute (SRI) CSIR - Kumasi.

According to the table, soils in Northern Region is relatively less acidic, fairly balanced in organic matter, lowest in nitrogen content, very low in phosphorous and lowest in calcium. Because of the heavy rainfalls and prolonged dry season, soils in the Northern Region are very susceptible to erosion and leaching of soil nutrients. According to Diao and Sarpong (2007), Northern Region is among the regions experiencing severe form of both sheet and gully erosion. Oppong-Anane (2006) explains that this erosion is concentrated in the interior part of the region which is very low in organic matter content coupled with high concentration of iron. Other cultural practices like bush burning exacerbate the already poor conditions of the soil. Aside exposing the soil to erosion, existing nutrients are easily leached away in the yearly heavy rainfall and wind (Ayikene et al. 2013; Wood, 2013)

### 4.1.2. Sampled Data

#### 4.1.2.1. Selected Districts

The districts with the white shadings in figure 4.1 are the selected districts for the sample. These were selected from combined random and purposeful sampling techniques. The table below shows the maize acreage of each of the selected districts in hectares for the 2013/2014 farming season, and their farmer representation in the final sample.

From these districts, a sample of 121 farmers was finally interviewed. In formation on their maize output (kg), land size (acre), labor (hours), machinery (hours), nitrogen (kg), phosphorous (kg) and pesticides (liters) were gathered in a face to face interview. However, all these were converted to per-unit land area (acre). Table 4.5 represents the summary of the sample data. Apart from the Coefficient of Variation (COV), all other estimates by themselves cannot explain any comparison among the output and input variables. The unitless COV however, explains the dispersion of variables in a standardized way relative to the mean.

Table 4.4. Selected Districts for the Sample Selection

| No | District | Acronyms | Maize acreage (Hectares) | Selected farmers |
|---|---|---|---|---|
| 1 | Bunkpurugu/Yunyoo | B/Y | 1,943 | 12 |
| 2 | Central Gonja | CeG | 3,520 | 13 |
| 3 | East Gonja | EaG | 4,650 | 11 |
| 4 | East Mamprusi | EaM | 2,024 | 10 |
| 5 | Gushiegu | Gus | 5,347 | 12 |
| 6 | Saboba | Sab | 1,764 | 17 |
| 7 | Savelugu/Nanton | S/N | 9,345 | 10 |
| 8 | Tamale Metro | Tam | 8,345 | 12 |
| 9 | Tolon/Kumbungu | T/K | 12,345 | 10 |
| 10 | Yendi | Yen | 10,120 | 14 |

Source: Statistics, Research and Info. Directorate (SRID), Min. of Food and Agric.- May, 2014

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**4.1.2.2. Summary of sampled Data**

Standard deviation which also seeks to measure dispersions is incapacitated in comparing among these variables because the units of measurements are different. From the table, pesticide use is the most dispersed variable compared with machinery use, which has the least dispersion. The results reflect a generally high dispersion among the inputs which eventually translate to the high dispersion in the output. Family labor, which constitutes most of the labor input used have a great variation among farmers, hence a relatively high variation. This dispersion would have been lesser if hired labor were used. However, agriculture has a strong connection and dependence on the use of family labor than any other sector (Johansson, 2005). From the sample data, farmers use about 55% of their total agricultural land for maize production. This cannot be generalized for the region since this study targeted serious maize farmers.

Table 4.5. Statistical Summary of Sampled Data (per acre)

| | Maize output (kg)-Y | Labor hours-X1 | Machinery hours-X2 | Nitrogen (N) (kg)-X3 | Phosphorus (P) (kg)-X4 | Pesticide use (l)-X5 |
|---|---|---|---|---|---|---|
| Mean | 526.97 | 178.84 | 4.42 | 18.55 | 8.69 | 1.03 |
| MIN | 117.25 | 52.00 | 1.00 | 7.50 | 3.33 | 0.20 |
| MAX | 1000.0 | 542.36 | 6.00 | 46.00 | 20.00 | 4.00 |
| STD DEV | 199.38 | 76.69 | 1.3 | 6.44 | 3.14 | 0.53 |
| COV | 37.84 | 42.88 | 29.42 | 34.74 | 36.14 | 51.37 |
| Median | 501.75 | 169.93 | 5.00 | 19.00 | 8.33 | 1.00 |
| Unit price (GH₵) | 1.45 | 2.25 | 17.23 | 2.33 | 3.56 | 11.22 |

Source: Author's field data

In the case of nitrogen, phosphorus and pesticide, the variation resulted from the economic situation of farmers. The quantities of these inputs are not determined by the standard requirement, but the ability of the farmer to afford them. Pesticide use is the worse abused among all of them. Because it involves the addition of water, any quantity they can afford would eventually cover the whole farm. This confirms its highest COV from the table. The fact that they hire machinery at a cost is responsible for its lowest variation.

**4.1.2.3. Labor Use**

The labor employed by the farmers is mostly family labor. It is on few occasions that they employ hired labor. The use of hired labor becomes necessary at the weeding stage. The labor ratio, which measures the ratio of the family labor to the total amount of labor, is 0.99, indicating the reliance on family labor. The region is known for high fertility rate and family size. From this data, there is an

average of 5.5 and 12.7 persons per farmer's household for nuclear and extended families respectively.

Table 4.6 shows the labor distribution across age and gender of labor. Gender contribution to agricultural labor is fairly balanced; 50.5% (male) and 49.5% (Female). The balance is lost when it is segregated into various age ranges. More male children (58.94) work in the farm as compared with female children (41.06%). This is attributable to the assigned traditional gender roles. Cooking and fetching drinking water and general housekeeping are traditionally the work of females and they are groomed in those activities at that age.

Table 4.6. Distribution of Labor among Age Groups and Gender

| Age Group | Male | Female | Total | Male (%) | Female (%) | Total Composition (%) |
|---|---|---|---|---|---|---|
| 0-14 | 13,569.20 | 9,453.75 | 23,022.95 | 58.94 | 41.06 | 23.33 |
| 15-49 | 31,545.00 | 38,675.00 | 70,220.00 | 44.92 | 55.08 | 71.14 |
| 50+ | 4,732.70 | 725.25 | 5,457.95 | 86.71 | 13.29 | 5.53 |
| Total | 49,846.90 | 48,854.00 | 98,700.90 | 50.50 | 49.50 | 100 |

In the middle age category (15-49), more females work on the farms than males. Aside working in the farms, females are also responsible for the food of the workers. They either prepare the food on the farm or transport to the farm from the house. In the aged category, male farm outweigh female contribution to farm labor. Women at this age are generally weaker than their male counterpart. Older women have traditionally not been allowed to do physical jobs. Percentage wise, 71.14% of the labor was in the 15-49 age bracket followed by 23.3% for 0-14 age group. As expected, the aged contributed the least.

Table 4.7 shows the distribution of farm labor among the farming activities. On average small scale farmers use more labor per acre than large scale farmers. That is, 148.33 hours versus 112.1 hours. Land preparing receives the least amount of labor hours. Normally, it does not involve much work especially

when it is not a virgin land. On virgin lands trees and stumps have to be cleared before a tractor plough on it. For both small and large scale farmers harvesting takes most of the labor hours. Harvesting of crops is normally communal. People normally help family friends in the harvesting of their crops. That could explain why it recorded the largest proportion of labor use. The lower quantity of labor used in ploughing and harrowing is attributed to the use of tractors. Few farmers use their man power to do this activity nowadays.

Table 4.7. Distribution of Farm Labor in Farm Activities (hours)

| | Quantities | | | | Percentages (%) | | |
|---|---|---|---|---|---|---|---|
| Farm activities | <5 acres | >5 acres | average | | <5 acres | >5 acres | average |
| Land Preparation | 1.25 | 2.05 | 1.65 | | 0.84 | 1.83 | 1.34 |
| Ploughing and Harrowing | 5.00 | 3.60 | 4.30 | | 3.37 | 3.21 | 3.29 |
| Sowing | 26.04 | 19.45 | 22.75 | | 17.56 | 17.35 | 17.45 |
| Fertilizer Application | 20.57 | 16.08 | 18.33 | | 13.87 | 14.34 | 14.11 |
| Weeding | 31.75 | 20.01 | 25.88 | | 21.40 | 17.85 | 19.63 |
| Pesticide Application | 16.72 | 9.40 | 13.06 | | 11.27 | 8.39 | 9.83 |
| Harvesting | 35.25 | 27.31 | 31.28 | | 23.76 | 24.36 | 24.06 |
| Transportation | 11.75 | 14.20 | 12.98 | | 7.92 | 12.67 | 10.29 |
| Total | 148.3 | 112.1 | 130.22 | | 100 | 100 | 100 |

**4.1.2.4. Machinery Use.**

The distribution of machinery across the farming activities is spelt out in table 4.8. Unlike labor, the distribution of machinery is concentrated to few activities; ploughing and harrowing, transporting harvest and pesticide application. Among them, ploughing and harrowing takes 62.4% and 68% for small and large scale farmers respectively. This means that tractors and cargo trucks are the machinery they have access to. The activities that do not use machinery like

sowing and harvesting have machineries responsible for them (that planters and harvesters), however access is a problem to the farmers.

Table 4.8. Distribution of Machine Hours in Farm Activities (hours)

| | Quantities | | | | Percentages (%) | | |
|---|---|---|---|---|---|---|---|
| Farm activities | <5 acres | >5 acres | average | | <5 acres | >5 acres | average |
| Land Preparation | 0.00 | 0.00 | 0.00 | | 0.00 | 0.00 | 0.00 |
| Ploughing and Harrowing | 3.16 | 1.36 | 2.26 | | 73.66 | 62.39 | 68.02 |
| Sowing | 0.00 | 0.00 | 0.00 | | 0.00 | 0.00 | 0.00 |
| Fertilizer Application | 0.00 | 0.00 | 0.00 | | 0.00 | 0.00 | 0.00 |
| Weeding | 0.00 | 0.00 | 0.00 | | 0.00 | 0.00 | 0.00 |
| Pesticide Application | 0.30 | 0.18 | 0.24 | | 6.99 | 8.26 | 7.62 |
| Harvesting | 0.00 | 0.00 | 0.00 | | 0.00 | 0.00 | 0.00 |
| Transportation | 0.83 | 0.64 | 0.74 | | 19.35 | 29.36 | 24.35 |
| Total | 4.29 | 2.18 | 3.24 | | 100 | 100 | 100 |

#### 4.1.2.5. Chemical Fertilizer

There were two main chemical fertilizers that were used by the sampled farmers; The NPK (15-15-15) and the NPK (23-10-5). Farmers have traditionally been using the former, which may explain why it was the most used. Out of the 811 bags of fertilizer used by the sample farmers, only 124 were NPK (23-10-5), representing 15%. The rest were NPK (15-15-15).

#### 4.1.2.6. Pesticide Use

Small scale farmers use more pesticide than large scale farmers. On average, small scale farmers used 1.07 liters per acre compared with 0.95 for large scale farmers.

#### 4.1.2.7. Input and Output Prices

The per-unit input prices as seen table 4.5 are averages. Apart from the unit price of labor, the rest are either fixed across all farmers or lack considerable variations. Fertilizer components like nitrogen and phosphorous are fixed for all farmers because the government regulates the prices of almost all chemical fertilizers in the country. For pesticides and machinery, there is little variation. The price of every pesticide and the cost of hiring a tractor for instance are known throughout each district. The little variations come from towns that are far from the distribution centers of these inputs. That of labor depends on how much price a farmer bargains with hire labor, hence the relatively high variability.

The per-unit output price is an average of retail prices over the period of October 2014 to June 2015. The starting period represents the estimated time of harvest, while the end period is the time of data collections. Farmers sell their outputs in piecemeal. That is, as and when they need money. At these different times, they face difference prices. However, they could not give the exact prices and dates these outputs were sold. The sale is normally done on their behalf, especially for the male farmers. The retail prices therefore are estimated from the regional weekly price data from the Statistics, Research and Information Directorate (SRID) of the MoFA. The average for this period per kilogram is 1.45 Ghana Cedis (GH₵1.45).

#### 4.1.2.8. Environmental Variables

The sample data also contained information on environmental variables that are suspected to have effects on various efficiency estimates. There are 12 variables in all, out of which 9 are represented by dummies. However, since the method used is a regression analysis, variables that do not vary among farmers were dropped. These variables are credit access, number of maize plots, FBO membership and improved seed. 98% of farmers did not receive any form of credit, about 93% had used one plot, 68% did not belong to any FBO, and 77% used own

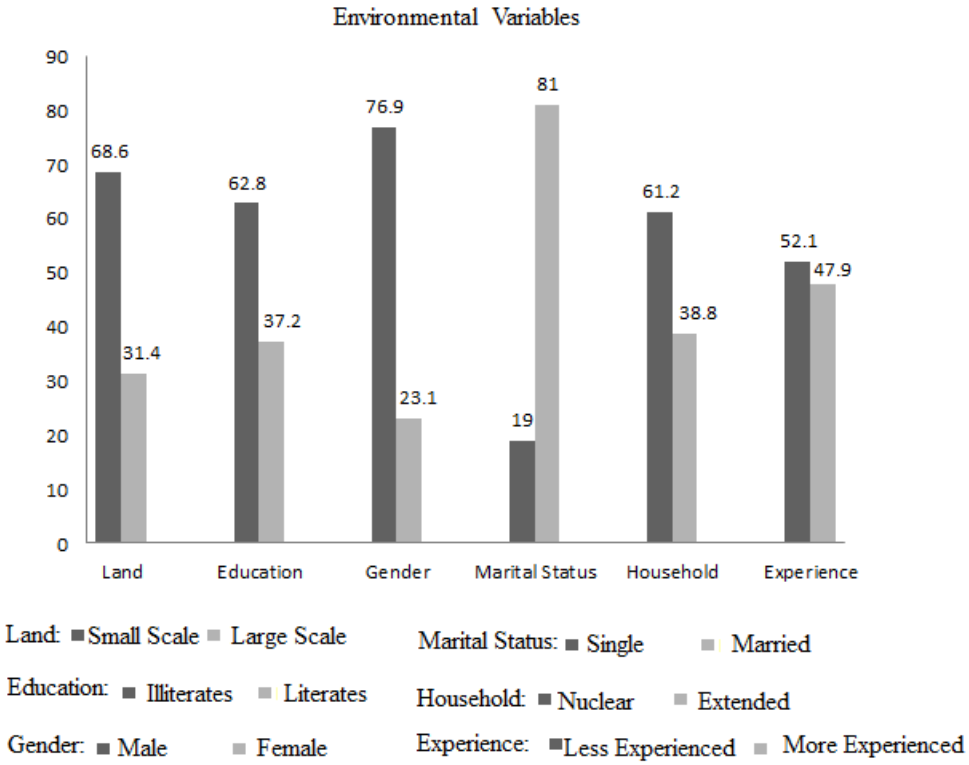
seed. These variables would be given a separate descriptive analysis in relation to the efficiency estimates. At the end, 8 variables were used, 6 were represented as dummies; the 6 are represented in figure 4.3 in percentage terms. These variables would further be tested for correlation both within themselves and the traditional inputs used. The highly correlated ones would be dropped.

A lot of farmers are small scale, producing on an average of 3 acre land. By the definition of literacy and gender in the methodology, 62.8% of the respondents are illiterates, whiles 23.1% are female farm managers. On the issue of gender, women are less proactive in dealings with the Agriculture Ministry; hence the number of registered male farmers is more than females. The sample therefore reflects the same pattern. In reality there are as many male farmers as female ones, however less females take decisions in the management of their farms, hence more male farm managers than female farm managers. The sample reflects this trend as women who really go to register with the Agriculture Ministry are the managers of their own farms. As mentioned earlier, the focus of this thesis is not just on farmers but farmers who make decisions and manage their own farms. The general literacy rate in the region is relatively low compared to the whole country. The pattern in the sample is therefore expected. Furthermore, farming has always been tagged as the occupation for the uneducated.

There is prevalence of early marriages in the region compared with the rest of the country. Therefore the large proportion of the sample being married is not unusual. Farmers from nuclear households were proportionally more than those from the extended family system. Farmers in extended families in most cases do not have full control of their farms in terms of decision making, hence reluctant in registering as a farmer with the Agriculture Ministry. The proportion of more experienced and less experienced farmers by the categorization is very close. The experienced are mostly older respondents compared with younger farmers in the less experienced category. The other variables not represented by dummies are extension contact and labor ratio. The coverage of extension services in the region

is low. Logistics and staff are mostly the contributing factor to this problem. Alternatively, farmers rather reach out for extension services in the district capitals.

In the light of this, about 68.6% of the sampled farmers did not have any contact with extension agents during the farming season. Few had contact once and fewer had more than once. With almost 99% labor ratio, it indicates that farmers rely heavily on family more than hired labor.




Source: Author's presentation from data

Figure 4.3. Environmental Variables in Percentages

### 4.2. Fishing for Outliers

#### 4.2.1. Interquartile Range (IQR) Method

This technique uses the first quartile (Q1), the third quartile (Q3) and the interquartile range (IQR) (Q3-Q1). It then establishes an upper and lower bound outside which are the possible outliers in the data. The lower bound is given as Q1 – 1.5(IQR), whiles the upper is Q3 + 1.5(IQR).

Table 4.9. Estimates for the Interquartile Range (IQR) Method

| | Maize output (kg)-Y | Labor hours-X1 | Machinery hours-X2 | Nitrogen (N) (kg)-X3 | Phosphorus (P) (kg)-X4 | Pesticide use (l)-X5 |
|---|---|---|---|---|---|---|
| Minimum | 117.25 | 52 | 1 | 7.5 | 3.33 | 0.2 |
| 1st quartile | 370 | 132.25 | 3.17 | 13.8 | 6.25 | 0.6 |
| 2nd quartile | 501.75 | 169.93 | 5 | 19 | 8.33 | 1 |
| 3rd quartile | 700 | 201.25 | 5.3 | 23 | 10 | 1.4 |
| Maximum | 1,000 | 542.36 | 6 | 46 | 20 | 4 |
| IQR | 330 | 69 | 2.13 | 9.2 | 3.75 | 0.8 |
| Lower bound | -125 | 28.75 | -0.03 | 0 | 0.625 | -0.6 |
| Upper bound | 1,195 | 304.75 | 8.5 | 36.8 | 15.63 | 2.6 |

For any of the variables, data below the lower bound or above the upper bound are potential outliers. From the data, maize output and machinery hours did not have any outliers. Outliers were found in labor hours (9), nitrogen (1), phosphorus (3) and pesticide use (1).

### 4.2.2. The Z Score Method

This method estimates the Z scores of all the farmers for each variable, using the mean and the standard deviation. Any data below or above 3 standard deviations from the mean is considered a possible outlier. Hence data with Z score less than -3 or greater than +3 is considered an outlier. Using the data together with the information in Table 4.5, the results were the same as in the Interquartile Range (IQR) method, except for the case of labor hours whose number of outliers reduced to one (1).

The Z score is given by the relation;

$$z = \frac{x - \bar{x}}{s} \tag{4.1}$$

Where $\bar{x}$ is the mean, s is the standard deviation and x is the observed data. From the two techniques, it is clear that, there exist outliers in the data. This could be due to extremely large household. In an analysis like efficiency measurement, the most productive farmers with whom the comparisons are made to estimate efficiency are technically 'outliers'. That is, they are so different from the other farmers. In light of this, a sensitivity analysis is conducted by comparing efficiency estimates with and without the possible outliers.

## 4.3. Hypothesis Testing

### 4.3.1 Main Hypotheses Tests

These hypotheses are constructed on the results of stochastic production frontier, with a VRS assumption and a half-normal distributional assumption on the inefficiency term. The returns to scale assumption has already been chosen and justified in the methodology.

The first hypothesis which is the most relevant of all, fairly reject the null hypothesis that there is no stochastic inefficiency in the production function. The

result from this test is so relevant that, if the null hypothesis were accepted, the extended procedure in estimating the cost function and subsequent input oriented TE, AE and CE would have been halted. It would have therefore meant that the inefficiency term u which plays a vital role in the formulation of the stochastic cost frontiers does not exist.

Table 4.10. Results of Hypotheses Tests

| Null Hypothesis | Log-likelihood function (H0) | Log-likelihood function (H1) | Test Statistic (λ) | Critical value ($\chi_i^2 0.05$) | Decision |
|---|---|---|---|---|---|
| 1. $H_0$: $\gamma = 0$ | -7.242 | -4.744 | 4.997 | $\chi_1^2 0.05 = 3.841$ | Reject |
| 2. $H_0$: $\beta_1 + \beta_2 + \ldots\ldots + \beta_5 = 1$ | -4.995 | -4.744 | 0.501 | $\chi_1^2 0.05 = 3.841$ | Accept |
| 3. $H_0$: $\delta_0 = \delta_1 = \delta_{2=} \ldots. = \delta_8 = 0$ | -4.744 | -4.287 | 0.914 | $\chi_1^2 0.05 = 3.841$ | Accept |
| 4. $H_0$: $\beta_{kj} = 0$ | -4.744 | 7.201 | 23.89 | $\chi_{15}^2 0.05 = 24.996$ | Accept |

The second hypothesis strongly accepted the hypothesis that the production function is exhibiting constant returns to scale. This means that the RTS statistic in table 4.11 is not significantly different from 1; hence a simultaneous percentage change in all inputs would lead to the same percentage change in maize output. The result of hypothesis 2 adds to the varying claims by researchers that agricultural production has typically been subjected to CRS; that is, from the output oriented point of view. Matsuyama (1991) makes the claim that agriculture is generally subjected to constant returns to scale, while manufacturing to increasing returns to scale. Kislev and Peterson (1991) also alluded to this opinion after investigating the

claim that agriculture is generally subjected to increasing returns to scale. Papers that supported the case of an IRS were examined and concluded that the hypothesis of increasing returns is not warranted. One of the examples is the assertion by Hayami and Ruttan (1985) that developed countries experiences IRS whiles developing countries exhibits CRS. Using the same data and representing countries with dummies rather, they found that the RTS which was 1.077 was not significantly different from 1. Mellor and Mudahar (1992) also made this generalization when a Cobb-Douglas production function is assumed. According to them evidences from studies in Asia support their claim of CRS. They cited studies in India like Khusro (1964), Krishna (1964), Rao (1965), Saini (1969), and Yotopoulos and Lau (1973). They also cited similar studies from other Asian countries like Yotopoulos and Lau (1979) and Lau, Lin, and Yotopoulos (1979) for Taiwan; Adulavidhaya et al. (1979) for Thailand; and Tamin (1979) for Malaysia. Sheng et al. (2015), after putting the claim of IRS to test on an Australian broadacre industry, found that a CRS or a mild DRS fit the scenario. Other supporters of this position are Van Zyl, et al. (1995), Binswanger, et al. (1993), and Johnson and Ruttan, (1994). It has to be noted that there are exceptional cases where agriculture can exhibit IRS. Examples are Kuroda (1979) and Richard and Onesimo (1986), all conducted in Japan. In the light of this both VRS and CRS assumptions are reported from both techniques. This would further deepen the discussion on the estimates.

The third hypothesis is meant to select the distributional assumption for the inefficiency term in the SFA approach. Gamma and truncated normal distributions were already eliminated and justified, leaving half-normal and exponential distributions. The choice of any of the remaining two is immaterial but, the study adopted the sequential approach to choose one of them. The test strongly accepted the suitability of half-normal distribution. This means that all estimates for SFA will follow the half-normal distribution

The fourth and final hypotheses establishes that the chosen production function (Cobb-Douglas) is appropriate for the study. The selection of the production function is independent of the results of this test.

### 4.3.2. The Alternative Tests

According to Coelli et al. (2005, p.258), the Z-test could be used to test hypothesis 1. This is done by either using the lambda parametrization referred to in the methodology ($\lambda = \sigma_u/\sigma_v$), or the variance of the inefficiency term ($\sigma_u^2$). That is, $H_0: \lambda = 0$ or $H_0: \sigma_u^2 = 0$. Employing the former which is reported in the LIMDEP output, the test statistic is given as: $Z = \tilde{\lambda}/se(\tilde{\lambda}) \sim N(0,1)$. Where $\tilde{\lambda}$ and $se(\tilde{\lambda})$ are the ML estimate of $\lambda$ and the standard error respectively. From results in table 4.11, the Z value of $\lambda$ is 5.121. Since this statistic exceeds $Z_{0.95}$=1.645, the hypothesis that there is no inefficiency in the model is rejected. The two methods agree in their decision on the null hypothesis.

Coelli et al. (2005, p.259) also proved the significance or otherwise of the MU in the truncated normal distribution estimates can be used to test hypothesis 3 This mode of the distribution (MU), which is restricted in the half-normal distribution to zero, is allowed to have a nonzero mode in the truncated normal distribution. The truncation is done below zero (Kumbhakar and Lovell, 2000 p. 83). From table 4.14, the coefficient and standard deviation of MU are -2.044 and 17.13 respectively. This results to a Z statistic of -0.119. Since the statistic is greater than the critical value of $Z_{0.05}$ = -1.96, the null hypothesis that the simpler half-normal distribution is adequate, is accepted. This result is in tandem with the ML ratio test.

## 4.4. Estimated Frontiers

### 4.4.1. Stochastic Production Frontier

The coefficients from both the VRS and the CRS assumptions are all statistically significant except for labor. These coefficients represent output

elasticities of various inputs used, which measures the response of maize output to changes in any of the inputs. Apart from output elasticity of labor being the only insignificant amongst the inputs, it also recorded the lowest output elasticity in both RTS scenarios.

Table 4.11. Stochastic Frontier Functions for Maize Production: Half-Normal Distribution

| | | Variable Returns to Scale | | | Constant Returns to Scale | | |
|---|---|---|---|---|---|---|---|
| Variable | PAR | Coef. | Std. Err | Z-Statistic | Coef. | Std. Err | Z-Statistic |
| Constant | $\beta_0$ | 4.546[a] | 0.324 | 14.043 | 4.361[a] | 0.211 | 20.687 |
| Ln (Labor) | $\beta_1$ | 0.013 | 0.052 | 0.247 | 0.033 | 0.043 | 0.762 |
| Ln (Machinery) | $\beta_2$ | 0.137[a] | 0.065 | 2.110 | 0.146[a] | 0.062 | 2.336 |
| Ln (Nitrogen) | $\beta_3$ | 0.387[a] | 0.132 | 2.924 | 0.397[a] | 0.133 | 2.990 |
| Ln (Phosphorous) | $\beta_4$ | 0.261[a] | 0.130 | 2.010 | 0.277[a] | 0.130 | 2.136 |
| Ln (Pesticide) | $\beta_5$ | 0.142[a] | 0.049 | 2.893 | 0.147[a] | 0.049 | 3.026 |
| RTS ($\sum \beta_i$) | | 0.94 | | | 1.00 | | |
| Lambda ($\sigma_u/\sigma_v$) | $\lambda$ | 1.961[a] | 0.383 | 5.121 | 1.828[a] | 0.348 | 5.256 |
| Sigma | $\sigma$ | 0.364[a] | 0.003 | 144.204 | 0.358[a] | 0.002 | 144.109 |
| Gamma ($\sigma_u^2/\sigma^2$) | $\gamma$ | 0.794[a] | 0.113 | 6.91 | 0.77[a] | 0.12 | 6.49 |
| Sigma squared | $\sigma^2$ | 0.132 | | | 0.128 | | |
| Variance of v | $\sigma_v^2$ | 0.027 | | | 0.03 | | |
| Variance of u | $\sigma_u^2$ | 0.105 | | | 0.099 | | |
| Log likelihood | LLH | -4.744 | | | -4.995 | | |

[a]Significant at 0.05 significance level

**4.4.1.1. Chemical Fertilizer**

Amongst the significant output elasticities, the chemical fertilizer components, nitrogen and phosphorous recorded the highest output elasticity. Furthermore, nitrogen recorded an exceptionally higher estimate than phosphorous; 0.387 against 0.261 for phosphorous. This means that output will increase by 0.387% and 0.261% when nitrogen and phosphorous use increase by 1% respectively. This obviously reflects the soil nutrient composition of the soil in the Northern Region. In table 4.3 which represents the various nutrient composition of the soil, it indicates the insufficiency of nitrogen and phosphorous in the soils in the Northern Region. The results show that increasing output will demand applying more nitrogen and phosphorous to the soil which already lacks them.

This calls for increase in fertilizer use but with a look at the chemical composition of the compound fertilizers. There were two main compound fertilizers used by the farmer; NPK (15-15-15) and NPK (23-10-5). Until recently farmers in the region were only exposed to NPK (15-15-15) for their maize farm. In fact, all fertilizers till date are still widely identified with NPK (15-15-15) among the rural farmers. With the historical usage of equal amount of these nutrient NPK (15-15-15), coupled with the climatic and soil conditions mean that, even if nitrogen and phosphorous were sufficient in the past, they will eventually depreciates as is seen today. Firstly, plants take in more of these two nutrients for vegetative growth. Secondly, as mentioned earlier, there is intense erosion and leaching of soil nutrients in the region. By the very nature of these two nutrients, they are easily washed away or leached. The recent introduction of NPK (23-10-5) has not changed the farmers' preference for the 15-15-15. From the data, very few farmers used the 23-10-5. The government still subsidizes these two compound fertilizers, but there has not been an effort to encourage them to go for a particular type, hence their preference for the 15-15-15. All studies involving efficiency analyses, estimation of production functions and productivity in the Ghana, have often represented the fertilizer component as the weight or quantity of the

compound fertilizer used. Other studies measure it in monetary terms. This method of representation disregards the individual contribution of nitrogen, phosphorus and potassium, to output. To the best of my knowledge, this is the first study to segregate these nutrients in this form of study in a Ghanaian context. These nutrients play different roles in the output of any crop. This means that, in as much the farmers are encouraged to use chemical fertilizers, more nitrogen usage is required. Perhaps, the encouragement of maize farmers to go in for the 23-10-5 rather than 15-15-15 would be better. Alternatively the subsidy on 15-15-15 can be reduced or that of 23-10-5 can be increased to discourage their preference for the former.

#### 4.4.1.2. Machinery Use

Machinery is yet another input with a significant estimate of output elasticity. Agricultural machination in the region is very low especially in the area of food crop production. That is why the average capital labor ratio is barely 3% in the sample. Among the interviewed farmers, none used planters in the sowing of the seeds, none used harrows, and none used harvesters. Ploughing with a tractor was the main machinery used, with few using trucks or tractors to transport output after harvest. This situation is blamed squarely on access to machines. All of these machines mentioned above with the exception tractors are barely in existence in most districts. Even with the tractors, some farmers cultivates late because of the time spent in searching for a tractor during the ploughing period. A significant output elasticity of machinery of 0.137 means more machination will increase output. Mechanization has been proven to increase overall output, productivity, efficiency, farm income, profits and sometimes employment (Verma, 2008). However in this context, even if farm machinery were accessible, farmers will not see it as viable option since they can execute those activities with a free labor resource (family labor). Probably, the lack of demand for machinery could possibly explain their absence in the region. The displacement of this labor by farm

machination is the concern of many policy makers in developing countries like Ghana, where there is already a labor surplus. However, some studies have disproved this idea of labor displacement. According to Verma, (2008), the researches of NCAER (1973), IIM, Ahmedabad (1975) and Sidhu and Grewal (1991), all disproves the displacement theory of agricultural labor by mechanization. Whiles the first two reported an increase in labor employment, the third did not see any significant difference in terms of labor employment. According to theses researches family labor contribution reduces drastically, but mechanization created vast opportunities for hired labor that in turn absorbed the idle family labor. The conclusions of Verma (2008) and that of Mohapatra (2016) confirm this opinion. They went further to state that most of the displaced labor from mechanization is absorbed back through the non-farm opportunities it creates. These non-farm activities include agribusiness, agro processing as well as manufacturing, repairs, servicing and sales of agricultural equipment.

#### 4.4.1.3. Pesticide Use

Pesticide use has been a controversial topic around the world especially in areas with already poor soil conditions. These chemical are used for various purposes such as weed control, pest, diseases etc. However, this study limited the pesticide use to only the total weed killer, which is normally used before sowing. It prevents weed from catching up with the maize plant at the early stages of growth. For pesticide, the results show a significant positive output elasticity of 0.142. In the context of the study, there are generally no severe diseases or pest associated with maize plants that requires the use of chemicals in the Northern Region. Even though pest and diseases is the second most important risk to agricultural production after drought, the most affected are cassava, cocoa and plantain. Furthermore, the Northern Regions are also found to be less exposed to these pest and diseases as compared with the southern regions (Choudhary et al. 2015). They attributed this to the high temperature and humidity in the Northern Regions

coupled with frequent bush burning that controls most of the insects and pets. The main known pests and diseases of maize according to Choudhary et al. (2015) are variegated grasshopper, locusts, stem borer, maize and large grain borer. Whiles there has not been any outbreak of pests for over three decades, the diseases have been put under control for about two decades. What is therefore left of the use of chemicals on maize farms is weed control. It therefore makes sense that, a chemical or pesticide that controls weeds will increase output of maize as reflected in the output elasticity of 0.142, all things being equal.

#### 4.4.1.4. Agricultural Labor

Labor is the only unique input among them all in terms of its output elasticity, statistical significance, and quantity. Most of the employed agricultural labor is family labor and that is what the Northern Region has in abundance. The region has a high fertility rate, low school attendance rate, high school dropout rate, high illiteracy and above all higher mean household size in the country. According to the Ghana Statistical Service (2014b), the Northern Region has been leading in the mean household size until 2013 when it became second to Upper West. With the national average at 4 persons per household, Northern Region had 7.7 in 2010 and 5.4 in 2013. The region also records the least school attendance rate of 50.4% compared with the national average 91%. Already there is a national phenomenon of labor migration from the north to the south in search of job opportunities. Some have largely blamed it on the falling standard of agricultural production. It is therefore not surprising that its output elasticity not only being statistically insignificant, but very low, that is 0.013.

**4.4.1.5. Other Coefficients**

The gamma or the variance ratio measures the extent to which the noise term $v_i$ and the inefficiency term $u_i$ affects the total deviation from the frontier. The sum of their variances make up the total variance of the total deviation ($\sigma^2 = \sigma_v^2 + \sigma_u^2$). The gamma estimate ($\gamma = \sigma_u^2/\sigma^2$) therefore indicates which of them is more responsible for the deviation from the frontier. A ratio of 0.79 means inefficiency is responsible for 79% of the shortfall between the established frontier and the actual values. This strengthens the case for the investigation into the causes of efficiency. The ratio is statistically significant.

The RTS estimate of 0.94 indicates DRS in the production of maize in the region. Even though it falls a little short of CRS (RTS=1), hypothesis 2 sees no difference between it and 1. A look at the estimates between the VRS and the CRS are telling the same story with the exception of the RTS. This gives more credence to the results of hypothesis 2.

**4.4.1.6. Input Allocative Efficiency Coefficient (IAEC)**

This coefficient differentiates the technical analysis done under the discussion on the production from its economic analysis, given unit prices. From the discussion under the stochastic production function, all the output elasticities were positive indicating that a unit increase in any of those inputs would results in a proportional increase in output by the magnitude of the output elasticity. However, not all the increases may be economically wise since the revenue from the corresponding output increase may be greater, equal or less than the cost of the unit increase in the said input. When they are equal, it is said that the input is used at an economic optimum, and in that case IAEC will be equal to 1. From the table 4.12, the coefficient of labor is less than 1, and that of machinery hours, nitrogen, phosphorous and pesticide use are greater than 1. This indicates that none of the inputs is optimally allocated relative to the economic optimum or the profit maximizing condition.

Table 4.12. Input Allocative Efficiency Coefficient

| Maize Output $\bar{Y} = 487.21$ | Labor Hours | Machinery | Nitrogen | Phosphorus | Pesticide Use |
|---|---|---|---|---|---|
| Geometric Mean | 164.26 | 4.14 | 17.42 | 8.15 | 0.9 |
| IAEC | 0.03 | 1.43 | 6.74 | 6.36 | 10.10 |

The findings suggest that even though labor has a positive output elasticity coefficient increasing its use is not economically feasible, rather, it should be reduced. That of machinery, nitrogen, phosphorus and pesticide can be increased according to the coefficient. It suggests they are less utilized and an increase in their usage will benefit farmers economically. This finding supports the slack analysis that shows a considerable amount of slacks in labor and suggested a reduction in its use. In terms of the distribution of this coefficient among the farmers, all farmers recorded a coefficient less than 1 for labor, indicating its general excessive usage across all farmers in the region. In the case of machinery use, only 7 farmers were excessively using it whiles the rest underutilized it. The rest of the inputs were all underutilized across all farmers in the sample.

#### 4.4.1.7. Marginal Rate of Technical Substitution (MRTS)

From the table 4.13, it can be observed that the amount of labor needed to be sacrificed for a unit increase in machinery is very low, that is, 0.002 hours of labor. That of nitrogen and phosphorus is 0.694 kg; nitrogen and pesticide use is 0.141 liters; and between phosphorous and pesticide is 0.204 liters. The highest substitutability rate is therefore found between nitrogen and phosphorus, which is not unusual. In comparison with the corresponding price ratios, all but $MRTS_{NPH}$ are lower. This indicates that labor use should be increased relative to machinery use, more nitrogen should be employed relative to pesticide, and finally

phosphorus use should be increased relative to pesticide use. In the case of nitrogen and phosphorous, more nitrogen is expected to be given up for increase in phosphorous use.

Table 4.13. Marginal Rate of Technical Substitution

| | $MRTS_{LM}$ | $MRTS_{NPH}$ | $MRTS_{NP}$ | $MRTS_{PHP}$ |
|---|---|---|---|---|
| $MRTS_{12}$ | 0.002 | 0.694 | 0.141 | 0.204 |
| $P_1/p_2$ | 0.131 | 0.654 | 0.208 | 0.317 |

**4.4.1.8. The Production Function**

This function is based on the estimates of the VRS frontier.

$$Y_i = 94.255\, X_1^{0.013} X_2^{0.137} X_3^{0.387} X_4^{0.261} X_5^{0.142} e^{v_i - u_i} \quad RTS = 0.94 \qquad (4.2)$$

However, to use this production function beyond this point means maize output has to be adjusted for statistical noise. That is $Y_i * e^{-v_i} = \widehat{Y}_i$

$$\widehat{Y}_i = 94.255\, X_1^{0.013} X_2^{0.137} X_3^{0.387} X_4^{0.261} X_5^{0.142} e^{-u_i} \quad RTS = 0.94 \qquad (4.3)$$

Or in its linearized form:

$$\ln\widehat{Y}_i = 4.546 + 0.013\ln X_1 + 0.137\ln X_2 + 0.387\ln X_3 + 0.261\ln X_4 + 0.142\ln X_5 - u_i \quad (4.4)$$

Table 4.14. Stochastic Frontier Functions for Maize Production: Truncated-Normal Distribution

| | | Variable Returns to Scale | | | Constant Returns to Scale | | |
|---|---|---|---|---|---|---|---|
| Variable | PAR | Coef. | Std. Err | Z-statistic | Coef. | Std. Err | Z-statistic |
| Constant | $\beta_0$ | 4.469[a] | 0.434 | 10.292 | 4.310[a] | 0.272 | 15.829 |
| Ln (Labor) | $\beta_1$ | 0.020 | 0.068 | 0.293 | 0.038 | 0.051 | 0.737 |
| Ln (Machinery) | $\beta_2$ | 0.136[b] | 0.075 | 1.819 | 0.145[a] | 0.071 | 2.045 |
| Ln (Nitrogen) | $\beta_3$ | 0.364[a] | 0.155 | 2.353 | 0.371[a] | 0.150 | 2.464 |
| Ln (Phosphorous) | $\beta_4$ | 0.284[b] | 0.158 | 1.799 | 0.298[a] | 0.149 | 1.997 |
| Ln (Pesticide) | $\beta_5$ | 0.143[a] | 0.050 | 2.889 | 0.149[a] | 0.050 | 3.006 |
| RTS ($\sum \beta_i$) | | 0.947 | | | 1.00 | | |
| MU | MU | -2.044 | 17.130 | -0.119 | -2.913 | 34.008 | -0.086 |
| Lambda ($\sigma_u/\sigma_v$) | $\lambda$ | 3.859 | 12.154 | 0.318 | 4.272 | 20.378 | 0.210 |
| Sigma | $\sigma$ | 0.713 | 2.221 | 0.321 | 0.807 | 3.786 | 0.213 |
| Gamma ($\sigma_u^2/\sigma^2$) | $\gamma$ | 0.937 | 0.01 | 8.89 | 0.948 | | |

[a]Significant at 0.05 significance level, [b]Significant at 0.1 significance level

The main purpose of this estimate is for testing hypothesis. However a closer comparison between it and the half- normal case reveals similar pattern. Furthermore the MU is not significant giving way to the use of half-normal distribution. It can also be observed that gamma is relatively high, attributing deviations from the frontier to mainly inefficiency.

### 4.4.2. Stochastic Cost Function for Maize Production

Since the production function in eqn 4.3 is dual, the corresponding stochastic cost function is;

$$C_i = f\left(\hat{Y}_i, P_i;\ \beta_i\right) = \mathrm{C_i} = \ 0.031 \mathrm{P_1}^{0.014} \mathrm{P_2}^{0.146} \mathrm{P_3}^{0.412}\ \mathrm{P_4}^{0.278} \mathrm{P_5}^{0.151}\ \hat{\mathrm{Y}}^{1.064} \qquad (4.5)$$

Or this in it linearized form;

$$\ln C_i = -3.474 + 0.014\ln P_1 + 0.146\ln P_2 + 0.412\ln P_3 + 0.278\ln P_4 + 0.151\ln P_5 + 1.064\ln \hat{Y} \quad (4.6)$$

### 4.4.3. Conditional Input Demand Functions for Maize Production

This function represents the demand function for the inputs employed in the analysis. This function generates the most economically or cost efficient input quantity given their prices and output produced. These are then further used in the estimation of cost and allocative efficiencies.

Labor:

$$\partial C_i / \partial P_1 = X_{d1} = X_1^c\left(P_k, \hat{Y}_i, \delta\right) = 0.0004 {P_1}^{-0.99} {P_2}^{0.15} {P_3}^{0.41} {P_4}^{0.28} {P_5}^{0.15} \hat{Y}^{1.06} \ldots\ldots\ldots (4.7)$$

Machinery:

$$\partial C_i / \partial P_2 = X_{d2} = X_2^c\left(P_k, \hat{Y}_i, \delta\right) = 0.0044 {P_1}^{0.01} {P_2}^{-0.85} {P_3}^{0.41} {P_4}^{0.28} {P_5}^{0.15} \hat{Y}^{1.06} \ldots\ldots\ldots (4.8)$$

Nitrogen:

$$\partial C_i / \partial P_3 = X_{d3} = X_3^c\left(P_k, \hat{Y}_i, \delta\right) = 0.0126 {P_1}^{0.01} {P_2}^{0.15} {P_3}^{-0.59} {P_4}^{0.28} {P_5}^{0.15} \hat{Y}^{1.06} \ldots\ldots\ldots (4.9)$$

Phosphorous:

$$\partial C_i / \partial P_4 = X_{d4} = X_4^c\left(P_k, \hat{Y}_i, \delta\right) = 0.009 {P_1}^{0.01} {P_2}^{0.15} {P_3}^{0.41} {P_4}^{-0.72} {P_5}^{0.15} \hat{Y}^{1.06} \ldots\ldots\ldots (4.10)$$

Pesticide:

$$\partial C_i / \partial P_5 = X_{d5} = X_5^c\left(P_k, \hat{Y}_i, \delta\right) = 0.0046 {P_1}^{0.01} {P_2}^{0.15} {P_3}^{0.41} {P_4}^{0.27} {P_5}^{-0.85} \hat{Y}^{1.06} \ldots\ldots\ldots (4.11)$$

### 4.5. Sensitivity Analysis

The presents of outliers in data are very crucial to the estimation of efficiencies both from DEA and SFA. The presence of outliers is said to overestimate inefficiency and noise in DEA and SFA respectively. The data were assessed for potential outliers using the Interquartile Range (IQR) and the Z score methods. Whiles the first technique identified 3 farmers as potential outliers, the later identified 11 which included all those identified in the first method. On this basis, 11 potential outliers were identified in the sampled data.

Table 4.15. DEA Estimates With and Without Outliers

| | Sample Mean | |
|---|---|---|
| Efficiencies | With outliers | Without outliers |
| $TE_{IVRS}$ | 0.793 | 0.795 |
| $AE_{IVRS}$ | 0.672 | 0.678 |
| $CE_{IVRS}$ | 0.53 | 0.536 |
| $TE_{OVRS}$ | 0.741 | 0.731 |
| $TE_{ICRS}$ | 0.685 | 0.677 |
| $AE_{ICRS}$ | 0.64 | 0.647 |
| $CE_{ICRS}$ | 0.44 | 0.441 |
| $TE_{OCRS}$ | 0.685 | 0.677 |
| SE | 0.864 | 0.851 |

Following the advice of (Ramanathan, 2003, p.179), a sensitivity analysis is conducted by estimating the frontiers without the potential outliers. That is, the sample size reduced to 110. In the case of the DEA results under VRS, the efficiency level increased as expected from 79.3% to 79.5%. However, the CRS estimates decreased from 68.5% to 67.7%. This was not expected as the presence of outliers is expected to decrease efficiency levels as in the case of the VRS. The other efficiencies under DEA are presented in table 4.15.

The marginal differences between those estimates indicate that DEA, contrary to the theoretical belief is not sensitive to the outliers in this data, that is, it is robust. However, like the case of Sharma et al. (1999), all the efficiency estimates under VRS improved.

SFA is also applied on the outlier free data. Per procedure, a stochastic frontier function has to be estimated first. The results of those estimates with both RTS assumptions are tabulated below.

Table 4.16. Stochastic Frontier Functions for Maize Production Without Outliers: Half-Normal Distribution

| | | Variable Returns to Scale | | | Constant Returns to Scale | | |
|---|---|---|---|---|---|---|---|
| Variable | PAR. | Coef. | Std. Err | Z-statistic | Coef. | Std. Err | Z-statistic |
| Constant | $\beta_0$ | 4.897[a] | 0.405 | 12.095 | 4.429[a] | 0.242 | 18.316 |
| Ln (Labor) | $\beta_1$ | -0.069 | 0.067 | -1.033 | -0.006 | 0.049 | -0.116 |
| Ln (Machinery) | $\beta_2$ | 0.123[b] | 0.067 | 1.834 | 0.141[a] | 0.065 | 2.191 |
| Ln (Nitrogen) | $\beta_3$ | 0.437[a] | 0.147 | 2.973 | 0.435[a] | 0.149 | 2.916 |
| Ln (Phosphorous) | $\beta_4$ | 0.223 | 0.148 | 1.502 | 0.281[b] | 0.145 | 1.933 |
| Ln (Pesticide) | $\beta_5$ | 0.140[a] | 0.057 | 2.444 | 0.148[a] | 0.057 | 2.592 |
| Lambda ($\sigma_u/\sigma_v$) | $\lambda$ | 1.759[a] | 0.362 | 4.855 | 1.605[a] | 0.329 | 4.872 |
| Sigma | $\sigma$ | 0.361[a] | 0.003 | 130.576 | 0.355[a] | 0.003 | 130.38 |

[a] significant at 0.05 significance level [b] significant at 0.1 significance level

Estimates are very different from the data with the outliers. However, in both RTS assumptions, the procedure to estimate the output and input oriented efficiencies cannot be continued for two reasons. Firstly, the duality technique employed requires that none of the output elasticity be negative. Secondly the null hypothesis that inefficiency does not exist is statistically significant, implying there is no inefficiency. The results were similar for truncated-normal, exponential and gamma distributions. Suspecting a specification problem, a translog production was tried.

Aside recording more negative output elasticities, it also failed to establish the presence of technical inefficiency. In the absence of the SFA efficiency estimates from this data, it can only be concluded that the production function is sensitive to the presence of outliers. However, the rejection of the presence of inefficiency is in line with the theory that outliers increases inefficiency whiles their absence reduces it. This also strengthened the argument that outliers are

necessary for efficiency estimation since they are likely the reference point from which other DMU is referred for efficiency estimation.

### 4.6. Cost Share of Inputs

Cost share of any input is the proportion of the total observed cost of the input that makes up the total cost of that input.

Table 4.17. Inputs Cost Share (GH₵)

| Cost share Labor | Cost share Machinery | Cost share Nitrogen | Cost share Phosphorous | Cost share Pesticide |
|---|---|---|---|---|
| 0.683 | 0.145 | 0.087 | 0.062 | 0.023 |

From the table, the cost of labor consists of 68% of the total cost of producing maize in the Northern Region. As explained earlier, labor is an important input in the production process, but it is readily available by way of family labor. About 98% of the total labor employed is family labor. The fact that farmers do not pay for this kind of labor, makes them employ them on the farms even if they are doing little work. As a result, a lot of labor employed is not needed. This has translated into large amount of slacks as seen in the table 4.24. This means farmers with more family labor cost will be disadvantaged in the efficiency estimation that employs input orientation like this study. The approach adopted in this study is cost and input quantity minimization. This huge opportunity cost is a burden on the farmer's cost of production. In the cultural setting of the region, it is incumbent on every member of the household to participate in the activities in the farm.

Machinery use has the next highest cost share of about 14.5%. The activities of farmers that involve the use of machinery are few. It is mostly ploughing and sometimes transporting harvest from farms. Mechanization rate is very low. The availability of 'free' labor may be the reason behind the lack of

interest in mechanization. Fertilizer and pesticide come next in order; 8.7%, 6.2% and 2.3%.

### 4.7. Results of Efficiency Analyses

A host of efficiency estimates have been estimated and reported in this study. However in the final discussions and recommendation from this study, attention would be given to the input oriented estimates from both DEA and SFA. The other efficiencies are reported so as to compare and find out to what extent DEA and SFA agree. The efficiencies estimated under DEA are; the input oriented VRS technical, allocative and cost efficiencies ($TE_{IVRS}$, $AE_{IVRS}$ and $CE_{IVRS}$); the input oriented CRS technical, allocative and cost efficiencies ($TE_{ICRS}$, $AE_{ICRS}$ and $CE_{ICRS}$); the input oriented scale efficiency($SE_I$); the output oriented VRS technical efficiency ($TE_{OVRS}$); the output oriented CRS technical efficiency ($TE_{OCRS}$); the output oriented scale efficiency ($SE_O$). Under SFA, the input oriented VRS technical, allocative and cost efficiencies ($TE_{IVRS}$, $AE_{IVRS}$ and $CE_{IVRS}$); the input oriented CRS technical, allocative and cost efficiencies ($TE_{ICRS}$, $AE_{ICRS}$ and $CE_{ICRS}$); the output oriented VRS technical efficiency ($TE_{OVRS}$); the output oriented CRS technical efficiency ($TE_{OCRS}$). All these are reported and discussed under various sub headings. With the exception of output oriented estimates, all estimates would be regressed against the identified environmental variables to establish their relationships as well as statistical significance.

#### 4.7.1. Technical Efficiency

##### 4.7.1.1. Technical Efficiency Estimates

This measures a firm's ability to either produce a given output with the minimum input quantity, or achieve the maximum output with a given amount of inputs. These are known as input and output oriented efficiencies respectively. The

results are therefore reported in the same order with considerations to both CRS and VRS assumptions.

Starting with the VRS estimates ($TE_{IVRS}$), it can be observed that the average technical efficiency is fairly high in both techniques. Only 21% of output is lost through the farmers' inefficient management in the case of DEA and about 23% in the case of SFA. Theoretically as expected the average efficiency score of SFA should have been higher than that of the DEA. This is because DEA attribute all deviations from the frontier to inefficiency, whiles SFA segregates it into inefficiency and noise. Therefore DEA is expected to overestimate the efficiency (Johansson, 2005). However, the results turns out opposite in the VRS estimates. This is not unusual in VRS assumptions since VRS, aside being more flexible than the CRS allows the data to be tightly enveloped (Sharma et al. 1999).

Table 4.18. Input Oriented Technical Efficiencies for DEA and SFA

| | DEA-Input Oriented (N=121) | | SFA-INPUT ORIENTED (N=121) | |
|---|---|---|---|---|
| Efficiency level (%) | $TE_{IVRS}$ | $TE_{ICRS}$ | $TE_{IVRS}$ | $TE_{ICRS}$ |
| < 10 | 0 | 0 | 0 | 0 |
| ≥ 10 < 20 | 0 | 0 | 0 | 0 |
| ≥ 20 < 30 | 0 | 2 | 0 | 0 |
| ≥ 30 < 40 | 0 | 3 | 1 | 0 |
| ≥ 40 < 50 | 1 | 14 | 2 | 3 |
| ≥ 50 < 60 | 5 | 18 | 8 | 7 |
| ≥ 60 < 70 | 29 | 34 | 20 | 13 |
| ≥ 70 < 80 | 34 | 20 | 30 | 28 |
| ≥ 80 < 90 | 15 | 11 | 51 | 59 |
| ≥ 90 < 100 | 16 | 7 | 9 | 11 |
| 100 | 21 | 12 | 0 | 0 |
| | | | | |
| Mean | 0.793 | 0.685 | 0.771 | 0.787 |
| Minimum | 0.476 | 0.279 | 0.397 | 0.428 |
| Maximum | 1.000 | 1.000 | 0.95 | 0.95 |
| Std Deviation | 0.142 | 0.180 | 0.115 | 0.105 |
| COV | 5.584 | 3.81 | 6.704 | 7.495 |

This tight envelopment of the data results in the situation where the average efficiency score from DEA is higher than that of SFA. Results from Johansson (2005) and Alemdar and Ören (2006a) also behaved the same way. The minimum efficiency estimate is about 48% compared with highest of 100% in the DEA. The number of fully efficient farmers is 21. Compared with the SFA estimates, the minimum efficiency score is about 40% and the maximum is 95%.

The SFA did not only record much lower minimum efficiencies than the DEA, no farmer could reach full efficiency. It has to be emphasized that full efficiency in SFA is generally scares as it will indicate a complete absence of the noise effect. Apart from the relatively higher efficiency averages, it is also encouraging to note that 71% and 74% of the farmers scored above 70% efficiency level for DEA and SFA respectively. Per the COV statistic, efficiency estimates in the DEA are less dispersed around its mean than those of the SFA.

With the exception of some observations, the CRS estimates reveal almost the same pattern in terms of distribution as the VRS assumption. However, the wide difference between the RTS estimates under DEA is an indication of a substantial amount of scale inefficiency. The first of the exceptions are that the average CRS estimates are much lower than its VRS counterpart in DEA but slightly higher than in the SFA estimates. The other has to do with the comparison of the average efficiencies from both techniques. While the average estimate of DEA was higher than SFA under the VRS assumption, it is the reverse in the case of CRS. The result of the former is the expected theoretical results, but as explained earlier, under CRS the data in the DEA are less tightly enveloped. The other varied observation is that, the minimum efficiency score under SFA is higher than that of DEA under the CRS, which was the opposite under the VRS. DEA still record full efficiency but the number of fully efficient farmers has reduced to 12, whiles the highest efficiency score in SFA is still 95%.

The table for the output oriented estimates might look somehow similar to that of the input orientation. The similarity comes from the equality of the output oriented technical efficiencies under CRS and its counterpart in the input oriented estimation. This is based on the theory that, input and output oriented technical efficiency estimates must be equal under CRS assumption. Column 3 and 5 in both tables are the same in all aspects.

Table 4.19. Output Oriented Technical Efficiencies for DEA and SFA

| | DEA-Output Oriented (N=121) | | SFA-OUTPUT ORIENTED (N=121) | |
|---|---|---|---|---|
| Efficiency level (%) | $TE_{OVRS}$ | $TE_{OCRS}$ | $TE_{OVRS}$ | $TE_{OCRS}$ |
| < 10 | 0 | 0 | 0 | 0 |
| ≥ 10 < 20 | 0 | 0 | 0 | 0 |
| ≥ 20 < 30 | 1 | 2 | 0 | 0 |
| ≥ 30 < 40 | 3 | 3 | 0 | 0 |
| ≥ 40 < 50 | 10 | 14 | 3 | 3 |
| ≥ 50 < 60 | 17 | 18 | 7 | 7 |
| ≥ 60 < 70 | 19 | 34 | 18 | 13 |
| ≥ 70 < 80 | 19 | 20 | 22 | 28 |
| ≥ 80 < 90 | 17 | 11 | 60 | 58 |
| ≥ 90 < 100 | 17 | 7 | 11 | 12 |
| 100 | 18 | 12 | 0 | 0 |
| Mean | 0.741 | 0.685 | 0.782 | 0.787 |
| Minimum | 0.285 | 0.279 | 0.42 | 0.428 |
| Maximum | 1.000 | 1.000 | 0.952 | 0.950 |
| Std Deviation | 0.194 | 0.180 | 0.11 | 0.105 |
| COV | 3.82 | 3.806 | 7.109 | 7.495 |

The equality of the DEA estimates in this sense is not of much importance to this study than that of that SFA estimates. Even though they are consistent with the theory stated above, the DEA estimates are just the outputs of the same data from the same software (DEAP), hence are bound to be equal. That of SFA adds a boost to the cost related technique adopted in the estimation of the input oriented technical efficiency, which is more of a manual process. The fact that it is equal to the software generated output oriented efficiency authenticates the technique

employed. If there were inconsistencies or mistakes in the manual estimation, it would have been exposed by this result. That is, $TE_{ICRS}$ and $TE_{OCRS}$ would not have been equal.

Therefore, the output oriented VRS estimates are the only different estimates from the input oriented results in table 4.18, hence worth further discussion. The average efficiency estimates in DEA is lower than that of SFA, which though expected, sharply contradicts the results under the input orientation. It reveals that, under VRS, input orientation envelopes the data more than the output orientation in DEA analysis. Consistently, it has also recorded a lower minimum efficiency score of 28.5% in DEA compared with 42% in SFA. As expected SFA did not record any fully efficient farmer, whiles 18 farmers were fully efficient in DEA. Whiles the only 58.7% of the farmers scores above 70% efficiency in DEA, there were 76.9 % of them for SFA. Once again the DEA estimates are more dispersed than the SFA estimates.

#### 4.7.1.2. Environmental Variables

Whiles the inputs used in the estimation of the above efficiency estimates are assumed to be under the control of the farmers, the environmental factors are assumed otherwise. A tobit regression analysis was conducted on the input oriented efficiency estimates for both CRS and VRS across DEA and SFA approaches. To avert the problem of correlation between the inputs and the environmental variables, correlation coefficients and technical effect model were estimated. The correlation coefficients did not reveal a strong relationship. The highest significant correlation coefficients recorded were 50.4% and 54.2%, which is between labor hours used and maize farming experience, and land area respectively. This means that all the environmental variables are qualified to be included in the tobit regression equation, which is reported in Table 4.20. However, the fact that most of the analysis is based on the point-biserial correlation rather than the Pearson's means that the comparison of the coefficients are not entirely consistent. This calls

for the estimation of the inefficiency effect model, reported in Table 4.21. It can be seen that from both tables that only labor ratio, which is significant under the tobit regression is found highly insignificant under the inefficiency effect model. This means that labor ratio variable would be dropped. The tobit regression analysis would continue with all the efficiencies without labor ratio. Starting with technical efficiency, the tobit regression output for the VRS assumption is represented in Table 4.22.

Unlike efficiency scores discussed above, the discussions of environmental factors have to be based on the agreement between the two techniques. For studies that apply one method discussions are based on the single results from that technique, but in the case of this study, there need to be consistency in the discussion from both techniques. For example if a study that employs only DEA establishes a negative relationship between efficiency and a particular environmental variable, the discussion would go as such. However, if SFA is applied on the same data and it reports a positive relationship, the discussion cannot continue with the outcome of the DEA estimates. For all analyses under the environmental factors, results must first agree in terms of signs (+ or -), and secondly they must be statistically significant. Discussion of results would be based on the first condition, but for recommendations and conclusion, either one or both must be statistically significant in addition to fulfilling the first condition. A two sample t-test is further conducted on the variables that pass the criterion. For example if a variable like gender agrees with the two techniques in terms of sings and at the same time significant, the two sample t-test would reveal whether the difference in mean efficiency between male and female is statistically the same.

In the light of this, additional summarized columns are added to the tobit regression results. These columns represent signs and statistical significance (sig) respectively. The positive represents positive relationship and the negative represents negative relationship between the efficiency estimates and the environmental variables. A two asterisk signs (**) under the sign or significant

column means DEA and SFA have agreed on the said coefficient. One asterisk (*) under the statistical significance column means only one of the coefficients of the two techniques is significant. And empty space for both columns means no agreement between DEA and SFA; that is their results contradict each other. With the help of this pictorial presentation, it means that those environmental variables with two asterisk (**) under the sign column would be discussed and if any of them have one (*) or two (**) asterisk under the significance column, it qualifies for recommendation and further discussion. Furthermore if there is a reasonable explanation for contradictory coefficients, it would also be pointed out.

From table 4.22, extension contact has a positive coefficient from both DEA and SFA estimates. These coefficients are fairly close to each other. This means that, the more contacts farmers have with extension officers, the more their technical efficiencies will increase, albeit slightly. Extension activities are under the control of the MoFA, which is very understaffed. It is normally impossible for them to cover their allocated area during the farming season, due to size of the area, lack of financial support in terms of fuel, and bad roads which limits access to some communities. They normally visit communities that are closer to them, where an agricultural project is being implemented, or where there has been an emergency agricultural problem like an outbreak of pest and diseases. For most farmers, they rather reach out to them in the district capitals for advice and solutions on when to plant, chemical and fertilizer usage, how to benefit from an agricultural program etc. It is therefore normal that farmers who seek expect guidance on these things should perform better than those who do not. However, none of the estimates from both DEA and SFA is statistically significant.

The variable land area is meant to differentiate between large scale and small scale farmers. It is represented as a dummy variable (below 5 acres =0, and above 5 acres =1). Those below 5 acres (small scale farmers) consisted of 69% of the total.

Table 4.20. Environmental Factors- Input Oriented Technical Efficiencies- SFA VRS Estimates

| Input Oriented | Technical Efficiency- SFA | | |
|---|---|---|---|
| Factors | Coef. | Std. Err | t-ratio |
| Constant | 1.230[a] | 0.197 | 6.25 |
| Extension | 0.002 | 0.011 | 0.19 |
| Land area | -0.001 | 0.014 | 0.08 |
| Labor ratio | -0.575[a] | 0.194 | 2.96 |
| Education | -0.001 | 0.016 | 0.06 |
| Gender | -0.011 | 0.016 | 0.67 |
| Marital Status | 0.010 | 0.017 | 0.58 |
| Household | 0.172[a] | 0.014 | 12.36 |
| Experience | 0.007 | 0.016 | 0.45 |

[a] significant at 0.05 significance level.

Land area recorded negative coefficients for technical efficiency in under both techniques. This means that small scale farmers are more efficient in production, than the large scale ones. Feeding dependents is the most common reason for cultivation maize among the sampled farmers. This therefore means that scale is dependent on the family size or the number people that are dependent on the farmer. All things being equal, the small scale farmers should be more efficient than the large scale farmers for two main reasons; firstly, the small scale farmers would have much time to manage the their farms as compared with the large farmers.

Table 4.21. Inefficiency Effect Model- VRS estimates

| | Null Hypothesis | log likelihood function | LR test (mixed Chi-squared distributed) | Critical value | Decision |
|---|---|---|---|---|---|
| Presence of inefficiency (u) | H0: u=0[a] | -4.744 | 4.997 | $\chi_1^2 0.05 = 3.48$ | Reject |
| All (δ1, δ2,.. δ8) | H0: δ1,δ2…. δ8=0[a] | 48.423 | 111.33 | $\chi 9^2 0.05=16.919$ | Reject |
| Extension (δ1) | H0: δ1= 0 | 48.527 | -0.208 | $\chi_1^2 0.05=3.841$ | Accept |
| Land area (δ2) | H0: δ2= 0 | 48.515 | -0.184 | $\chi_1^2 0.05=3.841$ | Accept |
| Labor ratio (δ3) | H0: δ3= 0 | 51.992 | -7.139 | $\chi_1^2 0.05=3.841$ | Accept |
| Educ (δ4) | H0: δ4= 0 | 48.315 | 0.216 | $\chi_1^2 0.05=3.841$ | Accept |
| Gender (δ5) | H0: δ5= 0 | 48.062 | 0.721 | $\chi_1^2 0.05=3.841$ | Accept |
| Status (δ6) | H0: δ6= 0 | 48.521 | -0.197 | $\chi_1^2 0.05=3.841$ | Accept |
| Household(δ7) | H0: δ7= 0[a] | 16.201 | 64.444 | $\chi_1^2 0.05=3.841$ | Reject |
| Experience(δ8) | H0: δ8= 0 | 48.479 | -0.112 | $\chi_1^2 0.05=3.841$ | Accept |

[a] significant at 0.05 significance level.

Secondly, the large scale farmer would naturally have the family labor problem mentioned earlier. Since the orientation used here is input orientation, which requires the employment of the minimum input quantity possible, farmers with large family size would definitely be disadvantaged. There is no problem with other inputs as they are assumed to be used proportionally to the number of acres. The less managerial and supervisory role in the first reason makes the large scale farmers less technically inefficient as compared with the small farms. The second reason compounds the issues of opportunity cost of family labor as discussed earlier because, the technique adopted in the estimation of technical efficiency in SFA is directly related with cost. For emphasis, this conclusion is not a generalization on small and large scale farms but solely in the context of reason

why farmers increase their farm size in the region. However, both coefficients from both techniques are statistically insignificant.

Table 4.22. Environmental Factors- Input Oriented Technical Efficiencies- VRS Estimates

| | Technical Efficiency-DEA | | | Technical Efficiency- SFA | | | Agreement | |
|---|---|---|---|---|---|---|---|---|
| Factors | Coef. | Std. Err | t-ratio | Coef. | Std. Err | t-ratio | Sign (+/-) | Sig |
| Constant | 0.735[a] | 0.04 | 18.36 | 0.651[a] | 0.02 | 33.34 | | |
| Extension | 0.014 | 0.023 | 0.62 | 0.004 | 0.011 | 0.35 | ** | |
| Land area | -0.033 | 0.03 | -1.1 | -0.002 | 0.014 | -0.12 | ** | |
| Education | 0.062[b] | 0.033 | 1.91 | 0.007 | 0.016 | 0.46 | ** | * |
| Gender | 0.046 | 0.033 | 1.37 | -0.012 | 0.016 | -0.71 | | |
| Marital Status | -0.003 | 0.037 | -0.08 | 0.012 | 0.018 | 0.67 | | |
| Household | 0.109[a] | 0.029 | 3.73 | 0.179[a] | 0.014 | 12.63 | ** | ** |
| Experience | -0.083[a] | 0.033 | -2.5 | 0.013 | 0.016 | 0.81 | | * |

[a] significant at 0.05 significance level, [b] significant at 0.1 significance level.

Education has always produced mixed results in efficiency effects analyses. This has to do largely with societal context under which the study took place. This study reveals that illiterates are technically more efficient than literates. Some have argued that most literate farmers take farming as a second or part time occupation. By so doing, they do not pay much attention to their farms as they should leading to low productivity and efficiency. This study adopts this argument in the light of the results. The plethora of researches suggesting contrary, means more research is needed to know the relationship between education and inefficiency. However, only DEA is statistically significant.

Gender has a mixed results; positive for DEA and negative for SFA. Female farm owners or managers are more efficient than their male counterparts

with DEA estimates. However SFA estimates reports the opposite. Both of them are statistically insignificant.

Marital status, like gender reported contradictory and insignificant estimate. The only difference is in the signs where DEA rather reported negative and SFA positive. Single farmers have the technical efficiency advantage according to DEA results, But SFA estimates contradicts this claim.

Farmers in the nuclear family structure are more efficient than those in the extended family household structure for both DEA and SFA. One may be tempted to play the labor card here since nuclear families have less family labor than extended families. However, a cursory analysis of the data shows that, this has nothing to do with the labor. In reality those in the nuclear family structure used more labor on average than those in the extended families. They had the same average in terms of farm size. An explanation can be sort from the fact that farmers in the nuclear family system have more time and supervisory role on their farms than their counterparts in the extended family systems. There is a system in the family structure in the region, which makes it incumbent on all family members to participate in all economic and social activities related to the household. For example, all women must participate in women related activities like cooking, fetching water etc. Likewise, all men must participate especially in the energy demanding activities in the farms. Even though everyone is allowed to have their own private farms, they are obliged to participate in all the farming activities of the household as well as theirs. To make matters worse, all the farming activities come at the same time; their services on both the family farms and their farms are needed at the same time. For those in the nuclear family system, they only concentrate on their farms. This surely gives them the edge in all aspects of efficiencies over farmers in the extended family systems. All the estimates are statistically significant. Furthermore, the mean efficiency difference between nuclear and extended families is statistically significant, meaning their efficiencies are statistically different from each other.

Farm experience has contradictory results from both DEA and SFA. Whiles DEA estimates indicates that more experienced/older farmers are less efficient, SFA estimates states otherwise. Furthermore, the result under the DEA is significant whiles that of SFA is not.

Results under the CRS assumptions from table 4.23 are much similar to that of the VRS. Environmental variables, whose coefficients are the same in all respect as in the VRS, would have the same explanation under the CRS. Therefore discussions would concentrate on results that look different from the VRS results. In comparison only marital status variable is different; Whiles its coefficients contradicted each other in the VRS estimates, they both agreed in the CRS estimates.

Marital status has a positive coefficient which means that single farmers are more technically efficient than the married ones. The results can be directly linked to the labor problem discussed under land area. Single farmers naturally have less family labor at their disposal. This means that, they either reduce wastage in labor hours or resort to hired labor. Their ratio is slightly lower than the married ones (i.e. 0.986 versus 0.984), which indicates they used less family labor as compared with the married farmers. The evidence of avoiding wastage in labor hours is found in the average number of labor used by both categories. Whiles the married used an average of 188.4 hours, the singles used 138.1 hours of labor. By implication, the huge opportunity cost of labor is reduced which then improves their input oriented technical efficiency. Closely related is the efficiency advantage small scale farmers have over large scale ones as earlier discussed. Based on the reason behind large farms, single farmers do not need to have large farms because of their relatively smaller families or less dependents. Hence most of the singles are small scale farmers. This is evident in the average land size between married and single farmers in the sample. The average land size for married farmers is 4.163 acres compared with 3.130 acres for the single farmers.

Table 4.23. Environmental Factors Affecting CRS Input Oriented Technical Efficiencies

| | Technical Efficiency-DEA | | | Technical Efficiency- SFA | | | Agreement | |
|---|---|---|---|---|---|---|---|---|
| Factors | Coef. | Std. Err | t-ratio | Coef. | Std. Err | t-ratio | Sign (+/-) | Sig |
| Constant | 0.55[a] | 0.043 | 12.71 | 0.679[a] | 0.018 | 37.33 | | |
| Extension | 0.005 | 0.025 | 0.210 | 0.002 | 0.010 | 0.22 | ** | |
| Land area | -0.030 | 0.032 | -0.950 | -0.005 | 0.013 | -0.38 | ** | |
| Education | 0.026 | 0.035 | 0.750 | 0.009 | 0.015 | 0.59 | ** | |
| Gender | 0.021 | 0.036 | 0.580 | -0.011 | 0.015 | -0.72 | | |
| Marital Status | 0.052 | 0.039 | 1.320 | 0.011 | 0.017 | 0.66 | ** | |
| Household | 0.225[a] | 0.031 | 7.16 | 0.162[a] | 0.013 | 12.25 | ** | ** |
| Experience | -0.041 | 0.036 | -1.140 | 0.010 | 0.015 | 0.66 | | |

[a]significant at 0.05 significance level.

### 4.7.1.3. Input Slacks

The measurement of slacks has become so important from the inception of modern efficiency measurement.

Table 4.24. Input Slacks (per acre)

| | VRS | | | | |
|---|---|---|---|---|---|
| | Labor | Machinery | Nitrogen | Phosphorus | Pesticide |
| Average Slacks | 15.29 | 0.21 | 0.78 | 0.33 | 0.05 |
| % as slacks | 8.55 | 4.81 | 4.20 | 3.82 | 4.48 |
| Number of Farmers | 30 | 31 | 26 | 19 | 23 |
| | CRS | | | | |
| Average Slacks | 22.609 | 0.188 | 0.094 | 0.355 | 0.048 |
| % as slacks | 12.642 | 4.264 | 0.506 | 4.083 | 4.676 |
| Number of Farmers | 54 | 32 | 12 | 18 | 28 |

For the purposes of distinguishing ‘weak’ and ‘strong’ efficiencies, this study would toe the line of Daraio and Simar (2007, p.32), who argue that slacks

should always be reported. Reporting them also enhances the discussion on scale efficiency.

Unsurprisingly, labor has the largest percentage of slacks. It is almost twice the rest of the inputs in the VRS, and triple in the case of CRS. Next in order is machinery, pesticide, nitrogen and phosphorous. The case of labor has been explained earlier. Family labor is in abundance and the fact that they are free makes farmers use more of it. That of machinery can be attributed to the exploitation by tractor operators in terms of shoddy ploughing, reduced measurement and charging higher fees when farmers are desperate for their services. Pesticides are expensive and farmers often waste a lot of it in the application, hence the relatively higher slacks recorded. The misuse and overuse chemicals in agricultural production in the Northern Region is documented by Chapoto et al. (2015). The obvious reason why fertilizer use has the lowest slacks is the fact that its prices have been regulated and farmers have become perfected in its application over the years. In the order of number of farmers recording slacks under VRS, machinery recorded the highest of 31, followed by labor, 30. In the case of CRS, labor was the highest followed by machinery. Furthermore, out of the 21 fully efficient farmers under VRS, 18 were fully 'Pareto-Koopmans' efficient (strong efficiency); that is, they had zero slacks in all the inputs used. The rest were 'weakly' efficient (Farrell efficiency). In the case of CRS, all the 11 most efficient farmers were 'strongly' efficient.

### 4.7.2. Allocative Efficiency

#### 4.7.2.1. Allocative Efficiency Estimates

A cursory look at the estimates from both techniques shows differences in terms of average estimates and efficiency distribution. Starting with the VRS estimates, both DEA and SFA demonstrates a substantial amount of allocative inefficiency in the sample.

Table 4.25. Allocative Efficiency Estimates

| | DEA-Allocative Efficiency (N=121) | | SFA-Allocative Efficiency (N=121) | |
|---|---|---|---|---|
| Efficiency level (%) | $AE_{IVRS}$ | $AE_{ICRS}$ | $AE_{IVRS}$ | $AE_{ICRS}$ |
| < 10 | 0 | 0 | 0 | 0 |
| ≥ 10 < 20 | 0 | 0 | 27 | 14 |
| ≥ 20 < 30 | 1 | 2 | 55 | 56 |
| ≥ 30 < 40 | 5 | 12 | 28 | 31 |
| ≥ 40 < 50 | 16 | 10 | 9 | 17 |
| ≥ 50 < 60 | 19 | 26 | 2 | 3 |
| ≥ 60 < 70 | 22 | 22 | 0 | 0 |
| ≥ 70 < 80 | 29 | 27 | 0 | 0 |
| ≥ 80 < 90 | 22 | 15 | 0 | 0 |
| ≥ 90 < 100 | 3 | 5 | 0 | 0 |
| 100 | 4 | 2 | 0 | 0 |
| Mean | 0.672 | 0.640 | 0.270 | 0.296 |
| Minimum | 0.297 | 0.248 | 0.105 | 0.118 |
| Maximum | 1.000 | 1.000 | 0.531 | 0.570 |
| Std Deviation | 0.161 | 0.177 | 0.087 | 0.092 |
| COV | 4.174 | 3.616 | 3.103 | 3.217 |

However, that of SFA is worse. Average allocative inefficiency is about 33% in DEA compared with 73% in SFA. These estimates mean that maize farmers could reduce cost by 33% and 73 respectively if they could get the right input mix by allocating some inputs for others. This process of input allocation is primarily based on the substituting high cost inputs with cheaper ones and still produces the same output quantity. As a requirement for this reallocation, both quantities and unit prices of inputs must be known. The combined effects from the discussions on the input cost share, input slack analysis and the IAEC points

clearly to labor input as the culprit in this low allocative efficiency estimates especially under SFA. From these findings, it is clear that the most wasted input in the production turns to constitute close to 70% of the production cost. It also the input that is difficult to reallocate in the production process, since over 95% of them is family labor.

The distribution of the results are so different in the sense that about 82% of the farmers scored above 50% efficiency in the DEA estimates compared to 1.7% scoring above 50% in the SFA estimates. The DEA estimates recorded full efficiency whiles the highest SFA could record is 53%. Furthermore, 4 farmers were fully efficient under DEA. The COV indicates that the DEA estimates are much dispersed around the mean allocative efficiency than SFA.

In every way, the estimates of the CRS resemble that of the VRS in both techniques. The average efficiencies, the distribution of estimates, dispersion of estimates around the mean, as well as minimum and maximum estimates are all similar with that of the VRS. The number of fully efficient farmers fell from 4 in the VRS to 2 in the CRS.

#### 4.7.2.2. Environmental Variables

The effects of the same environmental variables on various efficiency estimates are bound to differ. The laid down principles for the discussing environmental variables is still the same, as in the technical efficiency. Extension reports contradictory coefficients from DEA and SFA. According to DEA estimates, more extension contacts increases allocative efficiency while the reverse is reported by the SFA estimates. In addition to this both are not statistically significant.

Land area depicts a negative relationship between scale of production and allocative efficiency from both techniques. Both DEA and SFA estimates suggest that small scale farmers are more efficient in input allocation than large scale farmers. This result can be explained in the context of the relationship between this

same variable and technical efficiency as discussed earlier. In the case of the technical efficiency, the larger farms come with larger labor hours which lead to inadequate supervision and accompanying high opportunity cost of labor. In this instance the ability of the farmer to reallocate inputs to produce output is hampered by labor. Whiles the farmer has the ability to substitute for any of the other inputs, the same cannot be done for labor. The substitution of labor would have been possible if labor were hired. Both estimates were statistically significant. The two sample test reveals that the mean efficiencies of large scale and small scale farmers are statistically different.

The coefficients for the education variable are all negative for both techniques. Unlike in the case of technical efficiency under CRS, where illiterate farmer are more efficient, they are less efficient in input allocation. Though these literate farmers do not give their farms the attention they deserve, they would naturally make more economic and cost effective decisions regarding the maize farms than the illiterate ones. This could explain why they are technically inefficient but allocatively more efficient compared with the illiterate farmers. The literate farmers are more cost discipline because they keep records on farm costs. Illiterate farmers should be given training in basic accounting and book keeping, so that they can have an idea when they are not cost discipline. Both estimates are statistically significant, however there seem not to be any difference between the allocative efficiencies of literates and illiterates.

Gender has yet again showed contradictory estimates; positive for DEA and negative for SFA. Whiles the former indicates female farm managers are more efficient, the latter indicates the opposite. Only the SFA estimate is significant.

Table 4.26. Environmental Factors Affecting VRS Allocative Efficiencies

| | Allocative Efficiency-DEA | | | Allocative Efficiency-SFA | | | Agreement | |
|---|---|---|---|---|---|---|---|---|
| Factors | Coef. | Std. Err | t-ratio | Coef. | Std. Err | t-ratio | Sign (+/-) | Sig |
| Constant | 0.770[a] | 0.037 | 20.87 | 0.317[a] | 0.020 | 15.67 | | |
| Extension | 0.013 | 0.021 | 0.61 | -0.007 | 0.011 | -0.58 | | |
| Land Area | -0.131[a] | 0.027 | -4.84 | -0.03[a] | 0.015 | -2.01 | ** | ** |
| Education | -0.073[a] | 0.030 | -2.42 | -0.031[b] | 0.016 | -1.88 | ** | ** |
| Gender | -0.003 | 0.031 | -0.09 | 0.035[a] | 0.017 | 2.08 | | * |
| Marital Status | 0.083[a] | 0.034 | 2.47 | 0.047[a] | 0.018 | 2.54 | ** | ** |
| Household | 0.050[b] | 0.027 | 1.89 | 0.0004 | 0.015 | 0.03 | ** | * |
| Experience | -0.125[a] | 0.030 | -4.12 | -0.069[a] | 0.017 | -4.15 | ** | ** |

[a]significant at 0.05 significance level; [b]significant at 0.10 significance level

The coefficient of the variable marital status indicates single farmers are more allocatively efficient than married ones. Drawing from the discussion on the same variable under technical efficiency, married farmers use more labor and have bigger scale than the unmarried farmers. The conclusion that, small scale farmers are more allocatively efficient reinforces this results that single farmers, who are mostly small scale farmers are more efficient than the married ones. All the coefficients from both techniques are statistically significant and statistically different from each other.

Next in line is 'household structure' variable. Farmers in nuclear family system according to the result are more allocatively efficient than those in the extended family structure. As established under the technical efficiency, labor is not the problem, but the ability of nuclear household farmers to have much time over activities and decisions on their farms. This could also possibly explain their allocative efficiency advantage over the farmers in extended. Input allocation involves a much managerial skills and time to execute. Farmers in the nuclear family systems have time for their farm activities than the extended family system. Estimates for DEA are significant whiles those of SFA are highly insignificant.

Furthermore, the mean efficiencies of the two family structures are statistically the same.

Farming experience could not be discussed under technical efficiency because estimates were contradictory in under DEA and SFA assumptions. Experience has always been an important part in the effective execution of any occupation. It was on that basis this variable was considered. However, the result of this study counteracts that claim in terms of allocative efficiency estimates. It shows that those who have more experience in the production of maize are less efficient in input allocation under both techniques. It is a fact that experience goes with age, hence it is normal that most of the experienced farmers would be married, have more family labor, and bigger farm size. This is supported by evidence from the collected data as 93% of the experienced farmers are married; the number of labor used by non-experienced farmers is 139.4 as against 221.7 hours by the experienced farmers; and finally the average farm size of the non-experienced is 3.5 acres compared with 4.5 acres for the experienced ones. As seen earlier, farmers with large family size, larger scale are less allocatively efficient. With information on experienced and 'inexperienced' farmers above, it is consistent that less experienced farmers are more efficient than the more experienced ones. Alternatively, it could be argued that since the less experienced farmers are younger, they easily adopt to technology. This might have given them the efficiency advantage over the older farmers. All estimates are also statistically significant, and mean efficiencies between the two groups are statistically different.

The results of the CRS estimates from techniques are so much identical that, there is no need for discussion. The only difference has to do with the variable 'household structure'. Whiles both coefficients are insignificant under the CRS, only estimates of DEA were significant in the VRS estimates.

Table 4.27. Environmental Factors Affecting CRS Allocative Efficiencies

| | Allocative Efficiency-DEA | | | Allocative Efficiency-SFA | | | Agreement | |
|---|---|---|---|---|---|---|---|---|
| Factors | Coef. | Std. Err | t-ratio | Coef. | Std. Err | t-ratio | Sign (+/-) | Sig |
| Constant | 0.780[a] | 0.040 | 19.45 | 0.347[a] | 0.022 | 16.1 | | |
| Extension | 0.008 | 0.023 | 0.36 | -0.007 | 0.012 | -0.58 | | |
| Land area | -0.142[a] | 0.029 | -4.83 | -0.032[a] | 0.016 | -2 | ** | ** |
| Education | -0.099[a] | 0.033 | -3.04 | -0.033[a] | 0.017 | -1.9 | ** | ** |
| Gender | -0.002 | 0.033 | -0.05 | 0.038[a] | 0.018 | 2.1 | | * |
| Marital Status | 0.067[b] | 0.037 | 1.84 | 0.049[a] | 0.020 | 2.53 | ** | ** |
| Household | 0.04 | 0.029 | 1.36 | 0.0005 | 0.016 | 0.03 | ** | |
| Experience | -0.148[a] | 0.033 | -4.51 | -0.074[a] | 0.018 | -4.18 | ** | ** |

[a] Significant at 0.05 significance level; [b] significant at 0.10 significance level.

### 4.7.3. Cost Efficiency

#### 4.7.3.1 Cost Efficiency Estimates

Cost efficiency which measures the overall efficiency of farmers portrays the farmer's potential to produces at the minimum cost possible given output, input quantities and prices.

The distribution of the cost efficiency estimates from both techniques is very similar to that of the allocative efficiency. This could possibly be due to relationship between the two estimates, as used in the indirect estimate of allocative efficiency estimates. Like the allocative efficiency estimates the scores are relatively low indicating a substantial amount of cost inefficiency. However, all the average cost efficiency estimates under all the RTS assumptions are higher than the average allocative efficiency estimates. The distribution of the VRS cost efficiency estimates under DEA is much dispersed than SFA counterpart. Whiles about 78% of the farmers scored above 40% efficiency level under DEA, the highest score under the SFA was less than 40%.

Table 4.28. Cost Efficiency Estimates

| Cost efficiencies | DEA-Cost Efficiency (N=121) | | SFA-Cost Efficiency (N=121) | |
|---|---|---|---|---|
| Efficiency level (%) | $CE_{IVRS}$ | $CE_{ICRS}$ | $CE_{IVRS}$ | $CE_{ICRS}$ |
| < 10 | 0 | 0 | 5 | 3 |
| ≥ 10 < 20 | 0 | 5 | 61 | 41 |
| ≥ 20 < 30 | 2 | 19 | 41 | 52 |
| ≥ 30 < 40 | 25 | 34 | 14 | 21 |
| ≥ 40 < 50 | 27 | 21 | 0 | 4 |
| ≥ 50 < 60 | 34 | 21 | 0 | 0 |
| ≥ 60 < 70 | 16 | 12 | 0 | 0 |
| ≥ 70 < 80 | 7 | 5 | 0 | 0 |
| ≥ 80 < 90 | 5 | 1 | 0 | 0 |
| ≥ 90 < 100 | 1 | 1 | 0 | 0 |
| 100 | 4 | 2 | 0 | 0 |
| Mean | 0.530 | 0.440 | 0.208 | 0.233 |
| Minimum | 0.240 | 0.120 | 0.060 | 0.073 |
| Maximum | 1.000 | 1.000 | 0.397 | 0.438 |
| Std Deviation | 0.162 | 0.179 | 0.073 | 0.078 |
| COV | 3.271 | 2.458 | 2.849 | 2.987 |

The DEA recorded an average of 53% reflecting an overall inefficiency of 47%, compared with an average inefficiency of 79% in the case of SFA. Furthermore, the DEA estimates recorded full efficiency with 4 farmers.

In comparison with the CRS estimates, there is a substantial reduction of the efficiency score under the DEA, but a slight increase in the SFA estimates. The fully efficient farmers under DEA have also dropped to 2 under the CRS assumption. The COV statistic reveals that DEA estimates are more dispersed than

that of SFA under the VRS, but the reverse is seen under the CRS estimates. The distribution of estimates is quite similar in both RTS assumptions.

In the context of the study, the low allocative and cost efficiencies are expected in the sense that farmers in the region do not see maize farming as a business but rather a social obligation to feed their families. This system defies the cost minimization objective needed in the estimation of these two efficiencies. Another aspect is the uneconomic use of inputs, especially labor. Labor as discussed already has a huge opportunity cost. Labor estimation and pricing in developing countries are normally challenging, and could also be blamed. This point is explained further later. The IAEC has also demonstrated that labor needs to be substituted for by the other inputs. Lastly, theoretically, low allocative efficiency estimates mean low cost efficiencies, since the product of technical and allocative efficiencies make up cost efficiency.

#### 4.7.3.2. Environmental Variables

Theoretically, cost efficiency is the combine effect of technical and allocative efficiencies. Therefore, it is normal that discussions on it would be drawn from the previous discussions on technical and allocative efficiencies.

Extension contact is found to be positive with DEA and negative with SFA. With these contradictory estimates coupled with both statistical insignificancies, discussion on this variable cannot be continued.

Land area variable reports negative coefficient for both techniques. This indicates that small scale farmers are more efficient than large scale farmers. In the previous discussions, small scale farmers were found to be more technically and allocatively efficient than large scale farmers. It therefore makes theoretical sense that they should also be more cost efficient since the combination of technical and allocative efficiency makes the cost efficiency. The discussion would follow the same pattern as in the two efficiencies, but would be viewed from the cost perspective. The larger family labor used by the large scale farmers has a huge

opportunity cost compared with small scale ones. This makes them less disadvantaged in terms of cost of production. All coefficients are statistically significant. The efficiencies of large scale and small farmers are statistically different.

Table 4.29. Environmental Factors Affecting VRS Cost Efficiencies

| | Cost Efficiency-DEA | | | Cost Efficiency-SFA | | | Agreement | |
|---|---|---|---|---|---|---|---|---|
| Factors | Coef. | Std. Err | t-ratio | Coef. | Std. Err | t-ratio | Sign (+/-) | Sig |
| Constant | 0.574[a] | 0.034 | 17.03 | 0.212[a] | 0.017 | 12.33 | | |
| Extension | 0.013 | 0.019 | 0.69 | -0.006 | 0.010 | -0.58 | | |
| Land area | -0.127[a] | 0.025 | -5.13 | -0.022[b] | 0.013 | -1.71 | ** | ** |
| Education | -0.028 | 0.027 | -1.02 | -0.022 | 0.014 | -1.57 | ** | |
| Gender | 0.029 | 0.028 | 1.01 | 0.028[b] | 0.014 | 1.94 | ** | * |
| Marital Status | 0.069[a] | 0.031 | 2.24 | 0.037[a] | 0.016 | 2.35 | ** | ** |
| Household | 0.104[a] | 0.024 | 4.26 | 0.048[a] | 0.012 | 3.88 | ** | ** |
| Experience | -0.153[a] | 0.028 | -5.54 | -0.05[a] | 0.014 | -3.55 | ** | ** |

[a] significant at 0.05 significance level; [b] significant at 0.10 significance level.

There is a negative relation between the education variable and the cost efficiency estimates from both techniques. This result means that illiterate farmers are less efficient in the overall efficiency. As discussed earlier, illiterate farmers have the advantage of technical efficiency over the literate farmers because of the attention they give to the production process. However literate farmers who considers farming as a second job may pay more attention to cost of production than the illiterate farmers. This may explain their advantage over the illiterate farmers in the instance. This cost efficiency advantage the literate farmer had in this instance theoretically means that their allocative efficiency advantage is much stronger than the technical efficiency disadvantage. However, none of the estimates under both techniques is statistically significant.

For the first time the 'gender' variable merits further discussion as it failed to meet the conditions under technical and allocative efficiencies respectively. According the results from both techniques, women farm owners are more cost efficient than their male counterparts. This fits into the general perception that women in the region are generally good economic managers of any business than men. Only the estimate for the SFA is significant. In addition the mean efficiencies of male and female are statistically the same.

Marital status indicates a cost efficiency advantage of the single farmers over the married ones. Logically, if they were more technically and allocatively efficient than the married farmers as discussed earlier, it follows that they should be more efficient in terms of cost efficiency. Aside this logical conclusion, married farmers as seen earlier have larger scale farms and more labor than the unmarried ones. Apart from the managerial difficulties the married farmers will face in managing large farms, they also accrue a substantial amount of cost resulting from the large family labor at their disposal. These in comparisons with the single farmers make them less cost efficient. It has also been established that small scale farmers are more technically, allocatively and cost efficient than large scale farmers. This result is consistent with this claim in the sense that most of the single farmers are small scale whiles most of the married are large scale farmers. That is, 78% of singles farmers are small scale, compared with 70% of married being large scale farmers. Both estimates are statistically significant, and there exist statistical difference between the mean efficiencies of married and single farmers

The table further show that farmers in the nuclear family system are more efficient in terms of cost than their colleagues in the extended family structure. Following the same theoretical argument in the previous variable, the results is expected since farmers in nuclear family structure has been technically and allocatively more efficient than those in the extended family system. Furthermore the inconveniences caused by having to participate in both family farms and private ones could also translate into cost for the farmers in the extended family structure.

Both estimates are significant. The mean efficiencies of nuclear and extended families are different.

Farming experience is negatively associated with cost efficiency. More experienced farmers by the definition of this study are less efficient than the inexperienced farmers. Aside establishing the allocative efficiency advantage of inexperienced farmers over the experienced farmers, it has also been established that almost all the experienced farmers are married, used more labor and possess larger farm scale. With this information, the conclusion is consistent with the previous results where married and large scale farmers were less cost efficient. In addition, the labor problem expressed earlier is not in favor of experienced farmers who have more family labor than inexperienced ones. The estimates of DEA and SFA are both statistically significant, and at the same time the difference between the mean efficiencies of experienced and inexperienced farmers is statistically different. The estimated coefficients under CRS in table 4.30 bear the same resemblance as the VRS.

Table 4.30. Environmental Factors Affecting CRS Cost Efficiencies

| | Cost Efficiency-DEA | | | Cost Efficiency-SFA | | | Agreement | |
|---|---|---|---|---|---|---|---|---|
| Factors | Coef. | Std. Err | t-ratio | Coef. | Std. Err | t-ratio | Sign (+/-) | Sig |
| Constant | 0.445[a] | 0.039 | 11.48 | 0.241[a] | 0.018 | 13.19 | | |
| Extension | 0.014 | 0.022 | 0.62 | -0.006 | 0.010 | -0.62 | | |
| Land area | -0.114[a] | 0.029 | -3.99 | -0.025[b] | 0.013 | -1.83 | ** | ** |
| Education | -0.050 | 0.032 | -1.59 | -0.024 | 0.015 | -1.61 | ** | |
| Gender | 0.027 | 0.032 | 0.84 | 0.03[a] | 0.015 | 1.97 | ** | * |
| Marital Status | 0.079[a] | 0.035 | 2.24 | 0.04[a] | 0.017 | 2.4 | ** | ** |
| Household | 0.164[a] | 0.028 | 5.84 | 0.048[a] | 0.013 | 3.62 | ** | ** |
| Experience | -0.133[a] | 0.032 | -4.19 | -0.055[a] | 0.015 | -3.7 | ** | ** |

[a] significant at 0.05 significance level; [b] significant at 0.10 significance level.

### 4.7.4. Scale Efficiency.

#### 4.7.4.1. Scale Efficiency Estimates

There is not comparison in the case of this efficiency because the study did not estimate its SFA results. However estimates from both orientations are reported. The input oriented scale inefficiency is about 14% indicating on average, farms are too big or too small relative to the MPSS. This means that despites combining all inputs in and most efficient way to produce maize output, they could be 14% more productive just by altering the scale of operation in all the input employed.

About 85% of the farmers scored more than 70% scale efficiency. 13 of them were fully efficient (100%), meaning they were operating at a scale where altering scale would reduce productivity; that is CRS. This number would naturally tally with the number of farmers operating on the CRS as seen in the table. However, a large chunk of the farmers (81%) were operating under IRS, indicating the possibility of increasing their productivity by increasing scale of production.

In the input oriented case, only 8% were recorded to be operating under DRS. This suggests scale of operation is below the MPSS, requiring an expansion in scale. Scale expansion and contraction is holistic. It involves all the inputs that are employed.

The output oriented counterpart in theory is expected to produce different estimates compared with the input oriented estimates. The first defines scale in the context of output whiles the later, inputs. This has manifested in the table above. Inefficiency is about 7% and 100% of the farmers scored above 70% scale efficiency. Aside that, the number of farmers operating under various scale is completely different; whiles few farmers where operating under DRS in the input orientation, they are the highest in the output oriented estimates.

Table 4.31. Scale Efficiency Estimates

| Efficiency level (%) | $SE_I$ (N=121) | $SE_O$ (N=121) |
|---|---|---|
| < 10 | 0 | 0 |
| ≥ 10 < 20 | 0 | 0 |
| ≥ 20 < 30 | 1 | 0 |
| ≥ 30 < 40 | 1 | 0 |
| ≥ 40 < 50 | 1 | 0 |
| ≥ 50 < 60 | 6 | 0 |
| ≥ 60 < 70 | 9 | 0 |
| ≥ 70 < 80 | 16 | 15 |
| ≥ 80 < 90 | 20 | 18 |
| ≥ 90 < 100 | 54 | 73 |
| 100 | 13 | 15 |
| Mean | 0.864 | 0.930 |
| Minimum | 0.288 | 0.728 |
| Maximum | 1.000 | 1.000 |
| Std Deviation | 0.153 | 0.080 |
| Number of farmers- CRS | 13 | 16 |
| Number of farmers- IRS | 98 | 40 |
| Number of farmers- DRS | 10 | 65 |

**4.7.4.2. Environmental Variables**

Unlike the other discussions, this is restricted to input oriented estimates. In reference to figure 3.1 under methodology, all points below the MPSS are either scale inefficient or both scale and technically inefficient. These points are also considered less productive relative to the MPSS. For most of the farmers in this study, they are both scale technically inefficient, hence would be located below the hypothetical diagram in figure 3.1. Since the lines from the origin represent the

productivity, it therefore means that the more efficient a farmer or group of farmers become, the more productive and scale efficient they are. That is, getting closer to the frontier and the MPSS point. Following this fact, the discussions of environmental variables under the scale efficiency would be done in the light of the technical efficiency results. This means that variables that produced contradictory results under the technical efficiency cannot be discussed here.

Extension contact has a positive coefficient with scale efficiency indicating that more extension contacts increases farmer's scale efficiency. In the absence of direct relationship between extension contact and scale of operation, inferences are drawn from previous discussions. Results from both techniques under both RTS assumptions point to the fact that extension contact increases technical efficiency. With this being established, increase in technical efficiency may lead to an increase in productivity, which may translates to an increase in scale efficiency. This consistency adds more credence to the previous discussions. However, just like in the case of technical efficiency, the relationship between extension contact and scale efficiency is not statistically significant.

Land area variable recorded a negative coefficient with scale efficiency. It indicates that large scale farmers are less scale efficient than the small scale ones. All the efficiency estimates have favored small scale farmers over large scale ones. In the case of technical efficiency, it was suggested that small scale farmers would have much time to manage their farms than the large scale farmers. This information suggests that reducing scale of operation would increase efficiency which translates into increased productivity and then scale efficiency. Like in the case of extension contact, this result is consistent with the previous findings, even though it is statistically insignificant.

Table 4.32. Environmental Factors Affecting Input Oriented Scale Efficiencies

| | Input oriented Scale efficiency | | |
|---|---|---|---|
| Factors | Coef. | Std. Err | t-ratio |
| Constant | 0.757[a] | 0.037 | 20.62 |
| Extension | 0.008 | 0.021 | 0.39 |
| Land area | -0.003 | 0.027 | -0.10 |
| Education | -0.028 | 0.030 | -0.93 |
| Gender | -0.027 | 0.031 | -0.87 |
| Marital Status | 0.062[b] | 0.034 | 1.85 |
| Household structure | 0.183[a] | 0.027 | 6.85 |
| Farming Experience | 0.030 | 0.030 | 0.98 |

[a]Significant at 0.05 significance level; [b] significant at 0.10 significance level.

Literate farmers according to the results are more efficient in terms of scale than illiterate farmers. This variable could not be discussed under technical efficiency because the results of DEA and SFA contradicted each other. However, the coefficient is not significant.

Gender also recorded a negative, indicating female farmers are less scale efficient. Like education, it did not also merit any discussion under the technical efficiency. The coefficient is not significant.

Marital status is positive and significant indicating a scale efficiency advantage that single farmers have over married farmers. The technical efficiency result under CRS indicates singles have technical efficiency advantage over married. Per the preamble set, single farmers are more productive, which means they are both closer to the frontier and the MPSS, thus higher scale efficiency than the married. This coefficient is significant, but the mean efficiency difference between married and single appears to be the same

The coefficient for the variable ‘household structure’ is positive, which indicates farmers in nuclear family system are more scale efficient. It is one of the

variables that have consistently reported a positive coefficient with all the efficiencies. By this, it means that farmers from the nuclear household are more productive than those in the extended family structure. This also gives them the scale efficiency advantage over them. The coefficient is highly significant. The mean efficiency estimate between nuclear and extended families is statistically different.

Farming experience recorded a positive insignificant coefficient. However, the contradictory coefficients it recorded under technical efficiency deny it further discussion.

### 4.8. Post Efficiency Analyses

#### 4.8.1. Paired T-Test

As discussed in the methodology statistical comparison and conclusions of these estimates depends on whether they are statistically equal or different. The normally used standard t-ratio cannot be used because the efficiency estimates from both techniques are not independent. The dependence of the estimates is expected since they are the same statistics estimated form two different techniques. Furthermore, the spearman correlation coefficient does not only estimate the correlation coefficient but also indicates the dependence or otherwise of the estimates involved. For all the pairs from DEA and SFA, the test in spearman rank correlation coefficient show that they are all dependent. Also, as seen from table 4.33, the standard deviations of the pairs are not the same, and so their variances. This information from the sample data justifies the use of the pair t-test.

The results of the paired t-test in table 4.33 indicate that the hypothesis that the mean differences between estimates from DEA and SFA is zero is strongly rejected in all cases. Therefore comparisons between the estimates of DEA and SFA are all statistically significant

### 4.8.2. The Mean Efficiencies of DEA and SFA

The mean efficiency estimates are presented in table 4.33. Generally, except in the case of input oriented technical efficiency under CRS all other estimates are higher in DEA than SFA. These differences between the estimates are closer to each other in average terms in the case of technical efficiency. However, there is a wide difference between estimates of allocative and cost efficiencies. Even though the generally low cost efficiencies have been attributed to uneconomic decisions by the farmers, the much lower estimates in SFA is a concern. The very low allocative efficiency estimates in SFA could be blamed for this. Cost efficiency is the product of technical and allocative efficiencies. Since technical efficiency is relatively higher, allocative efficiency could be the main reason for the very low cost efficiency. This explanation is consistent since the relatively higher allocative efficiency in the DEA contributed to relatively higher cost efficiency. Johansson (2005) arrived at the same conclusion after finding a 41% cost efficiency. Another observation among the two techniques is that VRS estimates are generally higher than CRS in DEA, whiles it is the reverse case under SFA.

In the exceptional case of VRS technical efficiency where DEA estimates are higher than the SFA, cast doubt on the choice of production function for the SFA. Not only is this an indication of tight envelopment, but the restrictions imposed on the functional form of the production function may be inappropriate (Johansson, 2005). Even though, the adopted technique dictated the choice of production, Cobb-Douglas production function statistically fits the data as seen in hypothesis 4.

All these differences have been confirmed by the statistical significance of the paired t-test.

Table 4.33. The Mean Efficiencies of DEA and SFA Estimates, Paired T-Test and Spearman Rank Correlation

| | Sample Mean | | Paired T-test | | | Spearman rank correlation |
|---|---|---|---|---|---|---|
| | DEA | SFA | Std Dev | Std Err. | t statistic | |
| $TE_{IVRS}$ | 0.793 (0.142) | 0.771 (0.115) | 0.144 | 1.587 | -2.578[a] | 0.37[b] |
| $AE_{IVRS}$ | 0.672 (0.161) | 0.27 (0.087) | 0.115 | 1.268 | -34.917[a] | 0.72[b] |
| $CE_{IVRS}$ | 0.53 (0.162) | 0.208 (0.073) | 0.128 | 1.408 | -25.563[a] | 0.63[b] |
| $TE_{OVRS}$ | 0.741 (0.194) | 0.782 (0.110) | 0.121 | 1.333 | 2.455[a] | 0.75[b] |
| $TE_{ICRS}$ | 0.685 (0.180) | 0.787 (0.105) | 0.115 | 1.261 | 8.505[a] | 0.77[b] |
| $AE_{ICRS}$ | 0.64 (0.177) | 0.296 (0.092) | 0.113 | 1.243 | -30.271[a] | 0.73[b] |
| $CE_{ICRS}$ | 0.44 (0.179) | 0.233 (0.078) | 0.118 | 1.300 | -17.762[a] | 0.71[b] |
| $TE_{OCRS}$ | 0.685 (0.180) | 0.787 (0.105) | 0.114 | 1.258 | 8.598[a] | 0.78[b] |

[a] significant at 0.05 significance level.
Subscripts CRS and VRS stand for constant and variable returns to scale, respectively.
Subscripts I and O stand for input and output orientations respectively.
The values in the parenthesis are the standard deviations for each estimate.
[b]Test of null hypotheses that each of the combinations is independent are rejected. Prob > |t| = 0.0

### 4.8.3. Spearman Rank Correlation Coefficient

With the exception of input oriented technical efficiency under VRS, there is a fairly strong correlation between the other estimates. This is clearly attributable to the tighter envelopment of the data in the DEA under VRS. The estimates from the DEA did not behave as expected hence bound not to correlate well with the SFA results. The other lower correlation coefficient is that of VRS cost efficiency. This result is also expected because the cost efficiency estimates is made up of the weak correlated technical efficiency and allocative efficiencies. The cost efficiency is therefore bound to inherit the traits and patterns in the technical efficiency estimates. The coefficient improved for the allocative efficiency because it is a derivative from the two efficiencies. The correlation coefficient tends to be higher in CRS estimates than the VRS. Furthermore, output oriented technical efficiencies

from both RTS assumptions have higher correlation coefficients than the input oriented ones.

### 4.8.4. Best and Worst Performing Farmers

Per the analysis each percentile or quartile contains approximately 30 farmers. That is, both the worst and the best performing farmers' categories contain 30 farmers each. The comparisons are based on estimates from the DEA and SFA.

Table 4.34. Best and Worst Performing Farmers

| | | Highest Performing | Lowest Performing |
|---|---|---|---|
| Input Oriented (VRS) | TE-DEA vs TE-SFA | 50% | 46.70% |
| | AE-DEA vs AE-SFA | 66.70% | 60.00% |
| | CE-DEA vs CE-SFA | 63.30% | 50% |
| Output Oriented(VRS) | TE-DEA vs TE-SFA | 70.00% | 86.70% |
| Input Oriented (CRS) | TE-DEA vs TE-SFA | 76.70% | 93.30% |
| | AE-DEA vs AE-SFA | 66.70% | 63.30% |
| | CE-DEA vs CE-SFA | 66.70% | 63.30% |
| Output Oriented (CRS) | TE-DEA vs TE-SFA | 76.70% | 93.30% |

This analysis goes further than comparing sample average efficiencies. This brings out other details that would not be revealed by the other comparisons. Unsurprisingly, the comparison within the estimates of input oriented technical efficiencies under VRS is the most unique among all the technical efficiency estimates. The two techniques agree significantly in identifying worst performing farmers than best performers under technical efficiency, except the VRS input oriented technical efficiency. With this efficiency estimate, DEA and SFA could only agree 46% of worst performers and 50% best performers, compared with an average of 90% worse performers and 73% best performing farmers for its CRS counterpart.

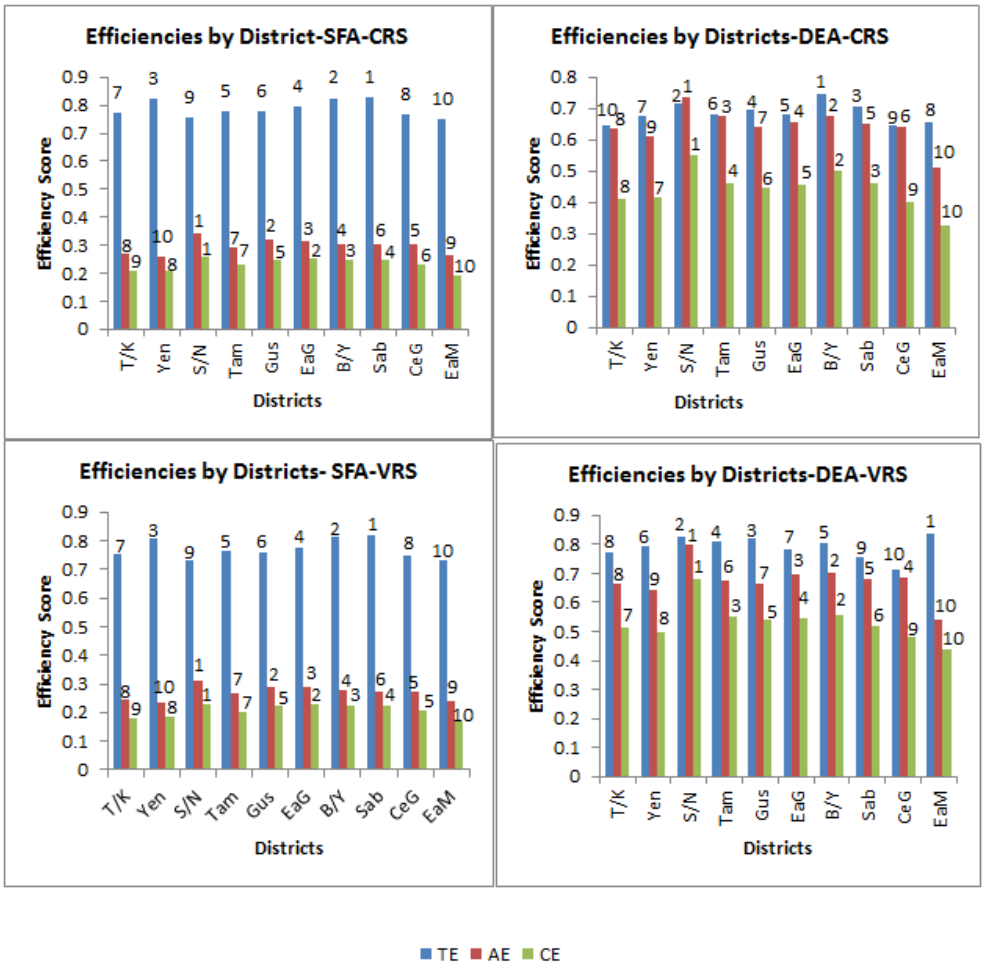
The AE and CE have been consistent in agreeing more on best performers than worse performers for both RTS assumptions. Generally, agreements under CRS are more profound than those under VRS across all efficiencies.

### 4.8.5. District Level Efficiencies

The efficiencies have also been broken down by districts to examine their performance per the efficiency estimates. The agreements and disagreements of DEA and SFA estimates are examined

Table 4.35. Best and Worst Performing Districts

| | | Highest Performing | Lowest Performing |
|---|---|---|---|
| Input Oriented (VRS) | TE-DEA vs TE-SFA | 0.00% | 50.00% |
| | AE-DEA vs AE-SFA | 75.00% | 75.00% |
| | CE-DEA vs CE-SFA | 75.00% | 75% |
| Input Oriented (CRS) | TE-DEA vs TE-SFA | 50.00% | 75.00% |
| | AE-DEA vs AE-SFA | 75.00% | 75.00% |
| | CE-DEA vs CE-SFA | 75.00% | 75.00% |




Source: Sample data.
Figure 4.4. Efficiencies by Districts

The numbers on each bar show the rank position of the district starting with VRS estimates in table 4.35, none of the four best performing districts under DEA appears is in the 4 best performing ranking under SFA. They however have two districts in common in the worse performing districts; representing 50%. In the case of AE, the 3 districts are common from DEA and SFA ranking of the best and worst performing districts. That is they share 75% of their best and worst performing districts per AE estimates. The CE also produced the same results as

the AE; that is 75% of districts identified as best and worst performing are common between DEA and SFA. In the case of CRS, technical efficiency estimates identifies 50% best performing and 75% worst performing districts. Both AE and CE again recorded 75% in both categories. The issue with tighter envelopment in the case of input oriented technical efficiency under VRS has come up here again. As observed the CRS input oriented technical efficiency recorded 50 % against 75, whiles the VRS recorded 0% against 50% for best and worst performing districts respectively.

In specific terms, no district can be pinpointed as the best performing under VRS technical efficiency. From figure 4.4 Tolon/Kumbungu and Central Gonja are considered worst performing districts. The CRS identified Saboba and Bunkpurugu/Yunyoo Districts as the best performing whiles Tolon/Kumbungu, Central Gonja and East Mamprusi Districts takes the low performing districts. In this instance the choice of the best performing district would be debatable because of the different results the RTS assumptions have reported. However, Tolon/Kumbungu and Central Gonja Districts takes the worst performing districts as they consistently appear in both RTS assumptions.

AE and CE have been consistent in identifying the high and low performing districts. Under VRS, they all identified Savelugu/Nanton, East Gonja and Bunkpurugu/Yunyoo as the best performers, and Tolon/Kumbungu, East Mamprusi and Yendi Districts as the low performing districts. These same districts are identifies under CRS for both AE and CE as the low performing. AE under CRS identified the same districts as the VRS, whiles CE only substituted East Gonja for Saboba District. It can therefore be concluded that, using AE as the yardstick Savelugu/Nanton, East Gonja and Bunkpurugu/Yunyoo are the best performing district, and using and CE, Savelugu/Nanton, Saboba and Bunkpurugu/Yunyoo are considered best. In the case of worst performing districts both estimates identified Tolon/Kumbungu, East Mamprusi and Yendi Districts.

**4.8.6. DEA or SFA Results?**

To a higher extent according to table 4.33 the two techniques agreed as reflected in the relatively higher correlation coefficient. However, $TE_{IVRS}$ is an exception as it recorded the lowest correlation. This has been attributed to the possibility of a tighter envelopment in the VRS frontier (Sharma et al. 1999), the possibility of outlier's sensitivity (Singh et al. (2001), or a misspecification of the production function in SFA (Johansson, 2005). The tighter envelopment of the VRS frontier is manifested in the higher $TE_{IVRS}$ relative to $TE_{ICRS}$. It could not be the problems of outliers as the sensitivity analysis proved the DEA results were not sensitive to outliers. The issue of misspecification of the production function has been proven not to be responsible in hypothesis 4.

The other noticeable difference is the very low AE and CE under SFA relative to DEA. Two possible suggestions have already been given to explain this. The issue of labor has been probed further, by estimating all the efficiencies without the labor variable. The results are presented in table 4.36 below. The AE and CE have improved significantly compared with the results that included labor (in the parenthesis). This further buttress the argument against the huge opportunity cost of labor. The nature of the agricultural labor in the context of developing countries could explain more of this phenomenon. As mentioned in the limitations of this study, labor measurement in the developing countries has always been a challenge in the sense that most labor is family labor. Aside the difficulty in keeping track of the activities of family labor on the farm, most farmers do not keep records. These lead to the overestimation of labor hours. The other issue has to do with pricing family labor hours. The closest approximation of family labor is the opportunity cost of them working on other farms as hired labor. However, in developing countries, the opportunity cost of these labors may actually be lower, since they are unlikely to find jobs aside their family farms. This means that the approximation of the opportunity cost may actually be an overestimation of the unit

price labor. These characteristics of agricultural labor in developing countries could be the reason why AE and CE are very low when labor is included.

Table 4.36. Efficiency Estimates Without Labor Variable

| | Sample Mean | |
|---|---|---|
| Efficiencies | DEA | SFA |
| $TE_{IVRS}$ | 0.728 | 0.767 |
| $AE_{IVRS}$ | 0.865 | 0.783 (0.270) |
| $CE_{IVRS}$ | 0.624 | 0.601 (0.208) |
| $TE_{ICRS}$ | 0.653 | 0.788 |
| $AE_{ICRS}$ | 0.857 | 0.791 (0.296) |
| $CE_{ICRS}$ | 0.558 | 0.624 (0.233) |

Some authors, who use these comparative techniques, express their confidence in one technique over the other when there seem to be contradictory or unexpected results from both techniques. Doing that defeats the essence of the comparative approach. Considering the various advantages and disadvantages each technique has over the other, there are bound to be these differences. It is the responsibility of the researcher to further research why the abnormality exists instead of dismissing the results. Johansson (2005) for instance expressed confidence in his DEA results more than the SFA. The reason, being the consistently higher DEA estimates which theoretically should have been lower than the SFA estimates. This he attributed to the possibility misspecification of the production function used (Cobb-Douglas) in the SFA. This study also faced similar problem. However unlike Johansson (2005), the appropriateness of the production function was tested and the result shows the specification was appropriate for the analysis. In a similar case of Singh et al. (2001), the SFA result was given priority

over DEA because the result of the AE in DEA was much smaller than the SFA. They attributed this to outliers in the DEA analysis. A similar problem is encountered in this study. However, a sensitivity analysis showed that outliers were not the cause of the problem. Investigating each variable's influence on the estimates show that labor variable could be responsible as shown in table 4.36.

This study therefore concludes that, despite these differences, there is no sufficient evidence to trust one result more than the other. This is because there seem to be enough evidence in the sample to explain these differences and abnormalities.

### 4.8.7. Other Environmental Variables

As mentioned earlier there were some variables that could not make it to the tobit analysis because of non-variability. However, a comparison is made to the estimated efficiencies, even though the results have no statistical significance backing.

From the table, those who did not receive any form of credit are found to be more efficient across all the efficiencies and techniques. Credit access and application has been a very big challenge to agricultural development in the region. Aside financial institutions' reluctance to give them loans, there are concerns of funds diversion from agriculture for which the loans are secured. It is expected that credit would boost productivity and efficiency. With this unexpected result, there may be funds diversion if the credits were in cash.

Farmers with single plot size are found to be more efficient than two, and two plot more than 3 plots. It implies that, more plots reduce efficiency. Researchers have arrived at this conclusion through regression analysis and advocated for land consolidation (Alemdar and Ören, 2006b). Farmers with many plots waste time, energy and fuel in moving between these plots, which negatively affect efficiency.

Table 4.37. Other Environmental Variables and Efficiencies

| | | SFA-TE VRS | SFA-AE VRS | SFA-CE VRS | DEA-TE VRS | DEA-AE VRS | DEA-CE VRS |
|---|---|---|---|---|---|---|---|
| Credit Access | yes | 0.483 | 0.201 | 0.099 | 0.774 | 0.537 | 0.415 |
| | no | 0.776 | 0.271 | 0.210 | 0.793 | 0.674 | 0.532 |
| Maize plots | 1 | 0.777 | 0.270 | 0.209 | 0.803 | 0.675 | 0.539 |
| | 2 | 0.712 | 0.269 | 0.191 | 0.679 | 0.641 | 0.434 |
| | 3 | 0.563 | 0.288 | 0.162 | 0.600 | 0.603 | 0.361 |
| FBO | yes | 0.769 | 0.276 | 0.215 | 0.800 | 0.672 | 0.535 |
| | no | 0.772 | 0.267 | 0.204 | 0.789 | 0.672 | 0.528 |
| Improved seed | own | 0.752 | 0.266 | 0.200 | 0.785 | 0.663 | 0.517 |
| | hybrid | 0.835 | 0.283 | 0.235 | 0.818 | 0.703 | 0.574 |

Generally farmers who belong to an FBO have more efficiency advantage over the others, even though the estimates look very close. On the use of hybrid seeds, there is a clear efficiency advantages over those who use own seed. Hybrid seeds naturally have advantage over farmers' seed. More so, farmers also lack the technology to store seeds without compromising its quality.

### 4.9. Farm analyses

#### 4.9.1. Gross profit

This is normally used as a measure of success for most businesses. For the sampled farmers, there is a profit of GH₵ 936.37, with GH₵ 244.9 per acre, check table 4.38. Overall, it can be reported that the firms are successful. However, further analysis needs to be conducted. From the same table it can be observed that small scale farmers have an average profit farm lesser than their counterparts who are large scale farmers; GH₵ 702.71 versus GH₵ 1,446.73. Theoretically this is

expected because of the scale advantage. On the other hand, the small scale farmers are more profitable in per acre basis than the large scale farmers; GH₵ 262.37 and GH₵ 206.73 respectively. Since they are facing the same output prices in this analysis, it means that small scale farmers are getting more income than large scale ones.

Table 4.38. Gross Profit per Acre (GH₵)

| | Total Revenue | Total Cost | Total Profit | Profit Per Acre | Number Of Farmers |
|---|---|---|---|---|---|
| Small scale (<5 acres) | 2,164.536 | 1,461.83 | 702.705 | 262.370 | 83 |
| Large scale(>5 acres) | 5,038.12 | 3,591.389 | 1,446.731 | 206.732 | 38 |
| Average | 3,066.984 | 2,130.617 | 936.366 | 244.897 | |

Another issue worth mentioning is the distribution of the profit estimates. Whiles the average is positive, some farmers did record negative values (losses). Refereeing to table 4.39 farmers recorded profits whiles 22 were operated in losses. The total amount of profits was double the amount of losses, indicating why the overall estimate is positive. Out of the total number of farmers who recorded losses, 50% were small scale while the other 50 % were large scale farmers. However in the context of profit, 72 % of them are small scale farmers. This reinforces the technical advantage small scale farmer have over the large scale ones.

Table 4.39. Profit and Loss (GH₵)

| | Average (GH₵) | Number of farmers | Small scale (<5 acres) | Large scale(>5 acres) |
|---|---|---|---|---|
| Profit | 1,222.14 | 99 | 72% | 28% |
| Loss | -588.22 | 22 | 50% | 50% |

Relationship between gross profit and technical and economic efficiencies is worth examining. This would be examined from both DEA and SFA estimates. The correlation coefficient for gross profit and technical efficiency are 0.55 and -0.06 for SFA and DEA estimates respectively. That of gross profit and SFA cost efficiency is 0.65, whiles it is 0.24 with DEA estimates. The apparent lack of relationship between profit and DEA technical efficiency can be attributed to the tighter envelopment of the data. On the whole profit correlates more with SFA estimates than DEA.

The relationship between profit and efficiency is further revealed in figure 4.5, where the average efficiency estimates of farmers operating under profit (profitable) and those who recorded losses (unprofitable) farmers. The efficiencies considered are technical and cost efficiencies from DEA and SFA. Since they all faced the same output price, it is expected that profitable farmers would be more efficiency than unprofitable ones. This is reflected in all except that of DEA technical efficiency. For this estimates unprofitable farmers are more efficient than those making profits. This anomaly could be attributed to the tighter envelopment of the DEA estimates as discussed earlier.

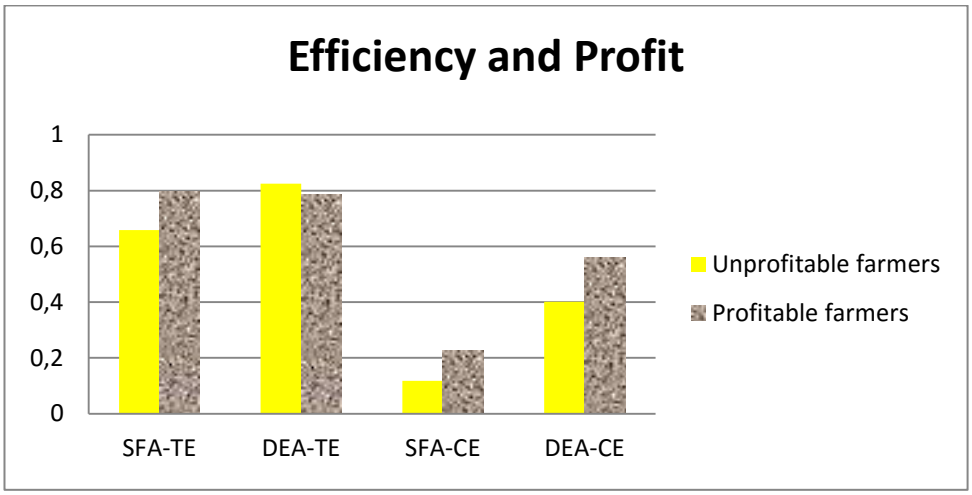



Figure 4.5. Profit and Efficiency

### 4.9.2. Cost of Inefficiency

It is also equally important to know how much it costs to a farmer for being inefficient. This analysis was divided into two; extra cost as the results of inefficiency and revenue lost which could have been earned if farmers were efficient. Farmers and government can evaluate these costs of being inefficient and decide whether it is worth improving their efficiencies or not. The total number of maize acreage in the region as at 2014 was 119,571 ha (295,466.38 ac) In table 4.40, the average cost of being inefficient is GH₵ 140.65 for DEA and GH₵ 116.85 for SFA, resulting in a total cost between GH₵ 34,525,501 and GH₵ 41,556,429 for the whole region. If the cost of improving these inefficiencies is higher than the COI, then it is better to be left inefficient. In terms of scale of operation, small scale farmers in both techniques records lower cost per-unit acre. Another indication of technical and cost efficiency advantage small scale farmers have over large scale.

Table 4.40. Cost of Inefficiency (GH₵)

| DEA | | | | | |
|---|---|---|---|---|---|
| Land Area (acres) | Total Cost of Production (GH₵) | Technically Efficient Cost of Production (GH₵) | Cost Of Inefficiency (GH₵) | Cost of Inefficiency Per Acre(GH₵) | Total Cost of Inefficiency for the Whole Region (GH₵) |
| Small scale (<5) | 1,461.83 | 1,103.68 | 358.16 | 116.98 | |
| Large scale(>5) | 3,591.39 | 2,320.87 | 1,270.52 | 192.34 | |
| Average | 2,130.62 | 1,485.94 | 644.68 | 140.65 | **41,556,429.88** |
| SFA | | | | | |
| Small scale (<5) | 1,461.83 | 1,127.58 | 334.25 | 113.78 | |
| Large scale(>5) | 3,591.39 | 2,815.38 | 776.01 | 123.57 | |
| Average | 2,130.62 | 1,657.63 | 472.98 | 116.85 | **34,525,501.38** |

Table 4.41, measures and output orientation of the production process. The cost of inefficiency to the farmer is measured in terms of how much revenue they loss from being inefficient. Approximately farmers lose GH₵ 1,096.04 and GH₵ 772.25 from DEA and SFA estimation respectively. The total revenue lost for the whole region ranges from GH₵ 58,153,442 to GH₵ 80,605,687. From the output perspective farmers and policy makers can consider how much maize farmers would earn if they are efficient. Then again the cost of reducing inefficiency is compared to this amount. In terms of per-unit acre, both small and large scale farmer lose almost the same amount of money for their inefficiency in the DEA estimation. However, small scale farmers lose more revenue under SFA. This means that largescale farmers have a technical advantage than the small scale farmers when farmers' objective is to maximize output rather than inputs.

Table 4.41. Lost Revenue from Inefficiency (GH₵)

| DEA | | | | | |
|---|---|---|---|---|---|
| | Observed Total Revenue (GH₵) | Technically Efficient Revenue(GH₵) | Revenue Lost(GH₵) | Revenue Lost Per Acre (GH₵) | Total Revenue lost to Inefficiency for the Whole Region (GH₵) |
| Small scale (<5 acres) | 2,164.54 | 2,980.45 | 815.91 | 272.67 | |
| Large scale(>5 acres) | 5,038.12 | 6,746.01 | 1,707.89 | 273.12 | |
| Average | 3,066.98 | 4,163.02 | 1,096.04 | 272.81 | **80,605,687.53** |
| SFA | | | | | |
| Small scale (<5 acres) | 2,164.54 | 2,740.36 | 575.83 | 200.91 | |
| Large scale(>5 acres) | 5,038.12 | 6,239.38 | 1,201.26 | 187.88 | |
| Average | 3,066.98 | 3,839.23 | 772.25 | 196.82 | **58,153,442.07** |

### 4.10. Challenges and Reasons for Maize Production

Sampled farmers where asked an open question for the challenges they face in the production of maize, as well as the reasons for producing it. Their responses are ordered in order of frequency.

Generally farm machinery in the region is scanty. Tractor is the main agricultural machinery used in the region for ploughing. When the rains start there is a mad rush for the services of tractors, which has to be on first come, first serve basis. Tractors are often old and frequently break down in the field. Those at the end of the waiting list sometimes do not get the chance to plough and some will get it when the appropriate time for ploughing has passed. Rain pattern in the region has been erratic and difficult to predict. The rains may not come at the time the crops need it or may come too much and flood the crops.

Table 4.42. Challenges in Maize Production

| Production | Frequency | Percentage (%) |
|---|---|---|
| Inadequate tractors | 118 | 97.5 |
| Unstable rainfall and drought | 93 | 76.9 |
| Input credit (for expansion) | 89 | 73.6 |
| Untimely announcement of fertilizer subsidy | 66 | 54.5 |
| Cattle herds men | 42 | 34.7 |
| Bush fires | 19 | 15.7 |
| Lack of labor | 9 | 7.4 |

Source: Sample data

Sometimes, there can be a prolonged drought leading to the withering of the germinated crops. Farmers always wish they expand their farms, but are limited by funds. Getting to the beginning of the farming season, farmers normally exhaust their stock and money they earned from the previous year. Input credit they think would help them produce at the desired scale they want. Sometimes too, because

every farmer relies on subsidized fertilizers, government sometimes delays in announcing the subsidy. Fertilizers may be available at the agro input shops but without the announcement by the government, farmers would be charged the full price if they want to buy. The following two issues (Cattle herds' men and Bush fires) are socio-cultural. Farmers sometime have their crops destroyed by grazing cattle or bush fires. In some part of the country, these issues have escalated into clashes. Lastly, lack of labor is also challenge for farmers who are strangers in the town or districts they are farming. In those instances, they rely mostly on hired labor and friends for help. But as mentioned earlier, everybody would be busy attending to their farms or family farms and may not have enough time. The fact that few farmers complained of labor scarcity is a manifestation of its abundance as discussed in the analysis.

Table 4.43. Reasons for Maize Production

| Reasons For Maize Production | Frequency | Percentage (%) |
|---|---|---|
| Food for the family | 121 | 100 |
| Important crop for any occasion | 115 | 95.0 |
| Easy to cultivate | 82 | 67.8 |
| No need for special land | 70 | 57.9 |
| Money | 23 | 19.0 |

Source: Sample data

Farming to feed the family was the most dominant response to the reasons for maize production. Closely following and related is the fact that maize is used for all occasions in addition to daily consumption. The fact is, maize is used in almost all the staple dishes prepared in the Northern Region, like weddings, outdooring, funerals and most social events. Some farmers think maize production is easy relative to other cereal production. Related to this is the fact that it can be produced anywhere in the region. Crops like rice, millet, sorghum and ground nuts

need specialized land for both vegetative growth and good harvest. Earning income was the least reason given for maize production. This reinforces the idea that farmers in there region are subsistent and do not consider farming as a business.

# 5. CONCLUSIONS AND RECOMMENDATIONS

## 5.1. Conclusions

### 5.1.1. Efficiency Estimates

This thesis sets out to measure technical, allocative and cost efficiencies of maize farmers in the Northern Region of Ghana. The first efficiency bothers on the actual production process. The second is concerned with input allocation for cost reduction whiles the cost efficiency measures the overall economic condition of the farmers. For an improvement in the general living conditions of these farmers, productivity has to increase and subsequently total cost of production should be as lowest as possible. The first will increase maize production and the second will improve their income level through higher farm income. Investigating technical efficiencies and their causes provide some answers to the first, and cost efficiencies and its effects partially contribute to discussion on the second. These contributed to discussions on how to improve the efficiency and productivity of maize farmers and at the same time increase their incomes so as to bridge the gap between the north and the south. In line with the first objective of estimating these efficiencies using DEA and SFA, both input and output orientations under CRS and VRS were estimated and analyzed. Scale efficiency has also been estimated by DEA. However, of interest to this study are the input oriented measures.

Under both techniques and RTS assumptions, there are considerable amount of inefficiency. In the context of the estimation technique employed, this inefficiency is defined as the extra cost of producing below the production frontier. DEA technical efficiency estimates are expected to be lower than the SFA estimates. However this is not the case under VRS. The larger efficiency estimate for DEA under VRS is an indication of how tight the data has been enveloped compared with CRS. This phenomenon is also an indication that DEA technical efficiency estimates maybe appropriate owing to the fact that an inappropriate

production function might have been employed in the SFA. However, the chosen production function has been proven to appropriate for the data.

Even though AE estimates are low, it is even worst for SFA estimates. The possible reasons are the general uneconomic decisions farmers make, the challenges in reallocating family labor, challenges in labor estimation and pricing. In response to why sampled farmers produce maize, feeding the family was the most dominant response. At any cost they are willing to produce it. They always see the option of buying maize for the family throughout the year as worse than producing themselves. Furthermore, the presents of slacks in the sample, especially that of labor could also explain the generally high allocative inefficiency. Slacks are considered as a form of allocative inefficiency, because it reflects inappropriate input mix. Aside slacks there is also a challenge in attaining an appropriate input mix if it has to involve labor. The fact that they do not pay for family labor means that they do not care how much of it is used on the farm. The size of the labor depends on the size of the family labor which is mostly large in the Northern Region. It is easy to reduce or increase other inputs, but not agricultural labor which is made up mostly of family labor. This would not have been a problem if the labor were hired.

Like the AE, CE also recorded low efficiency scores especially under SFA. The explanation for this is obviously related to both TE and AE, since they make up CE. However, allocative inefficiency takes the large proportion of the responsibility for the low CE estimates. That is, general inability of the farmers to relocate inputs for an appropriate input mix coupled with the uneconomic decisions they make in the production process. The issue of slacks, especially labor is also a contributing factor. The relatively high TE estimate indicates that it contributed to a little extend in the low CE. Aside not taking farming as a business, the other main hindrance to the achievement of the overall efficiency has to do more with their inability of reallocate inputs to achieve the cost minimizing objective, rather than their inability to produce in a technically efficient way.

Scale efficiency was estimated using only DEA. Inefficiency in this case is relatively lower compared with the other efficiencies.

In summary, using the average of the two techniques, technical, allocative and cost efficiencies of the sampled maize farmers under VRS are 78.2%, 47.1% and 36.9% respectively. For the CRS, they are 73.6%, 46.8% and 33.7% respectively. This makes VRS estimates relatively higher than the CRS. These differences between the DEA and SFA estimates were confirmed by the paired t-test. Scale efficiency is 86.4%. Furthermore, on the basis of the spearman ranked correlation coefficient, estimates of DEA and SFA tend to agree more in the case of CRS than VRS. All estimates under CRS have consistently recorded above 70% correlation coefficient. All but AE under VRS scored above 70%, with technical efficiency as low as 37% and CE, 63%. This is solely blamed on the tight envelopment of the VRS envelopment frontier. In the identification of best and worst performing farmers and districts, CRS estimates agree more on the identification than VRS estimates. This could also be related to the same reason given under the spearman correlation coefficient. Except in the case CRS TE, all other efficiencies across the RTS assumptions agreed more in identifying performing farmers and districts than low performing ones. Overall, Savelugu/Nanton and Bunkpurugu/Yunyoo Districts performed very well, whiles Tolon/Kumbungu, East Mamprusi, Yendi Central Gonja Districts consistently did not perform well under those efficiency estimates.

The other thing worth mentioning is the results of the estimated production function. It points to the low output elasticity of labor compared with the other inputs. There is little to add to output when labor increases. This is however statistically insignificant. With an already nutrient deficient soil in the region, increasing nitrogen and phosphorous application give the highest output increment. This has also been confirmed by the IAEC ratio which suggested a reduction in labor use and increase machinery, fertilizer and pesticide use.

### 5.1.2. Causes of Inefficiency

With the employment of the two techniques, the discussion on the environmental variables that affect various efficiencies has to be based on both the agreement of the signs and the statistical significance of the coefficients.

For technical efficiency, education and household variables recorded positive signs. These indicate that, illiterate and farmers in nuclear families are more technically efficient than literates and those in extended family systems. Literate farmers normally have other jobs or job searching, giving less attention to maize production. Farmers in extended families have lesser time for their individual farms because of other farming activities in the family house

In the case of allocative efficiency, land area, education, marital status, household structure and farming experience all recorded negative coefficients whiles only marital status had a positive sign. All these are significant and agreed by DEA and SFA as well as CRS and VRS. The conclusion from them is that small scale, single and less experienced farmers are more allocatively efficient than large scale, married and more experienced farmers respectively. The less efficient have more family labor than the more efficient group. Since feeding family is the main reason for maize production, scale of operation is proportional to family size. However, family labor as explained earlier is difficult to be reallocated or substituted because they do not pay for it. In that sense, small scale farmer have less family labor than the large scale and hence more allocativey efficient. In the same vein, married farmers and experienced farmers have larger families than single and less experienced farmers, hence less allocatively efficient. The education variable shows that literate farmers are more efficient. The underlining reason for this is different from the other three. It is assumed that, with their educational enlightenment, they make relatively better decisions in selecting the input mix for production. However, there is no significant difference between the allocative efficiencies of literates and illiterates as well as between nuclear and extended family systems.

Land area, marital Status, farming experience household structure and education are common variables found to affecting both AE and CE. With the exception of the education variable, the rest is as explained earlier under AE have large family labor problem, which makes it difficult to reallocate labor. However in the case of CE this family labor translates into huge observed cost of production. Since the denominator of the CE is observed cost, the more it increases the less CE scores. Hence groups with lesser family labor like small scale farmers, single farmers and less experienced farmers have CE advantage than large scale, married and experienced farmers. On education, again it would be assumed that the literates would make better economic decisions than the illiterates, hence their CE advantage. The results of the land area variable is reinforced by the findings from the profit analysis that shows that small scale farmers are more profitable than the large scale ones. Gender has not had the chance of being discussed in the previous two efficiencies, however, under CE; its coefficient is significant and agreed by the two techniques and two RTS assumptions. The positive coefficient indicates women farm managers are more cost efficient. The possible reason assigned is the fact that women are generally good in cost minimization than men, even though the general cost efficiency is very low. However, male and female farm managers are statistically the same in terms of their average cost efficiencies.

Efficiency estimates were compared with the other environmental variables that were not included in the tobit analysis. It showed that those who did not use credit were more efficient than those who used; the fewer the number of maize plots, the better in terms of efficiency; farmers in farmer groups tend to be more efficient than non-members; users of hybrid seeds are more efficient than users of own seeds. These findings however, cannot be tested, hence should be used with caution.

### 5.1.3. Assumptions and Limitations of the Study

Theoretically, the study assumes that all farmers are rational and make economic decisions of minimizing cost or maximizing profit. However, unlike in the developed countries, agriculture in the rural setting is not fully seen as a business and may make certain irrational decisions in the production process. For example, some farmers may want to expand their farms in terms of hectares, number of live animals and machinery for the purpose of prestige even if it is not profitable.

Finally, the study is based on a single farming season. Despite this season considered a normal year, results may not be a reflection of other years since environmental conditions are likely to change. The issue of measurement of labor in developing countries has been challenging since most agricultural labor are family members. The study has tried to measure it as accurately as possible, and yet results relating to labor especially should be used with caution. In a sample where these variables vary considerable, they should be investigated further for a statistical conclusion to be reached.

## 5.2. Recommendations

Recommendations from this study can be classified into public and farm specific recommendations. They can further be classified as long and short term. However, these classifications do not matter individually they are integrated into one another. They are enumerated below;

1. First and foremost, labor application in maize production should be reduced. There is a strong case for this recommendation. Labor variable has the lowest output elasticity even though it is not significant. It also has the largest amount of slacks. Cost wise, it is the highest burden on production cost. AE and CE significantly improved when labor content is withdrawn. The IAEC suggested the reduction of labor input as against the

other inputs. Furthermore, labor is the least of farmers' challenges in the region, indicating its abundance.

2. In as much as there is a strong case for the reduction of labor content in maize production, its implementation would be difficult if not impossible. There is no way of advising any farmer to reduce labor employment when he or she is not paying for them. Furthermore, the labor (family) would be the ultimate beneficiary of the maize output, hence they themselves see the need to work on the farm. Labor therefore is more like a fixed input in this case. In the short term, farmers can introduce on-farm complementary jobs to maize production, like bee keeping, animal rearing etc. In the long term, government should create employment opportunities to absorb this excess labor. Since the region is the second largest in terms of average number of people per household, birth control measures is another long term measure to reduce the family size.
3. Increasing educational infrastructure is another way of reducing the labor content in the production process. Even though basic education in Ghana is free, accessibility is still a problem for some rural areas. If the school attendance rate is increased in the region, the amount of labor usage on the farms would reduce.
4. In terms of technical efficiency, the efficiency advantage illiterate farmers have over literates farmers suggest that when maize farming is combined with other off farms jobs, efficiency reduces. Also, farmers in the extended family system should synchronize their activities or consolidate their farm lands. Land consolidation may also help in this situation. If all members of the family could get their farms closer to the family farms, much time and fuel can be saved running between farms. Labor can also be consolidated and work simultaneously on all farms. This suggestion is equally useful in AE and CE.

5. Illiterate farmers should be given training in basic accounting and book keeping, so that they can have an idea when they are not cost efficient. This may improve their AE and CE. Experienced and older farmers should delegate managerial roles of their farms to their matured and younger family members instead of using them merely as family labor.
6. Farmers could increase their output and productivity through fertilizer application and pesticide use. With nitrogen and phosphorus deficient soil, more fertilizer rich in these nutrients should be applied. They have used the NPK (15-15-15) for a long time. However, the heavy rain patterns easily wash away the nitrogen and the phosphorous. With the availability of the NPK (23-10-5), farmers should be encouraged to use that instead for their maize farms. This can be done through extension agents in the districts. More so, the prices of the two compound fertilizers are the same at the subsidized price. As a form of inducement, the subsidy on the NPK (23-20-5) can be increased. This idea will not only help maize farmers but improve the already nitrogen and phosphorus deficient soils in the region. Compost fertilizers should also be given a try. The raw materials needed in the preparation of composts are available in the rural communities. They need to be trained on better ways of making it. Pesticide use should also be encouraged but it comes with the additional responsibility of controlling its imports and application as its hazards can equally be devastating. The IAEC also supports this claim that fertilizer usage should be increased.
7. Farmers should be trained to consider farming more than just feeding their families. It should be a business in the sense they should aim at benefiting financially from it. In terms of production, they are relatively better as reflected in the technical efficiency estimate. However, cost minimization is the problem. This situation can also be observed from the lack of recorded information on cost and sales of agricultural output. As far as the observed cost tend to be huge, inefficiencies would persist. This means that

farmers in the region can easily improve their technical efficiencies and productivities but would find it difficult to improve their incomes, if the business mindset is not applied in the agricultural production.

8. In as much as recommendations have been made based on the research findings, it would be better if the challenges raised by the farmers could equally be given attention. Government can facilitate the acquisition of tractors by organized farmer groups through loans. Government can also provide some tractors to each District Agricultural Offices for the services of the farmers. On their second most pressing challenge, the government can provide infrastructure for irrigation and off season farming. The climate and environmental condition in the region limits farmers' ability to produce in the dry season. However, there is perennial flooding in the region in the raining season. These waters could be dammed and use for irrigation purposes. The government can also invest in the acquisition of modern meteorological equipment that can give much precise weather update for the benefit of farmers. Government can also encourage banks to give soft loans to farmers in the farming season. Announcement on fertilizer subsidies should be given earlier. The problem of cattle and bush fires can be solved locally. Consultations between cow owners and farmers can allocate a specific land for grazing. The problem of bush burning needs a lot of education and attitudinal change.
9. Researches should be conducted aimed at producing high yielding varieties of maize and other food crops in the region. The new varieties should also be relatively drought tolerant to cater for the erratic nature of rainfall in the region. Savannah Agricultural Research Institute (SARI) of The Council for Scientific and Industrial Research (CSIR) is a Government institution mandated for agricultural research in the region. However, the institute has not received much financial support from the Government. The institute has been dependent on external funding for operations. However, these

funding come with their specified objectives, which may not necessary reflect the needs of the region. This same attitude of the Government affects policies that are meant to improve the livelihood of the people in the region. Example is the Savannah Accelerated Development Authority (SADA), whose implementation has been very challenging.

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## CURRICULUM VITAE

Abdul-Basit Tampuli is my name. Born in Yendi in the Northern part of Ghana. I attended primary school to senior high level in the region. After which I was admitted to the Economics Department at the Kwame Nkrumah University of Science and Technology (KNUST), in Kumasi, Ghana. I later served as a teaching and research assistant in the same department after graduating with a first class honors. I was awarded a scholarship in 2007 to study Msc Development Management at the University of Agder, Kristiansand, Norway. Upon completion I started working at the Savannah Agricultural Research Institute (SARI) of the Council for Scientific and Industrial Research (CSIR) as a research scientist, responsible for linking farmers and farmer groups to the institute's research programs. I later gained admission into the Agricultural Economics Department of the Çukurova University to offer my PhD in Agricultural Economics.

# APPENDICES

**Appendix 1. Questionnaires**

Department of Agricultural Economics, Institute of Natural and Applied Sciences, Çukurova University, Adana, Turkey.

Topic:

MEASURING THE TECHNICAL AND ECONOMIC EFFICIENCIES OF MAIZE FARMING IN THE NORTHERN REGION OF GHANA: DETERMINISTIC AND STOCHASTIC APPROACHES

| | |
|---|---|
| Village and District | |
| Farmer's Full Name | |
| Telephone number | |
| Questionnaire Number | |
| Date | |

Northern Region Ghana- 2015

## 1. Inputs Used and Their Costs

### I. Land

A. What is the size of your maize Farm (acre)?.....

B. Owned ☐ or hired ☐

C. What is the cost per acre of farm land?

❖ Total cost of land (A * B) =…….

D. If own land, what is the prevailing cost of hiring an acre of land in the district?

……..……
.

E. If not available, what is the MoFA's (Ministry of Food and Agriculture) estimate on the cost of land?.....

## II. Labor

Information on Family Labor

| Number | Age* | Sex** | Education*** | Does he/she work in your maize farm? | How many hours do they work for the maize season | How many days spent on the maize farm for the season | Total cost of family labor in maize production**** | Work outside the family farm | | Non Agricultural jobs | | Total income per person in a year |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | Type of work | Total income in a year | Type of work | Total income in a year | |
| 1 (farmer) | | | | | | | | | | | | |
| 2 | | | | | | | | | | | | |
| 3 | | | | | | | | | | | | |
| 4 | | | | | | | | | | | | |
| 5 | | | | | | | | | | | | |
| 6 | | | | | | | | | | | | |
| 7 | | | | | | | | | | | | |
| 8 | | | | | | | | | | | | |
| **Total** | | | | | | | | | | | | |

*Age: labor contribution coefficients, 0-6 (Female and Male)=0, 7-14 (Female and Male)=0.50, 15–49 (Female)=0.75, 15–49(Male)=1, 50+(Female)=0.50, 50+(Male)=0.75

**Sex dummy variable; Male=1, Female=0

***Education- Dummy variable; Illiterate=1, Primary School=2, Junior High School=3, Senior High School=4, Tertiary Level=5

**** The prevailing cost of labor per hour in the district

A. How many are family labor and how many are hired?...../……..

Information on hired Labor

| No: | Age* | Sex** | **How many hours do they work per maize season** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Land preparation | Ploughing and Harrowing | sowing | Fertilizer application | weeding | Pesticide application | harvesting | transportation | sales |
| Date of activity | | | | | | | | | | | |
| Number of times | | | | | | | | | | | |
| How many days per activity? | | | | | | | | | | | |
| Was a machine used? | | | | | | | | | | | |
| 1 | | | | | | | | | | | |
| 2 | | | | | | | | | | | |
| 3 | | | | | | | | | | | |
| 4 | | | | | | | | | | | |
| 5 | | | | | | | | | | | |
| 6 | | | | | | | | | | | |
| 7 | | | | | | | | | | | |
| 8 | | | | | | | | | | | |

| No: | Age* | Sex** | **How many hours do they work per maize season** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Land preparation | Ploughing and Harrowing | sowing | Fertilizer application | weeding | Pesticide application | harvesting | transportation | sales |
| 9 | | | | | | | | | | | |
| 10 | | | | | | | | | | | |
| 11 | | | | | | | | | | | |
| 12 | | | | | | | | | | | |
| 13 | | | | | | | | | | | |
| 14 | | | | | | | | | | | |
| **Total hours** | | | | | | | | | | | |
| **Total days** | | | | | | | | | | | |
| | | | | | **Cost of Labor** | | | | | | |
| How is labor cost charged? | Hourly ☐<br>Per activity ☐<br>Per day ☐ | | | | | | | | | | |
| What is the hourly charge per acre for each activity? | | | | | | | | | | | |
| **Total cost** | | | | | | | | | | | |
| | | | | | | | | | | | |

| | | | Land preparation | Ploughing and Harrowing | sowing | Fertilizer application | weeding | Pesticide application | harvesting | transportation | sales |
|---|---|---|---|---|---|---|---|---|---|---|---|
| What is the daily charge per activity? | | | | | | | | | | | |
| **Total cost** | | | | | | | | | | | |
| What is the cost per activity? | | | | | | | | | | | |
| **Total cost** | | | | | | | | | | | |
| How much would I be charged if I want to hire the machine without an operator for each of the activities? | | | | | | | | | | | |

*Age: labor contribution coefficients, 0-6 (Female and Male)=0, 7-14 (Female and Male)=0.50, 15–49 (Female)=0.75, 15–49(Male)=1, 50+(Female)=0.50, 50+(Male)=0.75

**Sex dummy variable; Male=1, Female=0

B. Total number of hours and days used by labor

- Total number of hours used by family labor + total number of hours used by hired labor
  ……
- Total number of days used by family labor + total number of days used by hired labor
  ……

C. Cost of labor

- Total cost of family labor (hourly charge) + total cost of hired labor (hourly charge)……
  ……
- Total cost of family labor (daily charge) + total cost of hired labor (daily charge)……
  …….
- Total cost of family labor (activity charge) + total cost of hired labor (activity charge)……..

D. In case the activity is done using a machine, the difference between the cost of hiring a machine without an operator and hiring with operator will give the labor cost component of it.

   The number of hours spent by these labor will also be added to added to labor hours……

## III. Machinery

Machinery use

| No: | Hired or owned?* | How is labor usage charged?** | **How many hours do they work per maize season** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Land preparation | Ploughing and Harrowing | sowing | Fertilizer application | weeding | Pesticide application | harvesting | transportation | Storage and sales |
| Tractor | | | | | | | | | | | |
| Trailer | | | | | | | | | | | |
| Plow | | | | | | | | | | | |
| Planter | | | | | | | | | | | |
| Harvester | | | | | | | | | | | |
| Truck for transportation | | | | | | | | | | | |
| Sprayer | | | | | | | | | | | |
| Animal power and equipment | | | | | | | | | | | |
| | | | | | | | | | | | |
| | | | | | | | | | | | |
| | | | | | | | | | | | |
| **Total hours** | | | | | | | | | | | |
| **Total days** | | | | | | | | | | | |
| | | | | | | | | | | | |

| | | | | If equipment is hired, for each activity, Is it with an operator? | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Land preparation | Ploughing and Harrowing | sowing | Fertilizer application | weeding | Pesticide application | harvesting | transportation | Storage and sales |
| Tractor | | | | | | | | | | | |
| Trailer | | | | | | | | | | | |
| Plow | | | | | | | | | | | |
| Planter | | | | | | | | | | | |
| Harvester | | | | | | | | | | | |
| Truck for transportation | | | | | | | | | | | |
| Sprayer | | | | | | | | | | | |
| Animal power and equipment | | | | | | | | | | | |
| | | | | Cost of Machinery use*** | | | | | | | |
| What is the charge per use of each equipment in each activity | | | | | | | | | | | |
| Tractor | | | | | | | | | | | |
| Trailer | | | | | | | | | | | |
| Plow | | | | | | | | | | | |
| Planter | | | | | | | | | | | |
| Harvester | | | | | | | | | | | |
| Truck for transportation | | | | | | | | | | | |
| Sprayer | | | | | | | | | | | |
| Animal power and machines | | | | | | | | | | | |

| | Tractor | Trailer | Plow | Planter | Harvester | Truck for transportation | Sprayer | Animal power and equipment | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| What is the hourly charge per use of each equipment | | | | | | | | | | | |
| What is the daily charge per use of each equipment | | | | | | | | | | | |

*H (hired) and O (owned)

** PH (Per Hour), PA(Per Activity) and PD(Per Day)

***If the equipment is owned by the farmer, the prevailing charge for its use in the district will be used.

A. Total number of hours and days

- The summation of all the number of hours each equipment spent on each activity

  ……
  ……

- The summation of all the number of days each equipment was used for each activity

  ……
  ……

B. Total cost of machinery use

- The total number of hours multiply by the charge per hour for each equipment

  ……
  ……..

- The total number of days of each equipment in used in each activity multiply by the charge per day per each equipment

  ……
  …….

- The cost per each equipment used per each activity multiply by the charge per activity.

  ……
  ……..

C. How much would I be charged if I want to hire the machine without an operator for each of the activities? (The cost of an equipment operator will be computed and subtracted from the total cost to get the actual cost of only machine use)

……
……
……
……
……
……
……
……
……
……

**IV. Fertilizer Usage**

A. What type of fertilizer are you using? Compound ☐ Separate ☐
B. If compound, what elements/nutrients were present?
   Nitrogen ☐ Potassium ☐ Phosphorus ☐
C. What is the proportion of each element/nutrients in the compound?
   Nitrogen…….. Potassium……..……. Phosphorus…….
D. What is the combined weight of the compound fertilizer?.....
E. If separated, what elements/nutrients
   Nitrogen☐ Potassium☐ Phosphorus ☐
F. What is the total weight for each element?

   Nitrogen…….. Potassium……..……. Phosphorus…….

- ❖ Total weight will be the summation of all the individual weights of each element or nutrients.

……

G. If compound, what is the total cost?.....

- ❖ A ratio between each element's prevailing prices will be calculated. This ratio will be applied on the total cost to determine how much element in the compound cost.

  Ratio=……..

  Individual cost of elements/nutrients

  Nitrogen……..….. Potassium……..……. Phosphorus…….

H. If separate, what is the cost of each element/nutrient?

  Nitrogen…….……. Potassium……..…….. Phosphorus…….

## V. Pesticides Usage

A. What pesticides did you use?

.....

.....

.....

.....

B. What is the cost of each type of pesticide used?

.....

.....

.....

- ❖ The total cost of pesticide used will be calculated by multiplying the cost of each pesticide by its quantity and sum all the corresponding values thereby.

  .....
  .....
  .....
  .....

## VI. Seeds

A. What type of seed did you use? Improved ☐ Own seed ☐

B. If own seed, what quantity in kilograms did you use?.....

C. If improved seed, how many packets or quantity in kilograms did you use?.....

- ❖ The net weight of the packet will be multiplied by the number of packets to determine the total number of improved seed used

  ……

D. For improved seed, what was the price per packet?.....

- ❖ The total cost of improved seed will be calculated by multiplying the price per packet by the number of packets used

  …….

E. For own seed, the prevailing price of maize per kilogram would be used to calculate the cost of using own seed used.

  ……

**2. <u>Causes of Inefficiency</u>**

**VII. Extension services**

A. How many times have you visited or been visited by an extension agent?.....

**VIII. Use of improved seeds**

A. Do you use improved seeds? Yes ☐ No ☐ (Yes=1, No=0)

**IX. Education level**

Refer to labor information earlier Labor

X. **Male or female?**

Refer to labor information earlier Labor

**XI. Marital Status**

A. What is you marital status? Single ☐ Married ☐ Divorce ☐ (Single=1, Married=2, Divorce=3)

**XII. Age**

A. How old are you?.....

**XIII. Household structure**

A. Nucleus family ☐ Extended family ☐ (Nucleus=1, Extended=0)

**XIV. Maize Farming Experience**

A. How long have you been cultivating maize?.....

**XV. Credit Access**

A. Did you get credit of any form? Yes ☐ No ☐ (Yes=1, No=0)

B. If yes, cash or inputs? Cash ☐ Inputs ☐ (Cash=1,Inputs=0)

**XVI. Number of Maize Plots**

A. How many maize plots do you have?.....

**XVII. Farmer Based Organization (FBO)**

A. Are you a member of an FBO? Yes ☐ No ☐ (Yes=1, No=0)

### 3. Maize output

XVIII. How many bags did you harvest? (mini or maxi bags)……..

XIX. What quantity of the maize output (mini or maxi or) did you sell? ……..

XX. How much (maxi or mini) did you consumed? (The value to be determined with prevailing prices) .....

XXI. How much (maxi or mini) did you store as seeds?

XXII. At what price did you sell? (per kilogram, per maxi/mini bag)…….

XXIII. Which part of the year did you sell?.....

XXIV. What other crops did you grow?

| Crop | Total output | Quantity consumed | Quantity sold | Average unit price |
|---|---|---|---|---|
| | | | | |
| | | | | |
| | | | | |
| | | | | |
| | | | | |
| | | | | |
| | | | | |
| Total | | | | |

## 4. Other Information

XXV. What is your total arable land? …….

XXVI. Do you have access to irrigation facilities?.....

XXVII. Do you have livestock?

| Livestock | Number (livestock unit) | How many have been sold in last year farming season | What was the total monetary value from the sales | How many have been consumed? |
|---|---|---|---|---|
| Cattle | | | | |
| Buffalo | | | | |
| Sheep | | | | |
| Goats | | | | |
| Pigs | | | | |
| Horses | | | | |
| mules | | | | |
| Camels | | | | |
| Asses | | | | |
| Chickens | | | | |
| Ducks | | | | |
| Rabbits | | | | |
| Turkeys | | | | |
| Geese | | | | |
| **Total** | | | | |

XXVIII. How many times do you farm in a year?.....

XXIX. Assuming you don't farm in a certain year, what cost will you incur in the farming business?.....

XXX. How do you store you maize?.....

XXXI. Does it get spoiled?.....

XXXII. Why do you grow maize?.....

## 5. Constraints in maize farming

**XXXIII.** What general problems do you face in the cultivation of Maize?

A. Production

……

……

……

B. Harvesting

……

……

……

C. Storage

……

……

……

D. Marketing

……

……

……

**Appendix 2. Output Oriented Technical and Scale Efficiency Estimates: DEA and SFA**

| | DEA | | | | SFA | |
|---|---|---|---|---|---|---|
| Farmer | TE VRS | TE CRS | SE | RTS | TE-VRS | TE-CRS |
| 1 | 0.79 | 0.78 | 1.00 | IRS | 0.80 | 0.81 |
| 2 | 0.84 | 0.70 | 0.84 | DRS | 0.86 | 0.86 |
| 3 | 0.50 | 0.48 | 0.96 | IRS | 0.68 | 0.70 |
| 4 | 0.50 | 0.49 | 1.00 | DRS | 0.69 | 0.71 |
| 5 | 1.00 | 1.00 | 1.00 | CRS | 0.93 | 0.93 |
| 6 | 0.49 | 0.48 | 0.99 | DRS | 0.67 | 0.69 |
| 7 | 0.79 | 0.72 | 0.90 | DRS | 0.86 | 0.86 |
| 8 | 0.51 | 0.49 | 0.96 | DRS | 0.65 | 0.66 |
| 9 | 0.65 | 0.58 | 0.88 | DRS | 0.81 | 0.80 |
| 10 | 0.71 | 0.64 | 0.91 | DRS | 0.82 | 0.82 |
| 11 | 0.48 | 0.47 | 0.98 | DRS | 0.57 | 0.58 |
| 12 | 0.91 | 0.90 | 0.99 | IRS | 0.86 | 0.86 |
| 13 | 0.91 | 0.71 | 0.78 | DRS | 0.88 | 0.87 |
| 14 | 0.59 | 0.53 | 0.91 | IRS | 0.65 | 0.66 |
| 15 | 0.70 | 0.69 | 0.99 | DRS | 0.78 | 0.79 |
| 16 | 0.61 | 0.58 | 0.95 | IRS | 0.76 | 0.78 |
| 17 | 0.62 | 0.61 | 0.99 | DRS | 0.80 | 0.80 |
| 18 | 0.75 | 0.67 | 0.89 | DRS | 0.85 | 0.85 |
| 19 | 0.90 | 0.90 | 1.00 | DRS | 0.88 | 0.88 |
| 20 | 0.92 | 0.68 | 0.74 | DRS | 0.86 | 0.86 |
| 21 | 0.85 | 0.84 | 0.99 | IRS | 0.88 | 0.88 |
| 22 | 0.74 | 0.68 | 0.92 | DRS | 0.85 | 0.84 |
| 23 | 0.81 | 0.80 | 1.00 | IRS | 0.87 | 0.87 |

| | DEA | | | | SFA | |
|---|---|---|---|---|---|---|
| Farmer | TE VRS | TE CRS | SE | RTS | TE-VRS | TE-CRS |
| 22 | 0.74 | 0.68 | 0.92 | DRS | 0.85 | 0.84 |
| 23 | 0.81 | 0.80 | 1.00 | IRS | 0.87 | 0.87 |
| 24 | 0.73 | 0.58 | 0.95 | IRS | 0.85 | 0.85 |
| 25 | 0.57 | 0.57 | 1.00 | CRS | 0.73 | 0.75 |
| 26 | 0.84 | 0.76 | 0.91 | IRS | 0.81 | 0.82 |
| 27 | 0.72 | 0.69 | 0.96 | DRS | 0.77 | 0.77 |
| 28 | 0.44 | 0.44 | 0.99 | IRS | 0.64 | 0.65 |
| 29 | 1.00 | 1.00 | 1.00 | CRS | 0.77 | 0.80 |
| 30 | 0.53 | 0.51 | 0.97 | DRS | 0.57 | 0.58 |
| 31 | 0.81 | 0.67 | 0.82 | DRS | 0.86 | 0.85 |
| 32 | 1.00 | 1.00 | 1.00 | CRS | 0.88 | 0.88 |
| 33 | 0.33 | 0.31 | 0.94 | DRS | 0.47 | 0.48 |
| 34 | 0.57 | 0.49 | 0.87 | IRS | 0.62 | 0.64 |
| 35 | 1.00 | 1.00 | 1.00 | CRS | 0.90 | 0.90 |
| 36 | 1.00 | 1.00 | 1.00 | CRS | 0.92 | 0.92 |
| 37 | 0.50 | 0.50 | 1.00 | CRS | 0.65 | 0.66 |
| 38 | 0.63 | 0.59 | 0.94 | DRS | 0.75 | 0.75 |
| 39 | 0.61 | 0.44 | 0.73 | DRS | 0.65 | 0.65 |
| 40 | 0.37 | 0.36 | 0.99 | IRS | 0.53 | 0.54 |
| 41 | 1.00 | 1.00 | 1.00 | CRS | 0.94 | 0.94 |
| 42 | 0.53 | 0.52 | 0.99 | DRS | 0.70 | 0.72 |
| 43 | 0.93 | 0.73 | 0.79 | DRS | 0.87 | 0.86 |
| 44 | 1.00 | 0.94 | 0.94 | IRS | 0.92 | 0.92 |
| 45 | 1.00 | 0.76 | 0.76 | IRS | 0.85 | 0.86 |
| 46 | 1.00 | 1.00 | 1.00 | DRS | 0.90 | 0.90 |

| | DEA | | | | SFA | |
|---|---|---|---|---|---|---|
| Farmer | TE VRS | TE CRS | SE | RTS | TE-VRS | TE-CRS |
| 47 | 0.87 | 0.87 | 1.00 | CRS | 0.77 | 0.78 |
| 48 | 0.92 | 0.90 | 0.98 | IRS | 0.89 | 0.90 |
| 49 | 0.99 | 0.82 | 0.82 | IRS | 0.85 | 0.86 |
| 50 | 0.41 | 0.41 | 1.00 | IRS | 0.58 | 0.60 |
| 51 | 0.52 | 0.52 | 1.00 | IRS | 0.69 | 0.71 |
| 52 | 1.00 | 1.00 | 1.00 | CRS | 0.87 | 0.88 |
| 53 | 0.54 | 0.53 | 0.99 | IRS | 0.70 | 0.71 |
| 54 | 0.45 | 0.36 | 0.81 | DRS | 0.57 | 0.58 |
| 55 | 0.88 | 0.65 | 0.74 | IRS | 0.79 | 0.80 |
| 56 | 0.87 | 0.87 | 1.00 | DRS | 0.90 | 0.90 |
| 57 | 0.92 | 0.73 | 0.80 | DRS | 0.89 | 0.88 |
| 58 | 0.72 | 0.68 | 0.94 | DRS | 0.76 | 0.77 |
| 59 | 0.80 | 0.61 | 0.77 | DRS | 0.76 | 0.76 |
| 60 | 0.72 | 0.62 | 0.87 | DRS | 0.80 | 0.80 |
| 61 | 0.63 | 0.62 | 0.99 | DRS | 0.77 | 0.77 |
| 62 | 0.56 | 0.55 | 0.99 | IRS | 0.71 | 0.72 |
| 63 | 0.71 | 0.56 | 0.78 | DRS | 0.78 | 0.78 |
| 64 | 0.70 | 0.68 | 0.98 | DRS | 0.80 | 0.81 |
| 65 | 0.99 | 0.91 | 0.92 | DRS | 0.87 | 0.87 |
| 66 | 0.93 | 0.69 | 0.75 | DRS | 0.85 | 0.84 |
| 67 | 0.89 | 0.79 | 0.90 | IRS | 0.78 | 0.79 |
| 68 | 0.97 | 0.86 | 0.89 | DRS | 0.91 | 0.91 |
| 69 | 0.41 | 0.40 | 0.99 | IRS | 0.58 | 0.60 |
| 70 | 0.96 | 0.95 | 0.98 | IRS | 0.91 | 0.91 |
| 71 | 0.76 | 0.74 | 0.98 | IRS | 0.85 | 0.85 |

| | DEA | | | | SFA | |
|---|---|---|---|---|---|---|
| Farmer | TE VRS | TE CRS | SE | RTS | TE-VRS | TE-CRS |
| 72 | 0.72 | 0.69 | 0.96 | DRS | 0.85 | 0.85 |
| 73 | 0.67 | 0.67 | 0.99 | IRS | 0.83 | 0.83 |
| 74 | 1.00 | 0.78 | 0.78 | IRS | 0.75 | 0.78 |
| 75 | 0.50 | 0.49 | 0.98 | DRS | 0.63 | 0.65 |
| 76 | 0.76 | 0.73 | 0.97 | DRS | 0.85 | 0.85 |
| 77 | 0.81 | 0.80 | 0.99 | IRS | 0.85 | 0.85 |
| 78 | 0.74 | 0.67 | 0.90 | DRS | 0.83 | 0.83 |
| 79 | 0.91 | 0.69 | 0.76 | DRS | 0.84 | 0.83 |
| 80 | 1.00 | 1.00 | 1.00 | CRS | 0.74 | 0.74 |
| 81 | 0.70 | 0.70 | 1.00 | IRS | 0.85 | 0.85 |
| 82 | 0.53 | 0.53 | 0.99 | IRS | 0.76 | 0.77 |
| 83 | 0.66 | 0.63 | 0.97 | DRS | 0.83 | 0.83 |
| 84 | 0.79 | 0.73 | 0.92 | DRS | 0.83 | 0.83 |
| 85 | 1.00 | 1.00 | 1.00 | CRS | 0.88 | 0.88 |
| 86 | 1.00 | 1.00 | 1.00 | CRS | 0.92 | 0.92 |
| 87 | 0.55 | 0.52 | 0.94 | DRS | 0.68 | 0.69 |
| 88 | 0.99 | 0.83 | 0.84 | DRS | 0.87 | 0.86 |
| 89 | 0.66 | 0.63 | 0.96 | DRS | 0.82 | 0.82 |
| 90 | 0.67 | 0.66 | 0.99 | IRS | 0.80 | 0.81 |
| 91 | 0.92 | 0.73 | 0.80 | DRS | 0.89 | 0.88 |
| 92 | 0.55 | 0.54 | 0.98 | DRS | 0.74 | 0.75 |
| 93 | 0.95 | 0.83 | 0.88 | DRS | 0.91 | 0.90 |
| 94 | 0.73 | 0.71 | 0.98 | IRS | 0.80 | 0.81 |
| 95 | 0.83 | 0.72 | 0.87 | DRS | 0.86 | 0.85 |
| 96 | 0.81 | 0.65 | 0.81 | DRS | 0.85 | 0.84 |

| | DEA | | | | SFA | |
|---|---|---|---|---|---|---|
| Farmer | TE VRS | TE CRS | SE | RTS | TE-VRS | TE-CRS |
| 97 | 0.68 | 0.68 | 1.00 | DRS | 0.83 | 0.83 |
| 98 | 0.72 | 0.60 | 0.84 | DRS | 0.81 | 0.80 |
| 99 | 1.00 | 1.00 | 1.00 | CRS | 0.80 | 0.81 |
| 100 | 0.54 | 0.53 | 0.99 | IRS | 0.70 | 0.71 |
| 101 | 0.82 | 0.66 | 0.80 | DRS | 0.81 | 0.81 |
| 102 | 0.64 | 0.62 | 0.97 | DRS | 0.72 | 0.73 |
| 103 | 0.47 | 0.46 | 0.98 | DRS | 0.62 | 0.63 |
| 104 | 0.62 | 0.62 | 1.00 | CRS | 0.68 | 0.69 |
| 105 | 0.63 | 0.62 | 0.98 | DRS | 0.80 | 0.81 |
| 106 | 0.65 | 0.64 | 0.99 | DRS | 0.84 | 0.84 |
| 107 | 0.81 | 0.71 | 0.88 | DRS | 0.84 | 0.83 |
| 108 | 0.94 | 0.70 | 0.75 | DRS | 0.86 | 0.85 |
| 109 | 0.52 | 0.45 | 0.86 | DRS | 0.71 | 0.71 |
| 110 | 0.45 | 0.44 | 0.99 | DRS | 0.55 | 0.56 |
| 111 | 1.00 | 0.95 | 0.95 | IRS | 0.88 | 0.88 |
| 112 | 1.00 | 0.84 | 0.84 | IRS | 0.81 | 0.83 |
| 113 | 0.98 | 0.97 | 0.99 | DRS | 0.86 | 0.85 |
| 114 | 0.81 | 0.74 | 0.91 | IRS | 0.70 | 0.72 |
| 115 | 0.87 | 0.80 | 0.92 | DRS | 0.90 | 0.89 |
| 116 | 0.54 | 0.52 | 0.95 | IRS | 0.69 | 0.70 |
| 117 | 0.67 | 0.64 | 0.96 | IRS | 0.82 | 0.83 |
| 118 | 0.63 | 0.61 | 0.97 | DRS | 0.77 | 0.78 |
| 119 | 1.00 | 1.00 | 1.00 | CRS | 0.95 | 0.95 |
| 120 | 0.31 | 0.29 | 0.94 | IRS | 0.42 | 0.43 |
| 121 | 0.29 | 0.28 | 0.98 | IRS | 0.48 | 0.50 |

**Appendix 3. Input Oriented Technical, Allocative, Cost and Scale Efficiency Estimates: DEA**

| Farmer | TE VRS | TE CRS | SE | RTS | AE-VRS | AE-CRS | CE-VRS | CE-CRS |
|---|---|---|---|---|---|---|---|---|
| 1 | 0.87 | 0.78 | 0.90 | IRS | 0.95 | 0.96 | 0.83 | 0.75 |
| 2 | 0.73 | 0.70 | 0.96 | IRS | 0.74 | 0.75 | 0.54 | 0.52 |
| 3 | 0.77 | 0.48 | 0.63 | IRS | 0.49 | 0.46 | 0.38 | 0.22 |
| 4 | 0.85 | 0.49 | 0.58 | IRS | 0.51 | 0.59 | 0.43 | 0.29 |
| 5 | 1.00 | 1.00 | 1.00 | CRS | 0.56 | 0.41 | 0.56 | 0.41 |
| 6 | 0.87 | 0.48 | 0.56 | IRS | 0.46 | 0.44 | 0.40 | 0.21 |
| 7 | 0.72 | 0.72 | 1.00 | CRS | 0.74 | 0.70 | 0.53 | 0.50 |
| 8 | 0.60 | 0.49 | 0.82 | IRS | 0.58 | 0.52 | 0.35 | 0.25 |
| 9 | 0.62 | 0.58 | 0.93 | IRS | 0.57 | 0.53 | 0.35 | 0.31 |
| 10 | 0.67 | 0.64 | 0.96 | IRS | 0.71 | 0.67 | 0.48 | 0.43 |
| 11 | 0.65 | 0.47 | 0.72 | IRS | 0.85 | 0.89 | 0.55 | 0.42 |
| 12 | 0.93 | 0.90 | 0.97 | IRS | 0.81 | 0.70 | 0.76 | 0.63 |
| 13 | 0.73 | 0.71 | 0.98 | DRS | 0.64 | 0.64 | 0.47 | 0.45 |
| 14 | 0.91 | 0.53 | 0.59 | IRS | 0.71 | 0.84 | 0.65 | 0.45 |
| 15 | 0.72 | 0.69 | 0.97 | IRS | 0.69 | 0.55 | 0.49 | 0.38 |
| 16 | 0.91 | 0.58 | 0.63 | IRS | 0.36 | 0.31 | 0.33 | 0.18 |
| 17 | 0.67 | 0.61 | 0.91 | IRS | 0.71 | 0.65 | 0.47 | 0.40 |
| 18 | 0.72 | 0.67 | 0.93 | IRS | 0.77 | 0.76 | 0.56 | 0.51 |
| 19 | 0.90 | 0.90 | 0.99 | IRS | 0.61 | 0.57 | 0.55 | 0.51 |
| 20 | 0.69 | 0.68 | 0.99 | IRS | 0.77 | 0.76 | 0.53 | 0.52 |
| 21 | 0.90 | 0.84 | 0.93 | IRS | 0.44 | 0.38 | 0.40 | 0.32 |
| 22 | 0.69 | 0.68 | 0.98 | IRS | 0.77 | 0.71 | 0.53 | 0.48 |

| Farmer | TE VRS | TE CRS | SE | RTS | AE-VRS | AE-CRS | CE-VRS | CE-CRS |
|---|---|---|---|---|---|---|---|---|
| 23 | 0.83 | 0.80 | 0.97 | IRS | 0.66 | 0.62 | 0.55 | 0.50 |
| 24 | 0.91 | 0.58 | 0.76 | IRS | 0.39 | 0.33 | 0.35 | 0.23 |
| 25 | 0.73 | 0.57 | 0.78 | IRS | 0.83 | 0.85 | 0.61 | 0.49 |
| 26 | 0.92 | 0.76 | 0.83 | IRS | 0.85 | 0.82 | 0.78 | 0.62 |
| 27 | 0.70 | 0.69 | 1.00 | DRS | 0.89 | 0.79 | 0.62 | 0.55 |
| 28 | 0.72 | 0.44 | 0.61 | IRS | 0.62 | 0.70 | 0.45 | 0.31 |
| 29 | 1.00 | 1.00 | 1.00 | CRS | 1.00 | 0.67 | 1.00 | 0.67 |
| 30 | 0.66 | 0.51 | 0.78 | IRS | 0.86 | 0.88 | 0.56 | 0.45 |
| 31 | 0.68 | 0.67 | 0.99 | IRS | 0.62 | 0.59 | 0.42 | 0.39 |
| 32 | 1.00 | 1.00 | 1.00 | CRS | 1.00 | 1.00 | 1.00 | 1.00 |
| 33 | 0.53 | 0.31 | 0.58 | IRS | 0.46 | 0.40 | 0.24 | 0.12 |
| 34 | 0.90 | 0.49 | 0.55 | IRS | 0.52 | 0.56 | 0.47 | 0.28 |
| 35 | 1.00 | 1.00 | 1.00 | CRS | 0.96 | 0.69 | 0.96 | 0.69 |
| 36 | 1.00 | 1.00 | 1.00 | CRS | 1.00 | 1.00 | 1.00 | 1.00 |
| 37 | 0.78 | 0.50 | 0.64 | IRS | 0.63 | 0.78 | 0.50 | 0.39 |
| 38 | 0.60 | 0.59 | 0.98 | IRS | 0.52 | 0.42 | 0.31 | 0.25 |
| 39 | 0.52 | 0.44 | 0.86 | IRS | 0.80 | 0.80 | 0.41 | 0.35 |
| 40 | 0.77 | 0.36 | 0.47 | IRS | 0.62 | 0.76 | 0.48 | 0.28 |
| 41 | 1.00 | 1.00 | 1.00 | CRS | 0.81 | 0.80 | 0.81 | 0.80 |
| 42 | 0.73 | 0.52 | 0.72 | IRS | 0.60 | 0.61 | 0.44 | 0.32 |
| 43 | 0.73 | 0.73 | 1.00 | IRS | 0.59 | 0.58 | 0.43 | 0.42 |
| 44 | 1.00 | 0.94 | 0.94 | IRS | 0.68 | 0.58 | 0.68 | 0.54 |
| 45 | 1.00 | 0.76 | 0.76 | IRS | 0.72 | 0.71 | 0.72 | 0.54 |
| 46 | 1.00 | 1.00 | 1.00 | DRS | 0.76 | 0.73 | 0.76 | 0.73 |
| 47 | 0.95 | 0.87 | 0.92 | IRS | 0.89 | 0.90 | 0.85 | 0.79 |
| 48 | 0.95 | 0.90 | 0.94 | IRS | 0.45 | 0.36 | 0.43 | 0.33 |

| Farmer | TE VRS | TE CRS | SE | RTS | AE-VRS | AE-CRS | CE-VRS | CE-CRS |
|---|---|---|---|---|---|---|---|---|
| 49 | 1.00 | 0.82 | 0.82 | IRS | 0.80 | 0.82 | 0.80 | 0.66 |
| 50 | 0.60 | 0.41 | 0.69 | IRS | 0.60 | 0.62 | 0.36 | 0.25 |
| 51 | 0.87 | 0.52 | 0.60 | IRS | 0.38 | 0.31 | 0.33 | 0.16 |
| 52 | 1.00 | 1.00 | 1.00 | CRS | 0.58 | 0.43 | 0.58 | 0.43 |
| 53 | 0.63 | 0.53 | 0.85 | IRS | 0.77 | 0.70 | 0.49 | 0.37 |
| 54 | 0.48 | 0.36 | 0.77 | IRS | 0.66 | 0.64 | 0.31 | 0.23 |
| 55 | 1.00 | 0.65 | 0.65 | IRS | 0.47 | 0.51 | 0.47 | 0.33 |
| 56 | 0.88 | 0.87 | 0.99 | IRS | 0.78 | 0.75 | 0.68 | 0.65 |
| 57 | 0.73 | 0.73 | 0.99 | DRS | 0.71 | 0.69 | 0.52 | 0.51 |
| 58 | 0.75 | 0.68 | 0.90 | IRS | 0.92 | 0.94 | 0.69 | 0.64 |
| 59 | 0.64 | 0.61 | 0.96 | IRS | 0.87 | 0.86 | 0.55 | 0.53 |
| 60 | 0.63 | 0.62 | 0.99 | IRS | 0.58 | 0.53 | 0.36 | 0.33 |
| 61 | 0.72 | 0.62 | 0.86 | IRS | 0.70 | 0.65 | 0.51 | 0.40 |
| 62 | 0.74 | 0.55 | 0.74 | IRS | 0.57 | 0.54 | 0.42 | 0.30 |
| 63 | 0.61 | 0.56 | 0.91 | IRS | 0.84 | 0.84 | 0.51 | 0.47 |
| 64 | 0.72 | 0.68 | 0.95 | IRS | 0.75 | 0.67 | 0.54 | 0.46 |
| 65 | 0.97 | 0.91 | 0.94 | DRS | 0.88 | 0.94 | 0.86 | 0.86 |
| 66 | 0.69 | 0.69 | 1.00 | IRS | 0.89 | 0.88 | 0.62 | 0.61 |
| 67 | 0.94 | 0.79 | 0.85 | IRS | 0.46 | 0.38 | 0.43 | 0.30 |
| 68 | 0.87 | 0.86 | 0.99 | DRS | 0.78 | 0.77 | 0.67 | 0.66 |
| 69 | 0.73 | 0.40 | 0.55 | IRS | 0.54 | 0.52 | 0.39 | 0.21 |
| 70 | 0.97 | 0.95 | 0.98 | IRS | 0.79 | 0.73 | 0.77 | 0.69 |
| 71 | 0.83 | 0.74 | 0.89 | IRS | 0.83 | 0.80 | 0.68 | 0.59 |
| 72 | 0.75 | 0.69 | 0.92 | IRS | 0.81 | 0.79 | 0.60 | 0.54 |
| 73 | 0.71 | 0.67 | 0.94 | IRS | 0.61 | 0.51 | 0.43 | 0.34 |
| 74 | 1.00 | 0.78 | 0.78 | IRS | 0.49 | 0.30 | 0.49 | 0.24 |

| Farmer | TE VRS | TE CRS | SE | RTS | AE-VRS | AE-CRS | CE-VRS | CE-CRS |
|---|---|---|---|---|---|---|---|---|
| 75 | 0.82 | 0.49 | 0.60 | IRS | 0.47 | 0.43 | 0.39 | 0.21 |
| 76 | 0.78 | 0.73 | 0.94 | IRS | 0.88 | 0.86 | 0.68 | 0.63 |
| 77 | 0.91 | 0.80 | 0.87 | IRS | 0.45 | 0.40 | 0.41 | 0.32 |
| 78 | 0.68 | 0.67 | 0.98 | IRS | 0.75 | 0.70 | 0.51 | 0.46 |
| 79 | 0.69 | 0.69 | 0.99 | IRS | 0.88 | 0.87 | 0.61 | 0.59 |
| 80 | 1.00 | 1.00 | 1.00 | CRS | 1.00 | 1.00 | 1.00 | 1.00 |
| 81 | 0.77 | 0.70 | 0.91 | IRS | 0.73 | 0.68 | 0.56 | 0.48 |
| 82 | 0.83 | 0.53 | 0.64 | IRS | 0.58 | 0.65 | 0.48 | 0.34 |
| 83 | 0.65 | 0.63 | 0.98 | IRS | 0.63 | 0.56 | 0.41 | 0.36 |
| 84 | 0.76 | 0.73 | 0.96 | IRS | 0.85 | 0.83 | 0.64 | 0.60 |
| 85 | 1.00 | 1.00 | 1.00 | CRS | 0.30 | 0.25 | 0.30 | 0.25 |
| 86 | 1.00 | 1.00 | 1.00 | CRS | 0.71 | 0.59 | 0.71 | 0.59 |
| 87 | 0.58 | 0.52 | 0.89 | IRS | 0.65 | 0.59 | 0.38 | 0.30 |
| 88 | 0.91 | 0.83 | 0.91 | DRS | 0.80 | 0.88 | 0.73 | 0.73 |
| 89 | 0.63 | 0.63 | 0.99 | IRS | 0.63 | 0.56 | 0.40 | 0.35 |
| 90 | 0.76 | 0.66 | 0.88 | IRS | 0.81 | 0.79 | 0.61 | 0.52 |
| 91 | 0.74 | 0.73 | 0.99 | IRS | 0.73 | 0.72 | 0.54 | 0.53 |
| 92 | 0.61 | 0.54 | 0.88 | IRS | 0.70 | 0.65 | 0.43 | 0.35 |
| 93 | 0.86 | 0.83 | 0.97 | DRS | 0.56 | 0.57 | 0.48 | 0.47 |
| 94 | 0.80 | 0.71 | 0.89 | IRS | 0.80 | 0.78 | 0.64 | 0.55 |
| 95 | 0.73 | 0.72 | 0.98 | IRS | 0.55 | 0.52 | 0.40 | 0.38 |
| 96 | 0.66 | 0.65 | 0.99 | IRS | 0.59 | 0.56 | 0.39 | 0.37 |
| 97 | 0.78 | 0.68 | 0.87 | IRS | 0.68 | 0.62 | 0.53 | 0.42 |
| 98 | 0.61 | 0.60 | 0.98 | IRS | 0.56 | 0.51 | 0.34 | 0.31 |
| 99 | 1.00 | 1.00 | 1.00 | CRS | 0.40 | 0.29 | 0.40 | 0.29 |
| 100 | 0.66 | 0.53 | 0.81 | IRS | 0.74 | 0.68 | 0.49 | 0.36 |

| Farmer | TE VRS | TE CRS | SE | RTS | AE-VRS | AE-CRS | CE-VRS | CE-CRS |
|---|---|---|---|---|---|---|---|---|
| 101 | 0.68 | 0.66 | 0.97 | IRS | 0.86 | 0.85 | 0.58 | 0.55 |
| 102 | 0.65 | 0.62 | 0.96 | IRS | 0.84 | 0.72 | 0.54 | 0.45 |
| 103 | 0.61 | 0.46 | 0.75 | IRS | 0.75 | 0.77 | 0.46 | 0.35 |
| 104 | 0.77 | 0.62 | 0.80 | IRS | 0.65 | 0.70 | 0.50 | 0.43 |
| 105 | 0.70 | 0.62 | 0.88 | IRS | 0.61 | 0.54 | 0.43 | 0.33 |
| 106 | 0.72 | 0.64 | 0.89 | IRS | 0.68 | 0.64 | 0.49 | 0.41 |
| 107 | 0.73 | 0.71 | 0.98 | IRS | 0.78 | 0.74 | 0.56 | 0.53 |
| 108 | 0.71 | 0.70 | 0.99 | DRS | 0.73 | 0.72 | 0.51 | 0.51 |
| 109 | 0.60 | 0.45 | 0.76 | IRS | 0.74 | 0.79 | 0.44 | 0.36 |
| 110 | 0.61 | 0.44 | 0.72 | IRS | 0.69 | 0.70 | 0.43 | 0.31 |
| 111 | 1.00 | 0.95 | 0.95 | IRS | 0.50 | 0.41 | 0.50 | 0.39 |
| 112 | 1.00 | 0.84 | 0.84 | IRS | 0.47 | 0.31 | 0.47 | 0.26 |
| 113 | 0.98 | 0.97 | 1.00 | DRS | 0.35 | 0.35 | 0.34 | 0.34 |
| 114 | 1.00 | 0.74 | 0.74 | IRS | 0.46 | 0.37 | 0.46 | 0.27 |
| 115 | 0.80 | 0.80 | 0.99 | IRS | 0.48 | 0.45 | 0.38 | 0.36 |
| 116 | 0.67 | 0.52 | 0.77 | IRS | 0.59 | 0.56 | 0.39 | 0.29 |
| 117 | 0.83 | 0.64 | 0.77 | IRS | 0.53 | 0.51 | 0.44 | 0.33 |
| 118 | 0.78 | 0.61 | 0.79 | IRS | 0.51 | 0.46 | 0.40 | 0.28 |
| 119 | 1.00 | 1.00 | 1.00 | CRS | 0.61 | 0.61 | 0.61 | 0.61 |
| 120 | 1.00 | 0.29 | 0.29 | IRS | 0.45 | 0.42 | 0.45 | 0.12 |
| 121 | 0.78 | 0.28 | 0.36 | IRS | 0.45 | 0.55 | 0.35 | 0.15 |

**Appendix 4. Input Oriented Technical, Allocative, Cost and Scale Efficiency Estimates: SFA**

| Farmer | TE-VRS | TE-CRS | AE-VRS | AE-CRS | CE-VRS | CE-CRS |
|---|---|---|---|---|---|---|
| 1 | 0.79 | 0.81 | 0.35 | 0.38 | 0.28 | 0.31 |
| 2 | 0.86 | 0.86 | 0.21 | 0.23 | 0.18 | 0.2 |
| 3 | 0.66 | 0.7 | 0.18 | 0.21 | 0.12 | 0.14 |
| 4 | 0.67 | 0.71 | 0.23 | 0.26 | 0.16 | 0.18 |
| 5 | 0.92 | 0.93 | 0.21 | 0.23 | 0.2 | 0.22 |
| 6 | 0.66 | 0.69 | 0.2 | 0.23 | 0.13 | 0.16 |
| 7 | 0.85 | 0.86 | 0.22 | 0.25 | 0.19 | 0.21 |
| 8 | 0.63 | 0.66 | 0.3 | 0.33 | 0.19 | 0.22 |
| 9 | 0.8 | 0.8 | 0.19 | 0.21 | 0.15 | 0.17 |
| 10 | 0.81 | 0.82 | 0.18 | 0.2 | 0.15 | 0.17 |
| 11 | 0.55 | 0.58 | 0.35 | 0.38 | 0.19 | 0.22 |
| 12 | 0.85 | 0.86 | 0.3 | 0.33 | 0.25 | 0.28 |
| 13 | 0.87 | 0.87 | 0.25 | 0.28 | 0.22 | 0.24 |
| 14 | 0.63 | 0.66 | 0.23 | 0.26 | 0.15 | 0.17 |
| 15 | 0.77 | 0.79 | 0.24 | 0.27 | 0.18 | 0.21 |
| 16 | 0.75 | 0.78 | 0.11 | 0.12 | 0.08 | 0.09 |
| 17 | 0.79 | 0.8 | 0.22 | 0.24 | 0.17 | 0.19 |
| 18 | 0.84 | 0.85 | 0.26 | 0.28 | 0.22 | 0.24 |
| 19 | 0.88 | 0.88 | 0.17 | 0.2 | 0.15 | 0.17 |
| 20 | 0.86 | 0.86 | 0.24 | 0.27 | 0.21 | 0.23 |
| 21 | 0.87 | 0.88 | 0.21 | 0.23 | 0.18 | 0.2 |
| 22 | 0.84 | 0.85 | 0.32 | 0.35 | 0.27 | 0.3 |
| 23 | 0.87 | 0.87 | 0.27 | 0.3 | 0.23 | 0.26 |
| 24 | 0.84 | 0.85 | 0.12 | 0.13 | 0.1 | 0.11 |

| Farmer | TE-VRS | TE-CRS | AE-VRS | AE-CRS | CE-VRS | CE-CRS |
|---|---|---|---|---|---|---|
| 25 | 0.72 | 0.75 | 0.4 | 0.43 | 0.29 | 0.32 |
| 26 | 0.8 | 0.82 | 0.25 | 0.28 | 0.2 | 0.23 |
| 27 | 0.76 | 0.77 | 0.35 | 0.39 | 0.27 | 0.3 |
| 28 | 0.62 | 0.65 | 0.21 | 0.23 | 0.13 | 0.15 |
| 29 | 0.76 | 0.8 | 0.35 | 0.38 | 0.26 | 0.3 |
| 30 | 0.55 | 0.58 | 0.53 | 0.57 | 0.29 | 0.33 |
| 31 | 0.85 | 0.85 | 0.29 | 0.32 | 0.25 | 0.27 |
| 32 | 0.88 | 0.88 | 0.37 | 0.4 | 0.32 | 0.36 |
| 33 | 0.45 | 0.48 | 0.16 | 0.18 | 0.07 | 0.09 |
| 34 | 0.6 | 0.63 | 0.3 | 0.33 | 0.18 | 0.21 |
| 35 | 0.89 | 0.9 | 0.22 | 0.24 | 0.19 | 0.22 |
| 36 | 0.92 | 0.92 | 0.42 | 0.46 | 0.39 | 0.42 |
| 37 | 0.63 | 0.66 | 0.31 | 0.34 | 0.2 | 0.23 |
| 38 | 0.74 | 0.75 | 0.18 | 0.2 | 0.14 | 0.15 |
| 39 | 0.63 | 0.65 | 0.28 | 0.31 | 0.18 | 0.2 |
| 40 | 0.51 | 0.54 | 0.27 | 0.3 | 0.14 | 0.16 |
| 41 | 0.94 | 0.94 | 0.27 | 0.3 | 0.25 | 0.28 |
| 42 | 0.69 | 0.72 | 0.27 | 0.29 | 0.18 | 0.21 |
| 43 | 0.86 | 0.86 | 0.27 | 0.3 | 0.23 | 0.25 |
| 44 | 0.92 | 0.92 | 0.22 | 0.24 | 0.2 | 0.22 |
| 45 | 0.84 | 0.86 | 0.29 | 0.32 | 0.24 | 0.27 |
| 46 | 0.9 | 0.9 | 0.32 | 0.35 | 0.29 | 0.31 |
| 47 | 0.76 | 0.78 | 0.52 | 0.56 | 0.4 | 0.44 |
| 48 | 0.89 | 0.9 | 0.19 | 0.21 | 0.17 | 0.19 |
| 49 | 0.84 | 0.86 | 0.34 | 0.37 | 0.29 | 0.32 |
| 50 | 0.56 | 0.6 | 0.29 | 0.32 | 0.16 | 0.19 |

| Farmer | TE-VRS | TE-CRS | AE-VRS | AE-CRS | CE-VRS | CE-CRS |
|---|---|---|---|---|---|---|
| 51 | 0.68 | 0.71 | 0.14 | 0.15 | 0.09 | 0.11 |
| 52 | 0.87 | 0.88 | 0.17 | 0.19 | 0.15 | 0.17 |
| 53 | 0.68 | 0.71 | 0.42 | 0.45 | 0.28 | 0.32 |
| 54 | 0.55 | 0.58 | 0.21 | 0.24 | 0.12 | 0.14 |
| 55 | 0.78 | 0.8 | 0.19 | 0.21 | 0.15 | 0.17 |
| 56 | 0.9 | 0.9 | 0.34 | 0.37 | 0.31 | 0.33 |
| 57 | 0.88 | 0.88 | 0.31 | 0.34 | 0.27 | 0.3 |
| 58 | 0.75 | 0.77 | 0.38 | 0.41 | 0.28 | 0.31 |
| 59 | 0.75 | 0.76 | 0.31 | 0.34 | 0.24 | 0.26 |
| 60 | 0.79 | 0.8 | 0.23 | 0.26 | 0.18 | 0.2 |
| 61 | 0.75 | 0.77 | 0.19 | 0.21 | 0.15 | 0.17 |
| 62 | 0.69 | 0.72 | 0.26 | 0.29 | 0.18 | 0.21 |
| 63 | 0.77 | 0.78 | 0.37 | 0.41 | 0.29 | 0.32 |
| 64 | 0.79 | 0.81 | 0.26 | 0.28 | 0.2 | 0.23 |
| 65 | 0.87 | 0.87 | 0.44 | 0.47 | 0.38 | 0.41 |
| 66 | 0.84 | 0.84 | 0.47 | 0.51 | 0.39 | 0.43 |
| 67 | 0.77 | 0.79 | 0.24 | 0.26 | 0.18 | 0.21 |
| 68 | 0.91 | 0.91 | 0.28 | 0.31 | 0.26 | 0.28 |
| 69 | 0.56 | 0.6 | 0.23 | 0.26 | 0.13 | 0.15 |
| 70 | 0.91 | 0.91 | 0.36 | 0.39 | 0.32 | 0.35 |
| 71 | 0.84 | 0.85 | 0.37 | 0.4 | 0.31 | 0.34 |
| 72 | 0.85 | 0.85 | 0.3 | 0.33 | 0.25 | 0.28 |
| 73 | 0.82 | 0.83 | 0.2 | 0.22 | 0.16 | 0.19 |
| 74 | 0.74 | 0.78 | 0.17 | 0.19 | 0.12 | 0.14 |
| 75 | 0.61 | 0.65 | 0.22 | 0.24 | 0.13 | 0.16 |
| 76 | 0.84 | 0.85 | 0.41 | 0.45 | 0.35 | 0.38 |

| Farmer | TE-VRS | TE-CRS | AE-VRS | AE-CRS | CE-VRS | CE-CRS |
|---|---|---|---|---|---|---|
| 77 | 0.84 | 0.85 | 0.2 | 0.22 | 0.16 | 0.19 |
| 78 | 0.83 | 0.83 | 0.25 | 0.28 | 0.21 | 0.23 |
| 79 | 0.83 | 0.83 | 0.4 | 0.44 | 0.33 | 0.36 |
| 80 | 0.72 | 0.74 | 0.38 | 0.42 | 0.28 | 0.31 |
| 81 | 0.84 | 0.85 | 0.23 | 0.26 | 0.2 | 0.22 |
| 82 | 0.75 | 0.77 | 0.24 | 0.27 | 0.18 | 0.21 |
| 83 | 0.82 | 0.83 | 0.18 | 0.2 | 0.15 | 0.17 |
| 84 | 0.82 | 0.83 | 0.34 | 0.37 | 0.28 | 0.31 |
| 85 | 0.88 | 0.88 | 0.14 | 0.15 | 0.12 | 0.13 |
| 86 | 0.91 | 0.92 | 0.18 | 0.2 | 0.17 | 0.19 |
| 87 | 0.67 | 0.69 | 0.34 | 0.37 | 0.22 | 0.25 |
| 88 | 0.86 | 0.86 | 0.4 | 0.44 | 0.34 | 0.38 |
| 89 | 0.81 | 0.82 | 0.22 | 0.24 | 0.18 | 0.2 |
| 90 | 0.79 | 0.81 | 0.27 | 0.29 | 0.21 | 0.24 |
| 91 | 0.88 | 0.88 | 0.41 | 0.45 | 0.36 | 0.39 |
| 92 | 0.73 | 0.75 | 0.3 | 0.33 | 0.22 | 0.25 |
| 93 | 0.9 | 0.9 | 0.2 | 0.22 | 0.18 | 0.2 |
| 94 | 0.79 | 0.81 | 0.27 | 0.3 | 0.22 | 0.24 |
| 95 | 0.85 | 0.85 | 0.23 | 0.25 | 0.19 | 0.21 |
| 96 | 0.84 | 0.84 | 0.3 | 0.32 | 0.25 | 0.27 |
| 97 | 0.82 | 0.83 | 0.19 | 0.22 | 0.16 | 0.18 |
| 98 | 0.8 | 0.8 | 0.23 | 0.25 | 0.18 | 0.2 |
| 99 | 0.79 | 0.81 | 0.18 | 0.2 | 0.14 | 0.16 |
| 100 | 0.68 | 0.71 | 0.21 | 0.23 | 0.14 | 0.16 |
| 101 | 0.8 | 0.81 | 0.3 | 0.33 | 0.24 | 0.27 |
| 102 | 0.7 | 0.73 | 0.32 | 0.35 | 0.23 | 0.25 |

| Farmer | TE-VRS | TE-CRS | AE-VRS | AE-CRS | CE-VRS | CE-CRS |
|---|---|---|---|---|---|---|
| 103 | 0.6 | 0.63 | 0.38 | 0.41 | 0.23 | 0.26 |
| 104 | 0.67 | 0.69 | 0.28 | 0.31 | 0.19 | 0.21 |
| 105 | 0.79 | 0.81 | 0.22 | 0.24 | 0.17 | 0.2 |
| 106 | 0.83 | 0.84 | 0.28 | 0.31 | 0.23 | 0.26 |
| 107 | 0.83 | 0.83 | 0.37 | 0.4 | 0.31 | 0.34 |
| 108 | 0.85 | 0.85 | 0.41 | 0.45 | 0.35 | 0.38 |
| 109 | 0.69 | 0.71 | 0.38 | 0.42 | 0.27 | 0.3 |
| 110 | 0.53 | 0.56 | 0.39 | 0.42 | 0.21 | 0.24 |
| 111 | 0.87 | 0.88 | 0.19 | 0.21 | 0.17 | 0.19 |
| 112 | 0.8 | 0.83 | 0.14 | 0.15 | 0.11 | 0.13 |
| 113 | 0.85 | 0.85 | 0.28 | 0.31 | 0.24 | 0.26 |
| 114 | 0.68 | 0.72 | 0.22 | 0.25 | 0.15 | 0.18 |
| 115 | 0.89 | 0.89 | 0.18 | 0.2 | 0.16 | 0.18 |
| 116 | 0.67 | 0.7 | 0.25 | 0.28 | 0.17 | 0.2 |
| 117 | 0.81 | 0.83 | 0.15 | 0.17 | 0.12 | 0.14 |
| 118 | 0.76 | 0.78 | 0.22 | 0.25 | 0.17 | 0.19 |
| 119 | 0.95 | 0.95 | 0.14 | 0.16 | 0.13 | 0.15 |
| 120 | 0.4 | 0.43 | 0.24 | 0.27 | 0.1 | 0.12 |
| 121 | 0.46 | 0.5 | 0.13 | 0.15 | 0.06 | 0.07 |