

CUKUROVA UNIVERSITY
INSTITUTE OF NATURAL AND APPLIED SCIENCES

PhD THESIS

**Cereal Production in Benin in a View of Climate Change and
Energy Use**

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Department of Agricultural Economics

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CONTENTS

ABSTRACT.....	I
ÖZ	II
GENİŞLETİLMİŞ ÖZET	III
ACKNOWLEDGEMENTS	VII
LIST OF TABLES	VIII
LIST OF FIGURES	IX
SYMBOLS AND ABBREVIATIONS	X
1. INTRODUCTION	1
2. PRELIMINARY WORK	5
3. MATERIAL AND METHOD	12
3.1. Study area.....	12
3.2 Analysis of the economic impact of climatic variations	13
3.2.1 Data used	13
3.2.2 Analysis method.....	14
3.3 Energy management analysis.....	19
3.3.1 Data used	19
3.3.2 Analysis method.....	20
4. RESULTS AND DISCUSSIONS	24
4.1. Time series of climatic parameters and volume of maize production in Benin	24
4.1.1 Evolution of climatic parameters	24
4.1.2. Evolution of atmospheric pollutants.....	26
4.1.3. Evolution of population density	28
4.1.4. Volume of production, area sown, and quantities of fertilizers used.	29
4.1.5. Significance of time series for maize production volume	30
4.2.2 Short-term effects of climatic and social factors through the error correction model (ECM)	32
4.2.3 Post-estimate diagnostics of the estimated error correction model (ECM).....	35
4.2 Prediction of maize production volume under the influence of climatic parameters.....	36
4.4 Structuring based on surface area	39
4.4.1 Area planted by farmers	39
4.4.2 Gender	40
4.4.3 Socio-cultural groups (ethnicity).....	41
4.4.4. Religion	41
4.4.5. Land tenure.....	42
4.4.6 Marital status	43

4.4.7 Membership of a producers' organization	43
4.4.8 Literacy (local language).....	44
4.4.9 Education level.....	44
4.4.10 Contact with a suitable structure	45
4.4.11 Main activity	46
4.4.12 Secondary activity	46
4.4.13 Access to credit	48
4.4.14 Breakdown of farmers by age (%)	48
4.4.15 Breakdown of producers by household size.....	50
4.4.16 Distribution of producers by number of farm assets (%)	52
4.4.17 Distribution of farmers by length of time in maize production.....	53
4.5. Analysis of energy source management methods	53
4.5.1. Manifestation and implications of climate change	53
4.5.2. Analysis of energy used	56
4.5.3. Comparison of energy from labor and agricultural inputs	61
4.5.4 Main management methods.....	62
4.6. Influence of management style on farm performance.....	63
4.6.1. Producer efficiency index.....	63
4.6.2. Comparative analysis of efficiency indices according to management modes	66
4.6.3. Determinants of farmer efficiency	67
4.7. Analysis of management constraints.....	70
4.7.1. Typology of constraints.....	70
4.7.2. Hierarchy of constraints	73
4.8. General discussion	75
4.8.1. Economic impact of climatic variations.....	75
4.8.2. Energy management approach	76
5. CONCLUSIONS.....	80
REFERENCES	82
CURRICULUM VITAE	96
APPENDICES	97
Appendice 1: ARDL and ARIMA models.....	98

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ABSTRACT

Climate change has become a critical issue affecting every country in the world, including Benin. The results of this scourge pose a serious threat to household food security. Given that maize is a staple cereal in Benin, this research aims to assess the impact of climate change on maize production, with a parallel focus on the efficiency of energy allocation methods used by producers in a context of climate change. To achieve this objective, both primary and secondary data were collected. Secondary data focused on climatic parameters, demographic factors, fertilizer application levels and emissions of environmental pollutants. Analysis of the ARDL and ARIMA models allow us to conclude that CO₂ and CH₄ emissions from food waste, temperature peaks, rainfall patterns and rural population density exert a significant influence on maize production volumes. Primary data collected from a sample of maize farmers focused on production data, the amount of energy allocated to production in the context of climate change, and the ways in which these energy sources are managed. Analysis of the data showed that, in order to limit the impact of climate change on maize production, farmers opted either for intensification of inputs or for an increase in labor. Moreover, according to the DEA and Tobit models carried out, the efficiency of these models is defined by the socio-economic characteristics of the producers, as well as by the quantities of inputs used in production. In the light of these results, policy frameworks aimed at limiting activities producing high levels of air pollutants, as well as regulating the excessive application of agricultural fertilizers, should be formulated to improve the efficiency of maize farmers.

Keywords: Cereal production, Climate change, Benin, Energy use, ARDL

İklim Değişikliği ve Enerji Kullanımı Bakımından Benin'de Tahıl Üretimi

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ÖZ

İklim değişikliği, Benin dahil dünyadaki her ülkeyi etkileyen kritik bir sorun haline gelmiştir. Bu sorun hane halklarının gıda güvenliğine ciddi tehditler oluşturuyor. Mısırın Benin’de temel bir tahıl olması göz önüne alındığında, bu araştırma iklim değişikliğinin mısır üretimine etkisini ve üreticilerin iklim değişikliği bağlamında kullandığı enerji tahsis yöntemlerinin verimliliğini değerlendirmeyi amaçlamaktadır. Bu hedefe ulaşmak için hem birincil hem de ikincil veriler toplandı. İkincil veriler iklim parametreleri, demografik faktörler, gübre uygulama düzeyleri ve çevresel kirleticilerin emisyonlarına odaklandı. ARDL ve ARIMA modellerinin analiz sonuçları, gıda atıklarından kaynaklanan CO₂ ve CH₄ emisyonlarının, sıcaklık piklerinin, yağış düzenlerinin ve kırsal nüfus yoğunluğunun mısır üretim miktarı üzerinde önemli bir etkiye sahip olduğunu ortaya koymuştur. Seçilen 230 mısır üreticisinden anketle toplanan birincil veriler, üretim verileri, iklim değişikliği bağlamında üretime tahsis edilen enerji miktarı ve bu enerji kaynaklarının nasıl yönetildiği gibi konulara odaklanmıştır. Verilerin analizi ile iklim değişikliğinin mısır üretimine olumsuz etkisini sınırlamak için üreticilerin ya girdi kullanımını yoğunlaştırdığı ya da işgücünü artırdığı sonucuna varılmıştır. Ayrıca, yürütülen DEA ve Tobit modellerine göre, bu modellerin etkinliği, üreticilerin sosyo-ekonomik özelliklerinin yanı sıra üretimde kullanılan girdilerin miktarları tarafından belirlenmektedir. Bu sonuçlar ışığında, yüksek seviyede hava kirleticileri üreten faaliyetleri sınırlamayı ve tarımsal gübrelerin aşırı kullanımını düzenlemeyi amaçlayan politika çerçevelerinin mısır üreticilerinin verimliliğini artırmak için oluşturulması gerekmektedir.

Anahtar Kelimeler: Tahıl üretimi, İklim değişikliği, Benin, Enerji kullanımı, ARDL

GENİŞLETİLMİŞ ÖZET

İklim değişikliğinden kaynaklanan tehlikelerinin gelecek yüzyıl boyunca dünyanın birçok yerinde, özellikle gelişmekte olan ülkelerde ve daha az finansal kaynağa sahip olanlarda artacağı öngörülmektedir. Afrika, özellikle Batı Afrika, iklim değişikliğinin etkilerine son derece duyarlı bir bölge olarak tanımlanmıştır. Bu çalışmanın genel amacı, Benin’de iklim değişikliği bağlamında tahıl üretiminde enerji kaynaklarının kullanımını daha iyi anlamaya katkıda bulunmaktır. Daha özel olarak bu çalışma, iklim değişikliğinin mısır üretimine ekonomik etkisini değerlendirmekte, iklim değişikliğine uyum bağlamında üreticilerin enerji kullanımı yöntemlerinin etkinliğini analiz etmekte ve bu uyum stratejilerinin benimsenmesi ile ilgili zorlukları değerlendirmektedir.

Üretim miktarlarına ek olarak, bu çalışmada iklim değişikliğinin mısır üretimine ekonomik etkisini değerlendirmek için çeşitli veriler kullanılmıştır. Bunlar özellikle yağış, minimum sıcaklık, maksimum sıcaklık ve karbondioksit (CO_2), metan (CH_4) ve azot oksit (N_2O) gibi atmosferik kirleticiler gibi iklim parametrelerine ilişkin verilerdir. Bu veriler, Birleşmiş Milletler Gıda ve Tarım Örgütü (FAO) ve Benin’in Fransız Havacılık Güvenlik Ajansı (ASECNA) tarafından 1990-2020 döneminde 30 yıllık bir süre boyunca toplanmıştır. İklim değişikliğinin üretime etkisini analiz etmenin yanı sıra üretim miktarlarını tahmin etmek için ARDL (Ardışık Bağılanımlı Dağıtılmış Gecikme) ve ARIMA (Ardışık Bağılanımlı Bütünleşik Entegre Hareketli Ortalama) modelleri kullanılmıştır.

Bu çalışmanın ilk bölümü, Benin’de mısır üretiminin, gerçekten iklim tehlikelerine maruz kaldığını doğrulamış ve ardından ana parametrelere odaklanmıştır. Farklı yönetim yöntemlerini ve mısır üretimindeki ana enerji kaynaklarını anlamak amacıyla Benin’deki 230 mısır yetiştiricisi ile anketler yapılmıştır. Enerji kullanımının iklim değişikliği bağlamında nasıl yönetildiği verilerine ek olarak, iki tür veri daha toplanmıştır. Bunlar, işgücü ve mısır üretimi için kullanılan tarımsal girdilerle ilgili verilerdir. Enerji eşdeğer katsayıları daha önceki çalışmalardan elde edilen veriler kullanılarak hesaplanmıştır. İşgücü açısından toplanan veriler, esas olarak mısır üretimi için yapılan çeşitli tarımsal faaliyetleri ve işlemleri içermiştir. Tarımsal girdiler olarak kullanılan veriler dikkate alındığında, çalışma her bir yetiştiricinin mısır üretimi için kullandığı kimyasal girdilerin (NPK, herbisit ve insektisit), miktarını içermiştir. Son olarak, mısır üretim sürecinde kullanılan yakıt miktarı da bir üretim girdisi olarak dikkate alınmıştır. Tüm bu faaliyetler, mısır üretimi ile ilişkilendirilen enerji kaynakları olarak kabul edilmiş ve bu faaliyetler, enerji eşdeğer katsayıları kullanılarak tümü enerji değerlerine dönüştürülmüştür. Tüm hesaplamalar, üreticilerin enerji kullanım yöntemlerine dayanmaktadır. Bu enerji kullanım yöntemlerinin etkinliği, DEA (Veri Zarf Analizi) yöntemi kullanılarak belirlenmiş, daha sonra bu modellerin etkinliğini belirleyen parametreler Tobit modelleri kullanılarak belirlenmiştir.

Sonuçlar genel olarak analiz edildiğinde, ulusal düzeyde mevsime bakılmaksızın yağışta bir azalma eğilimi görülmektedir. Bu durum, Benin'in, dünya genelinde ve özellikle Afrika'da diğer ülkeler gibi uzun süredir devam eden bir yağış azalma eğiliminden kaçamadığını göstermektedir. Toplam yağış azalırken, yıllık sıcaklık serilerinin analizi hem maksimum hem de minimum sıcaklıkta bir artış eğilimini göstermektedir. Bu artışlar, küresel bir ısınma eğiliminin bir parçası sayılabilir. Bazı yetiştiricilerin sürekli vurguladığı bir nokta, havanın giderek daha sıcak hale geldiği ve hatta ağaçların gölgesinde bile sıcaklığın dayanılmaz olduğu şeklindedir.

Atmosferik kirleticilerin emisyonu ile ilgili olarak, sonuçlar gıda atıkları ve tarımsal uygulamaların çoğunlukla metan ve azot oksit üretimine katkıda bulunduğunu göstermektedir, enerji kullanımı (özellikle elektrik) ve taşımacılık ise CO₂ salınımının ana kaynaklarını temsil etmektedir. Hem kırsal hem de kentsel nüfusun önemli ölçüde artmasıyla, bu kirleticilerin seviyesi artmaya devam edecek, üretim hacmi ve mısır ekilen alanlar da bugüne kadar önemli ölçüde artmaya devam edecektir.

Buna rağmen, üretim miktarının otokorelasyon fonksiyonu analizi, *t-1* zamanındaki üretim miktarı ile bir sonraki yılın üretimi arasında önemli bir ilişki olduğunu göstermiştir. Bu, üretim yılı boyunca edinilen deneyimin önemine bağlı olabilir. Bu şekilde, üretim yılları boyunca, yetiştiriciler üretim seviyelerini önemli ölçüde artırmalarını sağlayan stratejiler geliştirebilirler. Önceki yıllarda üretim miktarının etkisiyle birlikte, diğer modeller de sıcaklık ve yağışın mısır üretim miktarı üzerinde önemli bir etkisi olduğunu göstermiştir.

Bu iki iklim parametresinin yanı sıra, çalışmada ayrıca, atmosferik kirleticilerden CO₂ ve metan ile mısır üretim miktarı arasında negatif bir ilişki bulunmuştur. Bu mantıklı görünmektedir, çünkü bu kirleticiler toprak asitlik seviyelerini değiştirir ve düşük verimlere ve dolayısıyla üretim miktarlarına neden olur. Gecikme (DL) modeli, kırsal nüfus yoğunluğunun mısır üretim miktarı üzerinde önemli ve negatif bir etkisinin olduğunu göstermiştir. Ancak, tahminler önümüzdeki on ila otuz yıl boyunca mısır üretim miktarında sürekli bir artış öngörmektedir. Bu sonuçlar, Benin Tarım Bakanlığı'nın tahminlerini de doğrulamaktadır; Benin'in çeşitli agro-ekolojik bölgelerinde mısır üretim verimlerinin 2025'e kadar artacağı öngörülmektedir. Mısır üretim miktarının artacağına dair bu tahminler, bazılarının en verimli kesim olarak kabul ettiği kırsal nüfus yoğunluğunun artmasına da bağlanabilir. Dahası, tarımsal ürünlerin miktarında öngörülen artış, kırsal nüfusun miktarında öngörülen artışla güçlü bir şekilde ilişkilidir.

Yapılan anketler, yetiştiriciler arasında iklim değişikliği konusunda yüksek bir farkındalık seviyesinin olduğunu ortaya koymuştur. Anket yapılan katılımcıların %98'inden fazlası iklim değişikliği belirtilerinin biraz farkında olduklarını iddia etmiştir. Bu oran, etkili adaptif yönetim için yerel farkındalığın ve iklim değişikliğinin anlaşılmasının önemini vurgulamaktadır. Gözlemlenen ana değişiklikler; özellikle yağış rejimi bozuklukları, gecikmeler, erken sona erme ve yağışın kötü dağılımı olarak ifade edilmiştir. Ayrıca, artan sıcaklıklar ve sel gibi aşırı iklim olaylarının gerçekleştiği de gözlemlenmiştir.

İklim değışiklięi sonuçlarına gelince, su yetersizlięi ve ani sıcaklık değışimleri en sık bahsedilenlerdir. Artan sıcaklıklar, özellikle azalan yağışlarla birlikte, mısır gibi ürünlerin verimlerinde önemli bir etkiye sahiptir. Gecikmiş yağışlar, ürünlerin ekim tarihlerini etkilemekte ve ürün veriminin düşmesine neden olmakta, çiftçilerin özel adaptasyon yöntemlerini geliştirmeye zorlamaktadır.

Bu durumla başa çıkmak için, anket yapılan tüm yetiştiriciler kaynak yönetimine dayanan adaptasyon stratejileri geliştirmiştir. Mısır yetiştiricileri genellikle iki farklı kaynak yönetimi yaklaşımı kullanır. Bazıları kimyasal gübreler, insektisitler ve pestisitler gibi tarımsal girdilerin yoğunlaştırılmasını tercih ederken, diğerleri mekanik ve hayvansal çeki dahil olmak üzere işgücünün artırılmasını tercih eder. Bu seçimler, iklim zorluklarıyla başa çıkmak için benimsenen stratejilerin çeşitliliğini yansıtır ve çiftçilerin aldığı yönetim kararlarının karmaşıklığını vurgular. Tarımsal girdilerin yoğunlaştırılması, iklim değışiklięinin negatif etkilerini azaltmayı amaçlayan giderek daha yaygın olarak benimsenen bir uyum modu olarak birçok çalışmada sıkça bahsedilmiştir. İşgücünün artırılmasına yönelik yönetim yaklaşımının yüksek benimsenme oranına gelince, bu, özellikle Batı Afrika, Benin dahil olmak üzere bazı ülkelerde, çeki hayvanların tanıtılması çabalarının başarılı olduğunu ve mısır üreticilerinin kaynak yönetimi seçimlerini etkilediğini gösterir.

Ancak, çoęu çiftçi işgücünün artırılmasını tercih etse de bu, mısır işletmelerinde en fazla enerji yoğun yönetim biçimi olduęu anlamına gelmez. Aslında, bu üretilen enerji miktarı açısından girdi kullanımının belirgin bir üstünlüęe sahip olduęu gözlemlenmiştir. Sonuçlar, neredeyse tüm enerji tüketiminin tarımsal girdilerin kullanımından geldiğini göstermektedir. Elde edilen sonuçlar, mevcut iklim değışiklięi zorluklarına daha iyi uyum sağlamak için girdilere (tohumlar, kimyasal gübreler vb.) odaklanan yaklaşımlara doęru, bir paradigma değışiklięini yansıtmaktadır. Bu geçiş, iklim değışiklięi bağlamında enerji tüketiminin dağılımını etkiler.

Bu tarımsal girdiler arasında, kimyasal gübrenin (NPK) yoğun kullanımı daha yüksek enerji tüketimine neden olur. Bu gözlem, yoğun gübreleme tercihinin özellikle kompoze gübrenin sık kullanımı ile özdeşleştirdiğini, bu eğilimin tarımsal uygulamalardaki merkezi rolünü gösterir. Bu sonuçlar, kuzey Benin'deki çiftçilerin diğer araştırmacıların da belirttięi gibi, tarımsal girdiler açısından, kompoze gübrenin (NPK) daha yaygın olarak kullanıldığını, bunu ürenin takip ettiğini göstermektedir.

Verimlilik açısından sonuçlar, girdi kullanım stratejisinin, üretim kaynaklarını ve mısır üretimini daha iyi optimize ettiğini ve işgücünün artırılması stratejisinin önünde geldiğini göstermektedir. Bu sonuçlar, mısır işletmelerinin iklim baskıları karşısında dayanıklılıęını ve sürdürülebilirliğini güçlendirmek için girdi kullanımını yoğunlaştırma stratejisinin daha tutarlı ve potansiyel olarak kârlı bir çözüm olduęu sonucuna varılmıştır. Bunun yanında, tarımsal girdilerle birlikte, diğer ülkelerde yapılan araştırmalar, işgücünün artırılmasına odaklanan bir yönetim

yaklaşımının teknik verimlilik üzerinde önemli bir etkisinin olmadığını belirtmiştir. Bu, işgücünün artırılmasına odaklanan bir yönetim yaklaşımının düşük etkisini ortaya koymaktadır.

Yönetim stratejileri ne olursa olsun, yetiştiriciler değişken ölçek verimliliğinde yüksek bir etkinlik göstermektedir, ortalama endeks %96'nın üzerindedir. Bu iki kaynak yönetim stratejisinin etkinliğinin belirleyicileri; yaş, deneyim, ekilen alan ve tarımsal girdi kullanımı gibi faktörler stratejik önemde bulunmuştur. Bu farklı faktörlerin etkisinin pozitif olduğu gözlemlenmiştir. Genel bir eğilim olarak; yaşlı çiftçilerin genellikle mısır üretim miktarlarını artırma eğiliminde oldukları, deneyimli çiftçilerin mısır üretim miktarlarını artırma olasılığının daha yüksek olduğu, mısır üretim miktarının artan arazinin büyüklüğü ve tarımsal girdilerin kullanımı ile arttığı gözlemlenmiştir.

Yukarıdaki sonuçlar, tarımsal girdi yoğunlaştırma stratejisinin, işgücünün artırılması stratejisinden daha iyi bir uyum stratejisi olduğunu düşündürmektedir. Bununla birlikte, bu sonuçların kısmen farklı üretim miktarlarına dayanmasına rağmen, tarımsal girdi yoğunlaştırma stratejisi, en etkin adaptif strateji olarak öne çıkmaktadır.

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LIST OF TABLES

Table 1. Summary table of variables used for the model.....	17
Table 2. Standard energy equivalent of production inputs.....	20
Table 3. Description of variables used in the Tobit model	23
Table 4. Stationarity test of the different variables studied.....	32
Table 5. Estimation of short-term effects.....	34
Table 6. Long-term effects of climatic factors on production volume.....	35
Table 7. Results of short-term model diagnostic tests	35
Table 8. Average area of farmers by group.....	40
Table 9. Distribution of producers by gender	40
Table 10. Distribution of producers by socio-cultural group.....	41
Table 11. Distribution of producers by religion.....	42
Table 12. Distribution of producers by land tenure method	42
Table 13. Distribution of producers by marital status.....	43
Table 14. Distribution of producers by PO membership	44
Table 15. Distribution of producers by literacy level.....	44
Table 16. Distribution of producers by level of education.....	45
Table 17. Distribution of producers according to contact with a specialized structure	45
Table 18. Distribution of producers according to their main activities.....	46
Table 19. Distribution of producers according to secondary activities.....	47
Table 20. Distribution of producers according to access to credit	48
Table 21. Distribution of farmers by age group	49
Table 22. Distribution of producers by household size.....	51
Table 23. Distribution of producers by number of farm workers	52
Table 24. Distribution of producers according to seniority	53
Table 25. Maize farmers' perceptions of climate change	55
Table 26. Breakdown of energy requirements by farming activity.....	57
Table 27. Breakdown of energy expenditure on agricultural and production inputs	60
Table 28. Change management methods and adoption times by the producers.....	63
Table 29. Distribution of effectiveness levels by adaptation strategy.....	65
Table 30. Determinants of maize farmers' efficiency	69
Table 30. Determinants of maize farmers' efficiency (devamı)	70
Table 31. Hierarchy of constraints according to the management methods	74

LIST OF FIGURES

Figure 1. Map of the study area (Benin)	13
Figure 2. Summary diagram of the autoregressive and distributed lag models	15
Figure 3 . Evolution of total rainfall over time according to the seasons.....	25
Figure 4. Evolution of the maximum and minimum temperature	26
Figure 5. Air pollutant emissions by production source	28
Figure 6. Chronological evolution of population density from 1990 to 2020.....	29
Figure 7. Maize production volume over time, area and amount of fertilizer used	30
Figure 8. Autocorrelation at the level of maize production volume	31
Figure 9. Autocorrelation of residuals and normality test.....	36
Figure 10. Predicted explanatory parameter values from ARIMA	38
Figure 11. Predictions of maize production volume for the next ten years.....	39
Figure 12. Comparison of average energy requirements by agricultural activity	58
Figure 13. Comparison of energy quantities from input use.....	61
Figure 14. Comparative analysis of average total energies.....	62
Figure 15. Comparison of average efficiency indices by management mode.....	67
Figure 16. Typology of management constraints.....	72

SYMBOLS AND ABBREVIATIONS

ADF	: Augmented Dickey-Fuller
APSIM	: Agricultural Production Systems Simulator
ARDL	: Autoregressive Distributed Lag
ARIMA	: Auto Regressive Integrated Moving Average
CCR	: Charnes-Cooper-Rhodes
CRS	: Constant Returns to Scale
DEA	: Data Envelopment Analysis
DEAP	: Data Envelopment Analysis Programming
ECM	: Error Correction model
FAO	: Food and Agriculture Organization
HadCM3	: Hadley Center Coupled Model version 3
IPCC	: Intergovernmental Panel on Climate Change
KPSS	: Kwiatkowski-Phillips-Schmidt-Shin
PP	: Phillips-Perron
PSDSA	: Strategic Plan for the Development of the Agricultural Sector
RMSE	: Root Square Error
SFA	: Stochastic Frontier Analysis
SRES	: Special Report on Emissions Scenarios
WFP	: World Food Program

1. INTRODUCTION

Promoting the agricultural sector is a major factor in the socio-economic development of the world's intertropical regions, and Benin in particular (FAO, 2014; Miassi *et al.*, 2023). As a result, it is at the heart of strategies to reduce poverty and food security in most developing countries (Jama and Gonzalo, 2008). In Benin, agriculture accounts for over 85% of the country's official export earnings. It contributes around 36% to national GDP and provides employment for almost 75% of the working population (MAEP, 2010).

Particularly in northern Benin, agriculture remains the primary activity, most practiced by the population to satisfy all their food and socio-economic needs. According to the World Bank 2024 results, the agricultural sector occupies a large place in the economic activity sectors mainly in rural areas. However, in most of the regions, this sector faces several difficulties and the most important is related to soil degradation and climate change over the last three decades (IPCC, 2021). Climate change is manifested by an upward trend in the average temperature rate, a very wide variation in rainfall and an increase in the occurrence of extreme conditions such as flooding disasters, droughts, cyclones, tsunamis and so on. Overall, the earth has warmed by up to 0.76°C over the last century. These temperatures vary from 1.5 to 2°C depending on the zone, and the amount of rainfall varies from 10 to 20% (MAEP, 2020).

Soil degradation, which has led to gradual mining of agricultural land, has resulted in the destruction of soils and ecosystems in chemical, physical and biological terms (Floquet and Mongbo, 1998). As a result, there has been a significant drop in agricultural yields, leading to poverty and poor-quality food for the population, as well as degradation of natural ecosystems (Egah *et al.*, 2014). As for the effects of climate change, numerous studies have been carried out on the impact of climate change on cereal production in the sub-region and around the world, as in the case of Béja, a region in north-west Tunisia. Benin is facing climate change affecting many areas, including agriculture (DGEC, 2022). The current and potential impact of climate variability and change reflects the current climate facing West Africa as a whole, and Benin in particular. This climate is subject to major changes, amplified by natural and anthropogenic factors, both regional and local. Thus, the climates of West Africa and Benin are subject to great variability or modification according to time and analysis scales, the consequences of which remain harmful to long-term development (UNDP, 2019). In the agricultural sector, these impacts include changes to the agricultural sector's timetable, lower agricultural yields, disruptions to fishing and aquaculture activities, a significant reduction in the size of livestock, and so on. A projection of these impacts considering the reference situation (1981-2010) indicates, for example, a drop in yields of the EVDT maize variety of 16.7% and 8.9% respectively by 2030 and 2050. Cowpea yields, for example, would fall by 26.7% in 2030 and 26.1% in 2050 (UNDP, 2019). Contrary to these forecasts, Benin's agricultural sector is making progress in terms of production, despite the climatic

variability observed in 2020: rainfall of 980 mm in 53 days, compared with 1225 mm in 2019 (MAEP, 2020). All this has had a negative impact on producers' efforts, resulting in varying levels of production for different crops compared with 2019. However, this has not prevented a jump in production. Cereal production rose from 2,177,787 tonnes in 2019 to 2,203,105 tonnes in 2020, an increase of 1.2%. Unfortunately, the production volume decrease in 2022 (2,059,254 tonnes). In terms of industrial crops, cotton production set a record in Africa, rising from 714,714 tonnes in 2019 to 731,073 tonnes in 2020, an increase of 2.3%; cashew nut production rose from 130,276 tonnes in 2019 to 137,926 tonnes in 2020, an increase of 6%; pineapple production reached 362,964 tonnes in 2020, an increase of 3.6%. The same applies to animal and fish production (MAEP, 2020). Unlike legumes, their production remains unchanged at 586,470 tonnes in 2020. Tuber and root production has fallen from 7,955,450 tonnes in 2019 to 7,370,731 tonnes in 2020. The same applies to market garden production, which fell from 706,346 tonnes in 2019 to 634,167 tonnes in 2020. There has therefore been progress in several areas of production, but the results are still unsatisfactory considering the objectives set by sector in the Government's Action Program and the achievement of the SDGs, notably in its indicator "Eliminate hunger, ensure food security, improve nutrition and promote sustainable agriculture" by 2030 (MAEP, 2020).

Faced with these changes, and to familiarize themselves with the effects of climate change, producers of both cereals and tubers are turning to the use of certain energy sources in their production. Sometimes, these strategies and techniques are endogenous or introduced into the community by rural support structures. In the northern part of Benin, several endogenous management practices for soil fertilization, and other practices that respond to environmental constraints, have been adopted by various environmental protection programs and projects to pool efforts in the fight for sustainable land management (Teteli et al., 2022; Yabi et al., 2016). These include agroforestry and erosion control practices. Conservation agriculture with trees in the precise sense is based on protecting the soil with living or inert plant cover. In Sahelian countries, the possibility of practicing agriculture is at the mercy of this practice associated with certain anti-erosion developments, which therefore remain very important for producers (Bayala et al., 2011).

According to the 1992 United Nations Framework Convention on Climate Change in Rio de Janeiro, these techniques involve the gradual abandonment of fields at the top of the topo sequence; the cultivation of crops just in stream beds; the abandonment of water-demanding and/or long-cycle crops; the practice of mixed cropping on the same plots; and the abandonment of slash-and-burn and fallow farming. Teteli et al., (2022) and Yabi et al. (2016) have identified several agroforestry and anti-erosion practices in the Sudanian zone of Benin, including stone cordon systems, water-blocking bunds, anti-erosion hedgerows, agroforestry parks, etc. Agriculture represents the linking point between the two. Agriculture represents the link between climate change, food insecurity and poverty reduction. For most people living in high poverty and suffering from famine in developing countries, the main source of their income is agriculture. Most cases

observed indicate that people already affected by climate change will see their plight worsen. Agriculture therefore faces challenges such as: producing double the amount of food in developing countries by 2050, considering population growth and changing diets, and helping to reduce greenhouse gases while adapting to climate disruption (IFAD, 2010).

Despite the importance of energy sources in agricultural production, very few studies in Benin have looked at these strategies for adapting to and mitigating climate change. The aim of this study is to assess the impact of using these energy sources in cereal production in the context of climate change in Benin. This study will enable us to discover these energy sources and analyze them to make better use of them.

The general objective of this study is to contribute to a better understanding of the use of energy sources in cereal production in a context of climate change in Benin. This study more specifically:

- Assesses the economic impact of climate change on cereal production,

Numerous datasets were harnessed in this study, notably encompassing climatic factors such as rainfall, minimum temperature, and maximum temperature. Additionally, atmospheric pollutants, including carbon dioxide (CO₂), methane (CH₄), nitrous oxide (N₂O), and the national production volume of maize were examined. ARDL and ARIMA models merge these data by including both past values of the dependent variable and the independent variable in the explanatory variables. The ARDL and ARIMA models merge these data, including the past values of the dependent and independent variables.

- Analyze the effectiveness of energy management methods in adapting to climate change

To understand the different management modes and main energy sources related to maize production, energy equivalent coefficients were calculated based on data from previous studies. In fact, two types of data were collected: data relating to labor and data relating to agricultural inputs used for maize production. To assess technical efficiency, the study used the DEA (Data Envelopment Analysis) method. Indeed, the use of this method is justified by the fact that it is considered more appropriate for expressing the relationship between inputs or between outputs, compared with econometric methods where the choice of variables requires rigorous statistical study.

- Identify the determinants affecting the efficiency of the producers and evaluate the challenges associated with adopting these adaptation strategies.

To identify the main determinants of the efficiency indices obtained through the DEA method, the study used a Tobit-type econometric model for which the three dependent variables (efficiency of constant returns to scale, efficiency of variable returns to scale and scale efficiency). Descriptive statistics were also used to calculate average scores, facilitating identification of the constraints for which the highest scores were recorded. Then, a Kendall W test was applied to reinforce the results of the descriptive statistical analysis, a methodology frequently used in similar studies.



2. PRELIMINARY WORK

The study carried out by Bellia (2003) in Beauce, assessed the impacts of global warming on wheat production. The main aim was to determine the impact of the increase in the greenhouse effect on a winter wheat crop. The data collection considered the average yields stimulated from the soil-atmosphere-crop system model STICS and the climatic data (minimum and maximum temperatures, precipitation, evapotranspiration, radiation, dew point temperature and wind speed) recorded by the stations of Champhol from 1995 to 1997 and Versailles from 1968 to 1997. The climatic data underwent various CO₂ forcings using general circulation models from the Hadley Center and the Dynamic Meteorology Laboratory in France. The results show that the increase in temperature leads to a drop in wheat yield. Similarly, the fertilizing effect of CO₂ reduces the negative impact of temperatures with an increase in yields. We also note that the aerosol presents in the atmosphere, reducing global warming, has a negative effect on wheat yield but contributes to the increase in their variability. The author concluded that the doubling of CO₂ leads to a slight drop in wheat yield in Beauce. It is therefore important to anticipate the various effects of climate change, to minimize the vulnerabilities of agriculture and to assess the risks and competition generated by the agricultural sector vis-à-vis the environment in the face of demography.

Gate et al. (2008) also studied wheat cropping systems in France to analyze the impacts of climate change on production growth and development. The main objective of this study was to estimate the impacts of key climatic factors on wheat physiology, yield components, as well as a quantification of the main climatic risks for wheat production. The methodology consisted of gathering historical weather data from 59 stations in the country from 1955 to 2005. The data was processed from the comparison of two time series which extend respectively over the period from 1955 to 1980 and from 1981 to 2005. The ARVALIS and EARL indices were used as stimulators of the dates of appearance of the main wheat growth stages. It appears from this study that the number of grains per m² was negatively affected through an increase in water content during plant development. Similarly, the weight of harvested wheat is negatively affected through increased drought. The authors proposed adaptation strategies to cope with these climate changes. These are mainly the use of early and tolerant varieties of wheat, the adoption of more suitable growth methods, nitrogen fertilization and the control of lodging.

Ali et al. (2011) analyzed the impact of climate change on the productivity of cereal crops (durum wheat, common wheat and barley) in the region of Beja in northwestern Tunisia. The study took place over the period from 1980 to 2009. Rainfall and temperature data were used to explain the yield. The method of analysis consisted in estimating the regression models on the three cereal crops, those of durum wheat, common wheat and barley. The Hadley Center Coupled Model version 3 (HadCM3) was used to project the impact of the effects of climate change on cereal yield to 2030. The results from this research indicate the yields of the three crops depend on climatic

variables and technical progress. The projections carried out have shown that the impact of the effects of climate change on cereal yields will be very significant by 2030. To do this, new adaptation strategies aimed at reducing the effects of climate change on cereal yield at long-term could include, among other things: the encouragement of research into the identification of new agricultural techniques, the dissemination of varieties tolerant to the decrease in rainfall, during critical periods of growth, and of early varieties.

Tidjani and Akponikpe (2012) assessed producers' strategies for adapting to climate change by taking the case of maize production in northern Benin. The main aim was to determine the most effective and efficient strategies for adapting producers to climate variability and change for maize production in this zone which is very affected by climate change. The method involved using a mathematical crop stimulation model Agricultural Production Systems Simulator (APSIM) to climate, water and nutrient dynamics in the soil. A calibration step was carried out on the historical yields of improved and local varieties from 1995 to 2001 and those from 2002 to 2007 for validation. The Root Square Error (RMSE) comparison index was calculated from the observed and stimulated yields and the mean square of the stimulation errors. It emerges from this study that the real risk scenarios of low yields for all maize varieties in Tanguiéta are those of increased temperatures and decreased rainfall. Based on the peasant methods of adaptation to climate change evaluated, Tidjani and Akponikpè (2012) proposed the adoption of improved maize varieties with a short cycle. They advise against the adoption of late sowing simultaneously for the improved variety and the local maize variety and recommends respecting the normal sowing density to cope with these climatic changes.

The same work was continued by Grami and Rejeb (2015) in the same region and on the same crops using the same method. The period of analysis was from 1990 to 2013. In addition to the yield variables (rainfall, temperature, and technical progress), Grami and Rejeb (2015) added the variable "area sown by crop". After analysis, we note that the yield of production depends on climatic variables, sown area and technical progress. The projection of the effects of climate change on cereal crops has shown that this impact will be more accentuated in the long term. According to them, to adapt and reduce these negative effects it is necessary to take measures such as the encouragement of scientific research to identify a new agricultural technological package adapted to climate change.

Furthermore, Djohy *et al.* (2015) studied the impacts of climatic variations on maize production in the municipality of Parakou. The data considered for this study are rainfall and temperature collected over the period 1995-2012 and area and yield estimates for maize over the period 1965-2012. To this was added the socio-anthropological data from a collection of data carried out on 87 peri-urban households in Parakou following a random sampling. Data processing consisted in using the Lamb index to achieve the distribution of wet years and dry years. Pettitt's, Lee's and Heghinian's tests were performed to detect maximum breakage. However, that of Hubert

made it possible to know if there are several breaks in a chronological series of data. It results from this impact study that there is a unimodal precipitation regime characterized by a rainy season from May to October and a dry season from November to April. The annual frequency of precipitation from 1965 to 2012 shows a trend marked by 51% of surplus years, 2% of average years and 47% of deficit years. Similarly, a temperature increases of 2.4°C was noted. Maize production and yield are negatively affected by the effects of the impact of climate change variation. The authors finally proposed a readjustment of the agricultural calendar considering the perception that producers have of the evolution of the climate towards new balances.

Chourghal (2016), meanwhile, to initiate research on the impact of climate change on the cultivation of durum wheat in Algeria. He chose two representative stations considering the available climate data: one station (Algiers) in the center of the region and the other (Bordj Bou Arreridj) in the east. Climate data were observed in Algiers and Bordj Bou Arreridj respectively from 1978 to 2007 and from 1980 to 2009. The ARPEGE climate model from MétéoFrance, executed according to the Special Report on Emissions Scenarios (SRES) medium A1B, was used to make projections to run an agro-meteorological crop model initially validated with field data. Analyzes show that rainfall will decrease throughout the year and specifically in summer in the Algiers region. However, summer rainfall will increase significantly in the Bordj Bou Arreridj region. Chourghal (2016) predicts an improvement in autumn rainfall, a reduction in the crop cycle and the harvest date will take place rather in the coming climate. He finds that yields will drop in the future in Algiers while in Bordj Bou Arreridj, dynamic sowing will tend to keep yields intact. To adapt to these effects of climate change, he proposes the adoption of early sowing.

Dumrul and Kilicarslan (2017) assessed the economic impacts of climate change on the agricultural sector in Turkey using the Autoregressive Distributed Lag (ARDL) approach. The data collected covered the period from 1961 to 2013 and was related to the country's climate data and its agricultural GDP. The economic effects of climate change on agriculture were analyzed using a time series approach. It appears from the analysis of the information obtained that the increase in rainfall volumes has a positive impact on agricultural GDP, while the increase in temperature has a negative effect on the latter. With a view to minimizing the harmful effects of climate change on agricultural production in Turkey, the authors of this research suggest establishing policies as well as development strategies with a view to combating climate change.

Bougma *et al.* (2018) studied the impact of climate change on millet production in the Sahelian and Sudano-Sahelian zones of Burkina. The main objective of this study was to identify the main climate change indicators related to agriculture and climate as well as climate change indicators perceived by rural producers. A total of 63 rural producers native to the village and aged at least 50 years old were surveyed in 21 villages, including 11 in the Sahelian zone and 10 in the Sudano-Sahelian zone. Meteorological data was collected at five synoptic stations in Burkina from 1980 to 2010. Statistical analysis of the data required the use of Excel software to analyze the

temperature data. The standardized index (ISP) was used to analyze the rainfall data to identify the three types of seasons. The results of this research indicate that producers are aware of the advent of climate change and its manifestations. For them, climate change has a negative impact on agricultural activities, particularly that of millet cultivation, and is characterized by a drop in yield. From this study, it also emerges that producers adopt endogenous resilience strategies such as the use of early varieties, new farming techniques and crop diversification to adapt to climate change.

Ahoyo Adjovi *et al.* (2019) conducted similar work in Benin, more specifically in the commune of Bohicon. The objective this time being to analyze the effects of climatic variation on a few cereals, in particular maize, sorghum, and soybeans, they decided to consider the climatological data for the period 1995-2015 and a few statistical parameters including the area and production yield of these three speculations. The results of this study indicate that crops such as soybeans and sorghum are less dependent on climatic hazards than that of maize in this commune. For this reason, maize producers very often make use of either an intensification of the use of chemical fertilizers, or an extension of cultivated land, or a readjustment of the agricultural calendar. It therefore proposes as a solution approach to direct efforts towards the creation of new resistant and short-cycle varieties to guarantee household food security and secure their income.

Gossiaux (2020) has listed the various studies carried out in recent years on the effects of an increase in temperature on the performance of different economic activities to study the link that ties the economy to the climate, and to analyze the mechanisms by which the increase temperatures affect the growth of countries. In general, it appears from this study that the increase in temperatures above the optimal threshold of 13°C has adverse effects on economic activities. Countries affected by increases in their average annual temperature suffer reductions in their total output and income in many of their heat-unprotected sectors through losses in labor productivity, in the level of total investment, and in total factor productivity, thus leading to slower economic growth in the warmer year. Poor countries will therefore suffer more from the impacts of global warming compared to developed economies located in colder areas due to their geographical location. Macroeconomic inequalities could increase due to the double phenomenon of a slowdown in the growth of poor countries and developing countries, and a probable acceleration of growth in developed countries.

Ajavon *et al.* (2020) conducted studies on the effect of climate change on rice production in the departments of Zou and Collines in Benin. The main objective is to analyze the effects of climate change on rice production in these regions. To achieve this, the various data analyzed were collected at the level of Météo-Benin (MAEP/DSA) and then at the level of the CT-SAGSA. Indeed, for a more reliable result, they considered the data covering the period 1987 to 2016. Thus, the analysis of the data collected consisted initially in subjecting them to a descriptive analysis in Excel and then in econometric modeling following an ARDL approach with Eviews software. The Pesaran Shin and Smith cointegration test shows a proportional evolution between rice production

and climatic factors. This evolution is remarkable in the long term and in the short term. Unlike humidity, which has a negative effect on rice production in the short and long term, rainfall has a remarkable positive effect only in the short term.

Bensbahou and Seyagh (2020) in their article on CO₂ emissions and economic growth in Morocco, addressed the themes of climate change and economic growth. According to them, these two factors have impacts that are changing proportionally every day in the world. The main objective of this research is to assess the effects of economic growth on CO₂ emissions in Morocco. To achieve this, the analysis made is that of ARDL and by considering CO₂ emissions as an indicator to measure the state of the environment. The collected data were subjected to an empirical validity test of the environmental Kuznets curve over the period of 1980-2018, following the autoregressive step-lag model ARDL. The data used for the analysis include, among others: CO₂ emissions (metric tons per capita), fossil fuel consumption, electricity consumption, GDP per capita and GDP per capita squared. At the end of the analyses, the empirical validity test of the environmental Kuznets curve presents an inverted U-shaped curve between GDP and CO₂ emissions. This means that CO₂ emissions increase in proportion to GDP until the inflection point, where CO₂ emissions gradually decrease.

Et-Touile and Arib (2021) assessed the impacts of climate change and the area of arable land on food security in Morocco. The method of analysis used in this study is that of the cointegration of ARDL (Autoregressive with Scaled Delays). Climate data and those relating to the areas of arable land were collected over the period from 1971 to 2017. The results obtained show a proportional increase in rainfall and agricultural GDP. Conversely for temperature, an increase in temperature causes a drop in agricultural GDP. However, arable land has no direct influence on the country's food security. As a solution approach to this problem, they propose the establishment of an adaptation policy to fight against climate change.

Chandio et al. (2021) also worked in this direction by evaluating the effects of climate change on the production of the main food crops in Turkey between 1980 and 2016. Their objective was to assess the short and long-term effects of climatic and non-climatic factors on the production of wheat and rice based on the ARDL approach and the cointegration test of Johansen and Juselius. The results proved the climatic parameters negatively impacts wheat production in the short and long term. While non-climatic parameters such as area sown for production and domestic credit positively influence production during both periods. Furthermore, CO₂ and emissions have negatively affected rice production as well as domestic credit. Unlike other parameters such as temperature, rainfall and area sown for production have a positive impact on rice production.

To better understand the relationship between climate change and agriculture, Chandio et al. (2022) tried to assess the effects of climate change on cereal production in Bangladesh between 1988 and 2014. To achieve the results, they adopted the autoregressive distributive lag model (ARDL) and for the validation of the results obtained, several approaches econometrics have been

associated. This methodological approach is close to that of Tagwi (2022). The results showed that precipitation improves cereal production in the short and long term, unlike temperature and CO₂ which have a negative effect on cereal production in the short term. Cultivated area, financial development, energy consumption and rural labor have significantly impacted cereal production in Bangladesh from 1988 to 2014.

Maiga *et al.* (2022) attempted to assess the impact of climate change on the income of Malian producers over the period from 1990 to 2021. They used the ARDL estimator to perform the analyzes of the time series data. To better arrive at their results, they also tested the cointegration between the variables and the test unit to ensure that no variable is integrated at order 2. At the end of the analyses, they showed that the climate change negatively affects producers' incomes in Mali. The climatic parameters more precisely the precipitation and the ambient temperature at the level of the cultures influence the yield of the agricultural cultures and by extension the income of the producers. At the end of the study, the authors suggested building the capacities of producers in Mali on methods of adaptation to climate change.

Özdemir (2022) evaluated the effect of climatic variations on agricultural production in Asia from 1980 to 2016. The results obtained using the autoregressive dynamic and asymmetric panel shift, show a positive relationship between CO₂ emission and short-term agricultural productivity. But in the long term, this impact becomes negative.

Mafié (2022) analyzed the impact of climate change on agricultural productivity in Tanzania, specifically on maize and paddy cultivation, because being the basic food crops of the country. This study was based on data from national panel surveys carried out after agricultural campaigns from 2008 to 2013 (production data and socio-economic characteristics of producers) as well as climate data from Tanzania (temperature and rainfall). Starting from the Ordinary Least Squares (OLS) method, which is a model commonly used in econometrics, the author concludes that meteorological variables as well as the level of education of producers have a significant impact on agricultural productivity. The author therefore suggests political intervention to ensure that producers have mastery of strategies for adapting to climate change and that they can use the technologies and modern agricultural inputs offered to them.

Avandé *et al.* (2022), meanwhile, evaluated the adaptation strategies of rice producers to the effects of climate change in the commune of Malanville in Benin. The main objective of their study was to analyze the manifestations of climate change on rice production and the adaptation strategies developed by rice producers in northern Benin. The methodology consisted of collecting data from 80 rice producers in two districts of Malanville. The data were processed using descriptive statistics, statistical tests, and logistic regression to estimate the determinants of the adoption of adaptation strategies by rice producers. It emerges from this study that 100% of the rice producers perceive the manifestations of climate change which are, among others, the increase in rainfall, floods, delayed rains and violent winds. They found that formal education, experience of

the rice producer, area sown, area reserved for rice production, group membership and access to agricultural credit have a positive and significant effect on the choice rice producers to adapt to climate change. Finally, the authors identified the strategies adopted by rice producers to cope with these climate changes. These are the use of improved seeds, off-season cultivation, and the drainage of excess water.

Jayasooriya (2023) identified the relationships between sovereign risk and climate change in Asia. Analyzes were performed using the ARDL autoregressive panel lag model. The panel consisted of three regression variables. These are pooled mean group regression, mean group estimation and dynamic fixed effects regression. The results reveal that in the long term, the dynamic fixed effects regression is retained as the best model for all Asian countries. Integrating the results of this study into development strategies and policies will help limit the impact of climate variations on the various sectors of activity in Asian countries.



3. MATERIAL AND METHOD

3.1. Study area

The selection of Benin as a study area is justified by several crucial elements (figure 1). First, the survey covers all administrative divisions of the country, thus providing a complete representation of its territory. Indeed, having agriculture as the main source of the country's economy, the country is more susceptible to the repercussions of climate change (DGEC, 2022). This increased vulnerability of Benin to climate change makes the approach of a study focusing on the evaluation of the influence of this phenomenon on agricultural production relevant. Moreover, this is becoming more coherent, with particular emphasis on maize, recognized as the most widely cultivated crop and the predominant staple food (Akpo, 2020).

The investigation was conducted in Benin, focusing specifically on the country's northern region. This geographical selection stems from climate projections that signal northern Benin as the area most exposed to climatic vulnerabilities (Yegbemey *et al.*, 2014). And yet, despite these challenges, agricultural production is concentrated there. This region thus offers a privileged setting for studying producers' adaptation strategies in the face of pressing climatic challenges. Moreover, it is important to note that this region encompasses four of the country's eight agro-ecological zones, underlining the diversity and agricultural potential of this area. This variety of agro-ecological ecosystems provides a rich context in which to study farming practices and adaptation strategies, reflecting the diversity of challenges and opportunities facing producers in northern Benin. For the purposes of this research, the communes of N'Dali, Sinendé and Nikki were selected because they belong to Benin's third agroecological zone. This agroecological zone is recognized as the country's main food production region, where maize remains one of the predominant crops (Baco *et al.*, 2012). By specifically targeting this area, the study aims to deepen understanding of agricultural practices and dynamics related to maize cultivation in a specific ecological context. This will enable us to offer precise guidelines for developing effective adaptation strategies in this region of Benin.

The map below provides an overview of the study's geographic scope, encompassing the entirety of Benin:

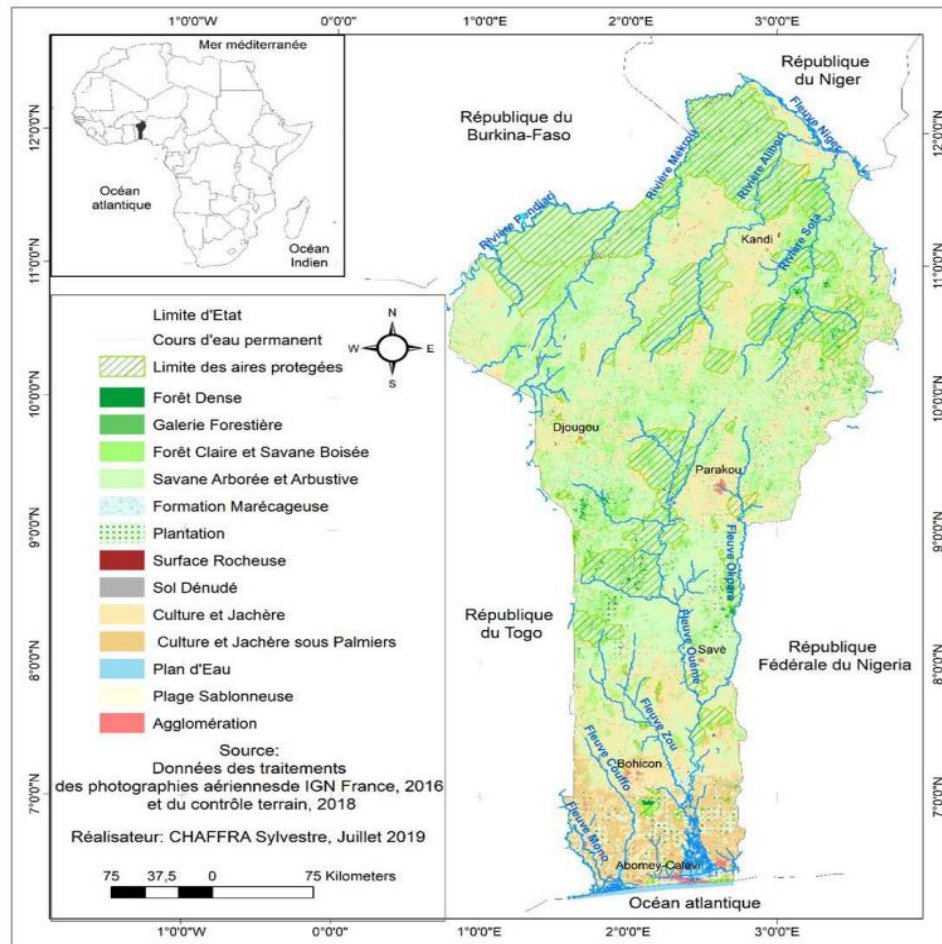


Figure 1. Map of the study area (Benin)

Source : DGEC, 2022.

3.2 Analysis of the economic impact of climatic variations

3.2.1 Data used

Numerous datasets were harnessed in this study, notably encompassing climatic factors such as rainfall, minimum temperature, and maximum temperature. Additionally, atmospheric pollutants, including carbon dioxide (CO₂), methane (CH₄), and nitrous oxide (N₂O), were examined. The rationale for selecting these parameters is rooted in the imperative of addressing climate change inquiries through the lens of these multifaceted components, particularly acknowledging their roles in shaping greenhouse gases and core climatic variables. These very indicators constitute the bedrock upon which the extensive assessment conducted by the Intergovernmental Panel on Climate Change (IPCC) in their latest summary report of the sixth assessment cycle (IPCC, 2021) relies. The impacts of these changes are far-reaching, spanning areas such as agriculture, grappling with intensified temperature fluctuations, climate-linked illnesses, compromised water access, and soil acidification. These risks collectively undermine food production, leading to diminished food security and economic repercussions across sectors, with agriculture bearing a significant brunt (IPCC, 2021).

Indeed, the negative influences of temperature and precipitation on agricultural output, specifically maize volume, have been underscored by researchers in previous studies (Dossa and miassi, 2023). Similarly, other scholars have highlighted the adverse relationship between atmospheric pollutants like CO₂ and CH₄ and the production of agricultural commodities, mediated through alterations in soil acidity (Casemir and Diaw, 2018). These premises rationalize the incorporation of these variables within the present study. Beyond the climatic markers, additional parameters, especially social indicators such as population density in both rural and urban areas, have been integrated. Demography emerges as another pivotal determinant of the developmental trajectory of agriculture (land productivity) in developing nations (Dossa and miassi, 2023).

Furthermore, as explanatory elements influencing the production volume under consideration, fertilizers (specifically Nitrogen, potassium K₂O, and phosphate fertilizers) were incorporated. The selection of these fertilizers stems from the understanding that, alongside the climate-related challenges discussed earlier, the diminished productivity of maize is significantly linked to declining soil fertility (Azontondé et al., 2010). Certain studies emphasize that the provision of essential mineral elements, particularly nitrogen, phosphate, and potassium fertilizers, augments maize yield and consequentially its production volume (Maliki et al., 2017).

Regarding metrics gauging maize production levels, both the average annual cultivated areas across the nation and the total annual production volumes (measured in tons) were considered. The rationale for including cultivated area stems from its established positive correlation with production volume within the literature (Cesaro, 2020). Meanwhile, the production volume (total tons) stands as a fundamental indicator signifying the significance of crop production during a specific timeframe for a given crop within distinct regions (OCDE, 2023).

Precipitation, maximum and minimum temperature data were procured from the Benin Agency for Air Navigation Safety (ASECNA), whereas data pertaining to other parameters (air pollutants, population density, fertilizers, and maize production indicators) were collected over a 30-year span (1990-2020) from the Food and Agriculture Organization of the United Nations (FAO) website.

3.2.2 Analysis method

The chronological evolution of parameters was assessed using time series, statistical analysis tools that track the trajectory of variables over time, providing meaningful predictions (Sakli, 2016). Unlike traditional statistical approaches, this study opted for dynamic lag (DL) models due to their ability to consider temporal dynamics, thereby improving the accuracy of predictions on the behavior of variables (Kuma, 2018). These models, like ARDLs, encompass both short-term effects and long-term dynamics. Furthermore, the difference between short-term and long-term effects is marked by "step lags", reflecting the different scales of response of the dependent variable to the variation of the independent variable.

The particularity of distributed lag (DL) models is linked to the fact that these models are divided into two categories: autoregressive (AR) models, which integrate past values of the dependent variable (Y_{t-q}) among the explanatory variables, and staggered lag models (DL), which use the past values of the independent variable (X_{t-q}) (figure 2). To do this, autoregressive distributed lag (ARDL) models merge these characteristics by including both past values of the dependent variable and the independent variable in the explanatory variables (Bensbahou and Seyagh, 2020; Kuma, 2018).

If we consider the dependent variable “ Y_t ” and the independent variable “ X_t ”, the general form of these different distributed lag (DL) models is as follows (Mestiri, 2022; Kuma, 2018):

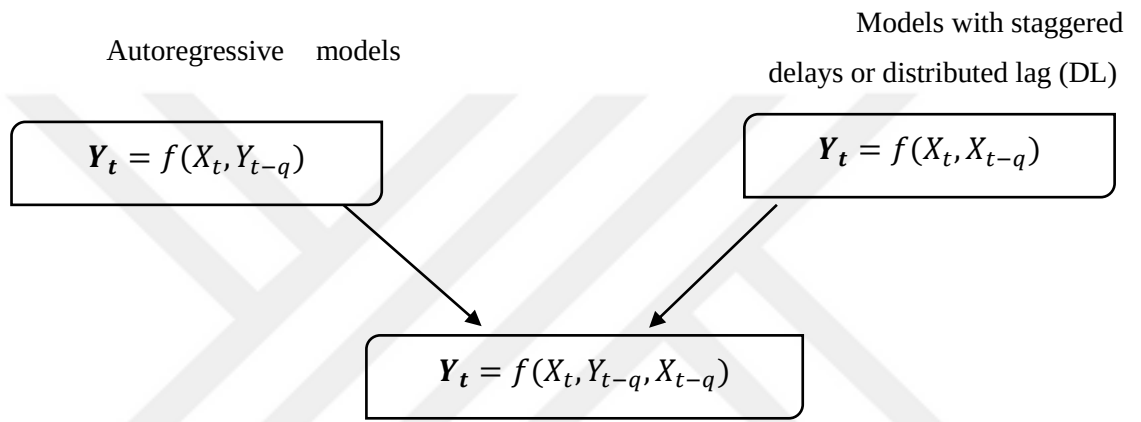


Figure 2. Summary diagram of the autoregressive and distributed lag models

However, ARDL models often face challenges related to error autocorrelation, especially when they include the lagged endogenous variable as an explanatory element (Bensbahou and Seyagh, 2020). To address this issue, the DL method was chosen to mitigate error autocorrelation, especially near the dependent variable. The general equation of the model applied in this study is then formulated as follows:

$$\begin{aligned}
 Y_t = & \beta_0 + \beta_1 * CH4_t + \beta_2 * N_2O_t + \beta_3 * CO2_t + \beta_4 * NitroFert_t + \beta_5 * \\
 & PhosFert_t + \beta_6 * PotasFert_t + \beta_7 * RuralPop_t + \beta_8 * UrbanPop_t + \beta_9 * \\
 & Rainfall_t + \beta_{10} * TempMax_t + \beta_{11} * TempMin_t + \beta_{12} * CH4_{(t-q)} + \beta_{13} * \\
 & N_2O_{(t-q)} + \beta_{14} * CO2_{(t-q)} + \beta_{15} * NitroFert_{(t-q)} + \beta_{16} * PhosFert_{(t-q)} + \beta_{17} * \\
 & PotasFert_{(t-q)} + \beta_{18} * RuralPop_{(t-q)} + \beta_{19} * UrbanPop_{(t-q)} + \beta_{20} * \\
 & Rainfall_{(t-q)} + \beta_{21} * TempMax_{(t-q)} + \beta_{22} * TempMin_{(t-q)} + \varepsilon_t \quad (1)
 \end{aligned}$$

With:

- $\varepsilon_t \sim (0, \sigma)$: designating the error term.
- $\beta_1; \beta_2, \dots, \beta_{11}$ reflecting the short-term effect of each explanatory variable in year t on the dependent variable in the same year t (Y_t); then $\beta_{12}; \beta_{13}; \dots; \beta_{22}$ translating the short-term effect of each explanatory variable shifted to the year $t - q$ on the dependent variable to the year t

The description of the variables has been given in Table 1.



Table 1. Summary table of variables used for the model

Variables	Description	Sources	Year
Y_t	National production volume of maize (The dependent variable)	FAO	1990-2020
CH_4	The amount of methane (kilo ton) in the atmosphere from three sources (agriculture, food waste and other (energy and transport))	CAM	1990-2020
N_2O	The amount of nitrous oxide (kilo ton) in the atmosphere from three sources (agriculture, food waste and other (energy and transport))	CAM	1990-2020
CO_2	The amount of carbon dioxide (kilo ton) in the atmosphere from three sources (agriculture, food waste and other (energy and transport))	CAM	1990-2020
<i>NitroFert</i>	Quantity of nitrogenous fertilizers (N) (in tons)	CAM	1990-2020
<i>PhosFert</i>	Quantity of phosphate fertilizers (P_2O_5) (in tons)	CAM	1990-2020
<i>PotasFert</i>	Quantity of potash (K_2O) used	CAM	1990-2020
<i>RuralPop</i>	Rural population density	CAM	1990-2020
<i>UrbanPop</i>	Urban population density	CAM	1990-2020
<i>Rainfall</i>	Annual rainfall (mm)	ASECNA	1990-2020
<i>TempMax</i>	Maximum temperature ($^{\circ}C$)	ASECNA	1990-2020
<i>TempMin</i>	Minimum temperature ($^{\circ}C$)	ASECNA	1990-2020

Considering the following long-run or equilibrium relation: $Y_t = a + \delta X_t + \mu$ (2), the long-run effect X_t on Y_t (or “ δ ”) is determined as follows: $\delta = \sum_{j=1}^q \beta_j$ (Bensbahou and Seyagh, 2020, Kuma, 2018).

The use of the models depends on the cointegration of the time series, implying that they have the same order of integration (Kuma, 2018). If levels of differentiation vary between series, an error correction model (ECM) is recommended (Kuma, 2018). To assess stationarity, the Augmented Dickey-Fuller (ADF) test, Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test, and Phillips-Perron (PP) test were used, followed by successive differentiations to make the series

stationary. An ECM model was then applied to present the results of the short- and long-term distributed lag (DL) models.

Predicting production volume remains a challenge in distributed lag and autoregressive models, often absent from previous studies (Kuma, 2018, Bensbahou and Seyagh, 2020 and Mestiri, 2022). In this research, the ARIMA approach was adopted to predict the explanatory values, influencing the volume of maize production. These forecasts were then used to directly estimate the production volume results in the distributed lag model, thus introducing a novelty in this study. Consider Y_t the ARIMA time series of an explanatory variable X_t written in the form of a linear transfer function of a series of noises:

$$Y_t = \sum_{j=0}^{\infty} \varphi_j \varepsilon_{t-j} \quad (3)$$

To obtain a forecast Y_{t+L} (L being any positive integer denoting a next year or time frame) of the explanatory variable X , the following equation was used (Sakli, 2016):

$$Y_{t+L} = \sum_{j=0}^{\infty} \varphi_j \varepsilon_{t+L-j} \quad (4)$$

The calculation of the conditional mathematical expectation of Y_{t+L} knowing its past to date $t - L$ is given by:

$$E(Y_{t+L} | Y_t, Y_{t-1}, \dots) = \hat{Y}_t(L) \text{ with:}$$

$$\bullet \quad \hat{Y}_t(L) = \varphi_L \hat{\varepsilon}_t + \varphi_{L+1} \hat{\varepsilon}_{t-1} + \dots \quad (5)$$

$$\bullet \quad Y_{t+L} = (\varepsilon_{t+L} + \varphi_1 \varepsilon_{t+L-1} + \dots + \varphi_{L-1} \varepsilon_{t+1}) + (\varphi_L \varepsilon_t + \varphi_{L+1} \varepsilon_{t-1} + \dots) \text{ (Sakli, 2016).} \quad (6)$$

To identify the parameters (p, q), characterizing the order of the autoregressive component (p) and that of the moving average component (q), the partial autocorrelation functions (PAFC) and that of simple autocorrelation (AFC) were respectively used as observed in the literature (Sakli, 2016). The choice of the parameters p and q was made following the observation of the correlograms of these functions.

To conduct each of the different analyzes developed, the R version 4.3.0 software was used, and Excel was used to enter the data obtained from our two sources (ASECNA and FAO).

3.3 Energy management analysis

3.3.1 Data used

To understand the different management modes and main energy sources related to maize production, energy equivalent coefficients were calculated based on data from previous studies (Akdemir et al., 2023; Hayran et al., 2023; Kosemani & Bamgboye, 2021; Ozkan et al., 2004). In fact, two types of data were collected: data relating to labor and data relating to agricultural inputs used for maize production. As far as labor is concerned, the data collected relate essentially to the various activities or operations carried out to ensure maize production. This mainly includes labor engaged in technical itineraries (grubbing, manual plowing, weeding, harvesting, transport of harvested products, application of chemical inputs including fertilizers, herbicides, and insecticides). This category also includes mechanical plowing (use of tractors) and animal-drawn plowing. Regarding data on agricultural inputs used, the study took into consideration the quantity of chemical fertilizers (NPK, herbicide and insecticide) used by each farmer for maize production. Finally, the quantity of fuel used during the maize production campaign is also considered as a production input. All these activities were considered as energy resources associated with maize production and were all transformed into energy values using an energy equivalent factor (Table 2). The same strategy has been applied in similar studies by several researchers (Akdemir et al., 2023; Hayran et al., 2023; Kosemani and Bamgboye, 2021; Ozkan et al., 2004).

Human labor expenditure was calculated by multiplying the number of farm workers involved in the process by the total number of hours of activity performed by the number of farm workers, and then by the equivalent energy of one hour of human activity (equation 1).

$$E_{labor} = e * (N * J * D) \quad (7)$$

Where e = Equivalence of one hour of activity in terms of energy (MJ), N = Total number of farm workers, D = Total number of days and D = Total working time in a day (Kosemani and Bamgboye, 2021). The same formula was applied to determine the amount of energy deployed by machines and during animal traction but considering "N" as the number of tractors or animals put into activity.

Energy inputs from fuel use and chemical inputs (NPK fertilizer, urea, herbicide, pesticide) were calculated using conventional equations used in previous studies, as shown in equation (2) (Kosemani and Bamgboye, 2021).

$$E_i = Q_i * e \quad (8)$$

With:

E_i = Energy emitted (MJ/ha); Q_i = Quantity of input (kg/ha); e = Energy equivalence (MJ/kg).

Table 2 lists all these sources and the energy equivalence for each.

Table 2. Standard energy equivalent of production inputs

Inputs	Unit	Energy equivalent (MJ/ha)	References
Labor (Human)* (x_1)	h	0.27	Kosemani and Bamgboye (2021); Akcaoz et al (2009); Bamgboye et al, (2006).
Fuel (x_2)	liter	56.31	Akcaoz et al (2009) ; Akdemir et al (2023) ; Mani et al (2007) ; Mandal et al (2002)
Tractor 50 kw (x_3)	h	64.30	Akcaoz et al (2009) ; Fluck (1985)
Animal traction (x_4)	h	5.90	Ruiz-Vega et al (2015)
Fertilizer: x_5, x_6			
N	Kg	60.60	Akcaoz et al (2009) ; Akdemir et al (2023) ; Mani et al (2007)
P	Kg	11.10	Akcaoz et al (2009) ; Akdemir et al (2023) ; Mani et al (2007)
K	kg	26.80	Akcaoz et al (2009) ; Akdemir et al (2023) ; Mani et al (2007)
Chemical treatments			
Herbicides (x_7)	kg	120.00	Kosemani and Bamgboye (2021)
Insecticide (x_8)	kg	278.00	Akcaoz et al (2009) ; Akdemir et al (2023) ; Meul et al (2007)

* Labor includes the following aspects: Grubbing, manual ploughing, weeding, harvesting, transport of harvested produce, application of chemical inputs (fertilization, herbicide, and insecticide).

Descriptive statistics and the mean comparison test were used to compare the quantities of energy from different sources to highlight the most energy-intensive activities in maize production in this area. However, a preliminary descriptive analysis (frequency calculation and Chi-square test) was carried out to assess farmers' perceptions of climate change.

3.3.2 Analysis method

To analyze efficiency, many studies use Stochastic Frontier Analysis (SFA) or Data Envelopment Analysis (DEA). In SFA, all farms are assumed to have the same estimated efficiency scores. But in the DEA, each farm has different efficiency scores. This makes it possible to focus on each production unit.

To assess technical efficiency, the study used the DEA method, which, thanks to Charnes and Cooper (1962), has been adapted to measure technical efficiency in a variety of contexts (Abanda and Saha, 2023). Indeed, the use of this method is justified by the fact that it is considered more appropriate for expressing the relationship between inputs or between outputs, compared with econometric methods where the choice of variables requires rigorous statistical study (Berre, 2014). Indeed, this explains its choice in several previous studies (Abanda and Saha, 2023; Abdulai et al., 2018; Hassan et al., 2014). This method is based on the linear programming technique. The term "envelopment" is used to express the assumption that the production frontier envelops all observations. The DEA method has two more widely used variants. The first variant is the Charnes-Cooper-Rhodes (CCR) model by Charnes et al. (1978), which considers constant returns to scale (CRS). This means that an increase in the quantity of inputs consumed leads to a proportional increase in the quantity of output produced (Abanda and Saha, 2023). The second variant is the Banker-Charnes-Cooper model of Banker et al. (1984), which considers variable returns to scale (VRS). In this case, an increase in the level of inputs can lead to a proportionally higher or lower quantity of outputs (Berre, 2014). In other words, marginal costs vary according to input or output levels. The ratio between the two variants (CRS/VRS) gives the technical efficiency itself, which is the efficiency of scale (Berre, 2014). Moreover, in both variants: Models can be said to be "input-oriented" if we are interested in inefficiency in terms of excess inputs, or "output-oriented" if we want to analyze efficiency in terms of outputs, as in the case of the present study. As input, the present study has considered the quantities of energy previously detailed to highlight the efficiency of each farm, considering as output the yield per hectare of maize from each farm.

To identify the main determinants of the differences in efficiency indices obtained through the DEA method, the study used a Tobit-type econometric model for which the three dependent variables (efficiency of constant returns to scale, efficiency of variable returns to scale and scale efficiency) are continuous and lie between 0 and 1. Indeed, this method is widely used to estimate the determinants of efficiency differences between producers, as all efficiency indices have 1 as their upper bound and 0 as their lower bound (Abdulai et al., 2018; Ji and Lee, 2010). The Tobit model describes a non-negative dependent variable, y_i , and an independent variable (vector) x_i .

Theoretically, the model is expressed as follows (Abdulai et al., 2018):

$$y_i^* = X_i\beta + u_i \quad (9)$$

$$y_i^* = \begin{cases} y_i^* = X_i\beta + \varepsilon_i & \text{si } y_i^* > 0 \\ 0 & \text{si } y_i^* < 0 \end{cases} \quad (10)$$

$$(11)$$

With:

Index $i=1,...,n$ (producers)

y_i is an unobserved (latent) dependent variable, representing in this case the efficiency indices of each producer obtained from the DEA;

x_i is a vector of explanatory variables, including socio-demographic variables and production parameters such as farm inputs;

β is a vector of unknown parameters designating the coefficient of each explanatory variable and

u_i is the error term.

Empirically, the estimate of the different technical efficiencies of each producer is regressed on a set of socio-economic factors to explain the determinants of their technical efficiencies at both constant and variable returns to scale (Bravo-Ureta and Pinheiro, 1993; Coelli et al., 2002). In formal terms, the model used is written:

$$Y_i^* = \beta_0 + \beta_1 Age + \beta_2 Exp + \beta_3 Sup + \beta_4 Sex + \beta_5 Insec + \beta_6 NPK + \beta_7 Alpha + \beta_8 ActPrin + \beta_9 Gest + \beta_{10} MOrg + \mu_i \quad (12)$$

Where:

Y_i^* = efficiency indices obtained from the DEA method

$i=1,2,3$; representing the three efficiency indices (technical efficiency with constant returns to scale (CRS); technical efficiency with variable returns to scale (VRS) and scale efficiency

$\beta_1; \beta_2; \dots, \beta_{10}$; ; each representing the coefficient associating with each respective explanatory variable

u_i = the error term.

The explanatory variables are producer age (Age), experience (Exp), area of maize sown (Sup), sex (Sex), amount of insecticide (Insec) and NPK used (NPK), literacy (Alpha), farming as main activity (ActPrin), management mode (Gest) and use of organic matter (MOrg). f

Table 3 shows a summary of these parameters with their expected effects on the various indices of technical efficiency.

Table 3. Description of variables used in the Tobit model

Variables	Description	Abbreviation	Unit	Expected effect
Dependent variables				
Y_1	Efficiency at constant return on scale (CRS)		-	-
Y_2	Technical efficiency with variable return on scale (VRS)		-	-
Y_3	Scale efficiency		-	-
Independent variables				
Age	Age of producer	Age	Year	±
Experience	Years of experience	Exp	Year	±
Maize acreage	Area planted	Sup	Hectare (ha)	±
Gender	Type of producer	Sex	0 = F; 1 = M	+
Insecticide	Total quantity of insecticide used	Insec	Liter	+
NPK	Total quantity of NPK used	NPK	Kg	+
Literacy	Producer's local-language literacy status	Alpha	0 = No; 1 = Yes	+
Main activity	Farming as main activity	ActPrin	0 = No; 1 = Yes	+
Management	The management method used by the farmer to adapt to climate change	Gest	1 = increase in work force ; 2 = increase in inputs	+
Organic matter	Whether or not to use organic matter	Morg	0 = No ; 1 = Yes	±

Farmers were asked to list and rate the relevance of the various constraints to maize production they faced, assigning a score from 0 to 3 to indicate the degree of importance of each problem. A score of 0 meant that the problem was considered irrelevant, while a score of 3 indicated very high relevance in the farmer's estimation. Initially, descriptive statistics were used to calculate average scores, facilitating identification of the constraints for which the highest scores were recorded. Then, a Kendall W test was applied to reinforce the results of the descriptive statistical analysis, a methodology frequently used in similar studies (Miassi et al., 2023).

In this study, SPSS (V25), Stata (V18) was used as the data processing software and DEAP (Data Envelopment Analysis Programming) was exploited to bring out the efficiency indices for each maize farmer.

4. RESULTS AND DISCUSSIONS

4.1. Time series of climatic parameters and volume of maize production in Benin

4.1.1 Evolution of climatic parameters

The assessment of rainfall evolution was conducted based on the three distinct seasons delineated by the climatic attributes defined by DGE (2022): the extended wet season spanning June, July, September, and October, the extensive dry season encompassing November to March, and the transitional period comprising April, May, and August. In this transitional phase, the northern-central region experiences a dry spell (April and May) succeeded by a rainy spell (August), while the southern region undergoes a wet phase (April and May) followed by a dry spell (August). A chronological analysis of total national rainfall between 1990 and 2020 (refer to Figure 3) demonstrates irregular oscillations in both the prolonged wet season and the dry season, even during the transitional phase. Nonetheless, the overall national rainfall remains higher during the extended wet season and the transitional period combined.

Notwithstanding the temporal fluctuations in total national rainfall, the linear trendline reveals a general declining pattern in rainfall levels over time, particularly during the extended wet season and the transitional period. In 2020, for instance, the average total national rainfall during the prolonged wet season dipped below 3500 mm, in contrast to the range of approximately 5000 mm between 2000 and 2010. Similarly, during the transitional months (April, May, and August), a substantial decrease is evident, with total rainfall exceeding 2000 mm or even 3000 mm in earlier years (1995, 1998, 2007, 2010), compared to less than 1500 mm nationwide in 2020. The dry season (November to March) also follows a somewhat declining trajectory, with a mere 50 mm total rainfall across the entire territory in 2020, contrasting with around 400 mm during the 1990s.

These findings corroborate the challenges posed by rainfall instability in Benin and other African nations, all grappling with the ramifications of climate change. Particularly concerning is the impact on water availability, which in turn gives rise to profound apprehensions for agricultural sustainability in Africa.

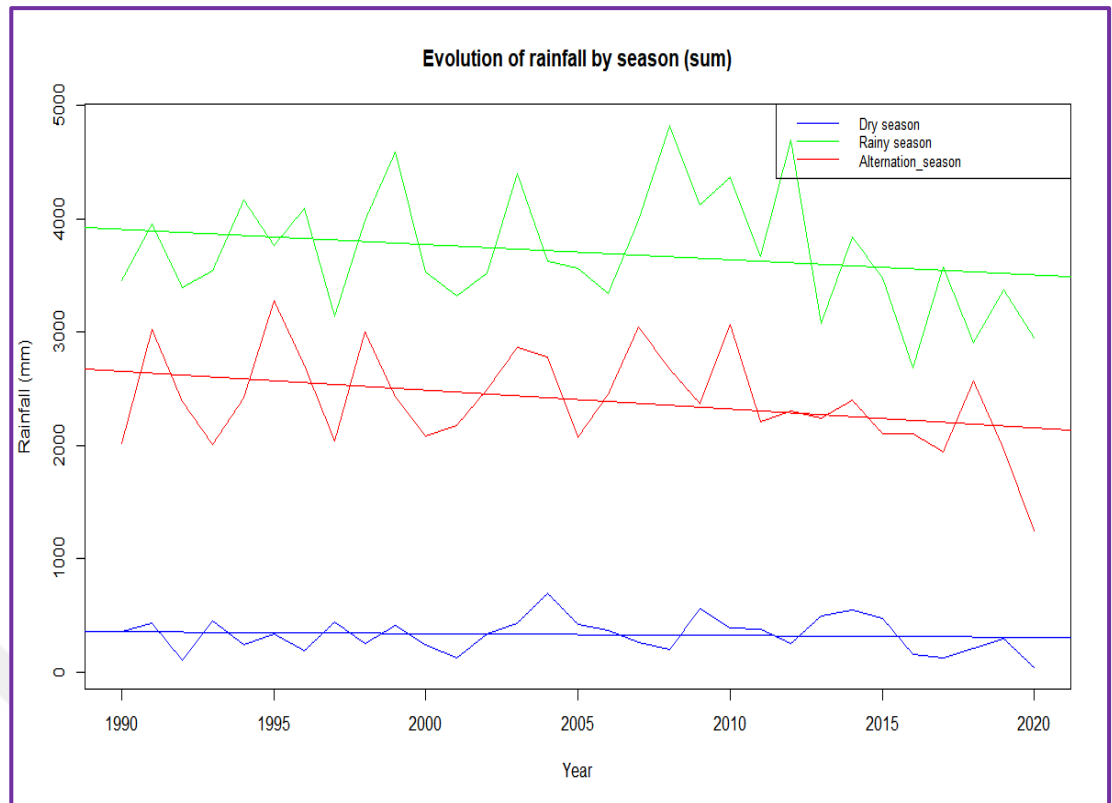


Figure 3 . Evolution of total rainfall over time according to the seasons

The analysis of the progression of maximum and minimum temperatures in Benin was conducted in alignment with the previously outlined three seasons. Naturally, there is a discernible pattern wherein temperatures, both at their peak and lowest, are elevated during the extended dry season, prevailing from November to March across the entire national expanse. Subsequently, the transitional period and the ensuing wet season manifest cooler temperatures. This anticipated pattern is inherently logical—during the dry season, the sun's dominance results in daily warmth, whereas the alternating and rainy seasons exhibit the converse phenomenon.

In contrast to total rainfall, the evaluation of annual maximum temperature data indicates fluctuations depicted by an ascending trajectory across all seasons. In 2020, for instance, temperatures occasionally soared to 38°C during the prolonged dry season, whereas in the 1990's, they scarcely exceeded 36°C. Similarly, during the transitional period, the mean maximum temperature reached 34°C or higher, compared to approximately 33°C in previous years. The same trend holds true for the extended wet season, with temperatures occasionally dipping below 31°C (1994, 1996, 1998, 1999, 2000, 2011), while hovering around 31.7°C for several years (2014-2017).

These findings align with those from reputable sources such as the Intergovernmental Panel on Climate Change (IPCC, 2021) and the National Aeronautics and Space Administration (NASA, 2023), underscoring the mounting global temperature increases that serve as a definitive hallmark of climate change. These increments are situated within the broader context of worldwide global

warming (Badameli and Dubreuil, 2015). Analogous outcomes are apparent concerning minimum temperatures, which exhibit an upward trajectory during the rainy season, particularly in the alternating phase. However, the assessment of minimum temperature data during the dry season delineates a downward trend (figure 4). In 2020, the average minimum temperature registered around 19°C, diverging from the 21°C plus range witnessed from 1990 to 2015. This might be attributed to sporadic instances of rainfall observed during the prolonged dry season, indicating the evolving seasonal dynamics encountered by agricultural producers. Similar observations have been made by other researchers like Djenontin (2010), Dedjan (2010), and Yegbemey *et al.* (2014), who noted that local communities, especially in northern Benin, have perceived shifts in their regional climate. These shifts are manifested through uneven rain distribution and occasional alterations in the onset of the rainy season.

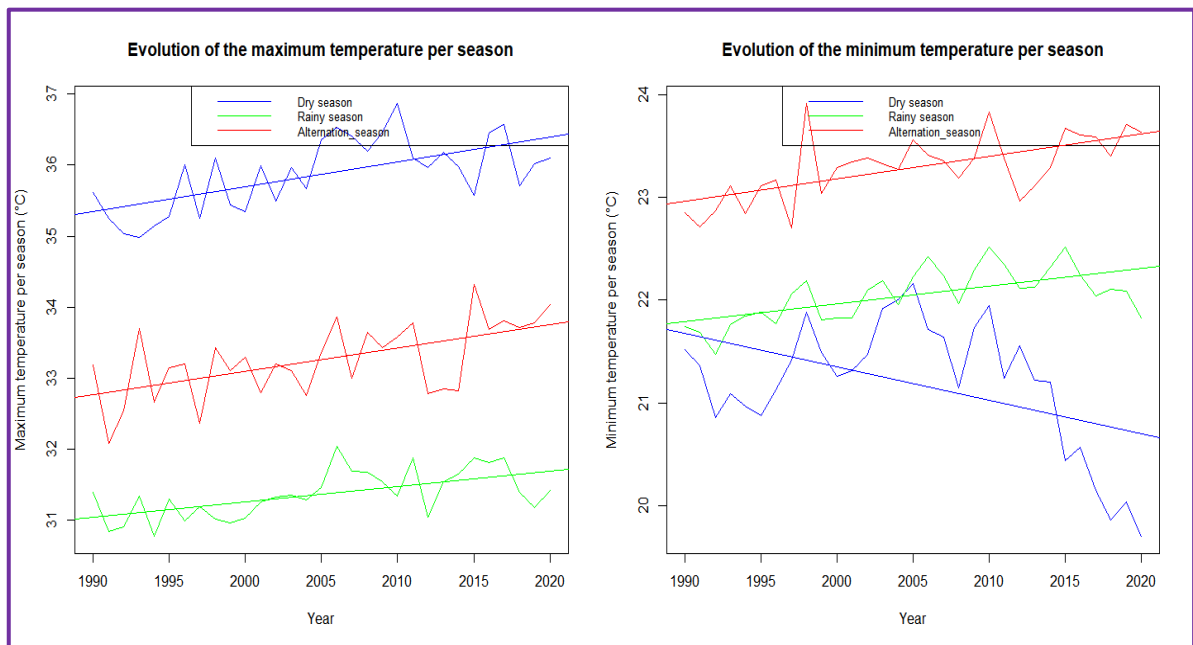


Figure 4. Evolution of the maximum and minimum temperature

4.1.2. Evolution of atmospheric pollutants

The subsequent visuals illustrate the chronological trajectory of atmospheric contaminants spanning time, specifically focusing on methane (CH₄), carbon dioxide (CO₂), and nitrous oxide (N₂O) (figure 5). This temporal assessment unveils the volumes of each pollutant, categorized by their originating emission sources—most notably, emissions stemming from agricultural activities (AS) (including incineration, synthetic fertilizer usage, bushfires, manure utilization, and crop residue), emissions linked to household food waste (FW) (encompassing household consumption, commercial products, and food processing), and emissions arising from energy and transportation practices.

A thorough examination of the methane emission series signals an ascending pattern in the quantity of methane discharged by household food waste and emissions resulting from energy

consumption and transportation. Conversely, the volume of methane released by agricultural practices displays a declining trend. This observation underscores that, in the context of methane pollution, food waste and activities entailing energy or electricity usage contribute predominantly to its natural generation. Furthermore, all three sources exhibit an escalating contribution to the release of nitrous oxide into the environment, with a particularly substantial contribution observed in 2020 from household food waste and agricultural practices.

Turning to the CO₂ emission series, it unveils an expanding and notable production attributed primarily to food waste and, more significantly, to other origins such as energy production, electricity generation, and transportation. The CO₂ emission volume from agricultural practices in 2020 is almost negligible, whereas emissions originating from household food waste, energy consumption, and transportation persistently ascend. These findings can be elucidated by the shared sources of methane and nitrous oxide production, notably agricultural practices. Within agriculture, the utilization of chemical fertilizers exacerbates nitrogen release into the environment. Similarly, processes like manure decomposition and rice production are tangible agricultural sources of methane emissions. Notably, in Benin, rice occupies a pivotal role among essential food crops and stands as the second most consumed cereal in households, following maize (Avandé et al., 2022; PSDSA, 2017). Its production has notably doubled in recent years, surpassing 220,000 tons in 2015 (Avandé et al., 2022), underscoring the substantial production intensity of this crop and thereby the potential for pollutant emission risks, such as methane. The surge in CO₂ emissions, on the other hand, is primarily attributed to electricity and heat generation (Salahuddin et al., 2018), as well as energy consumption, often involving coal and electricity (Balogan, 2021).

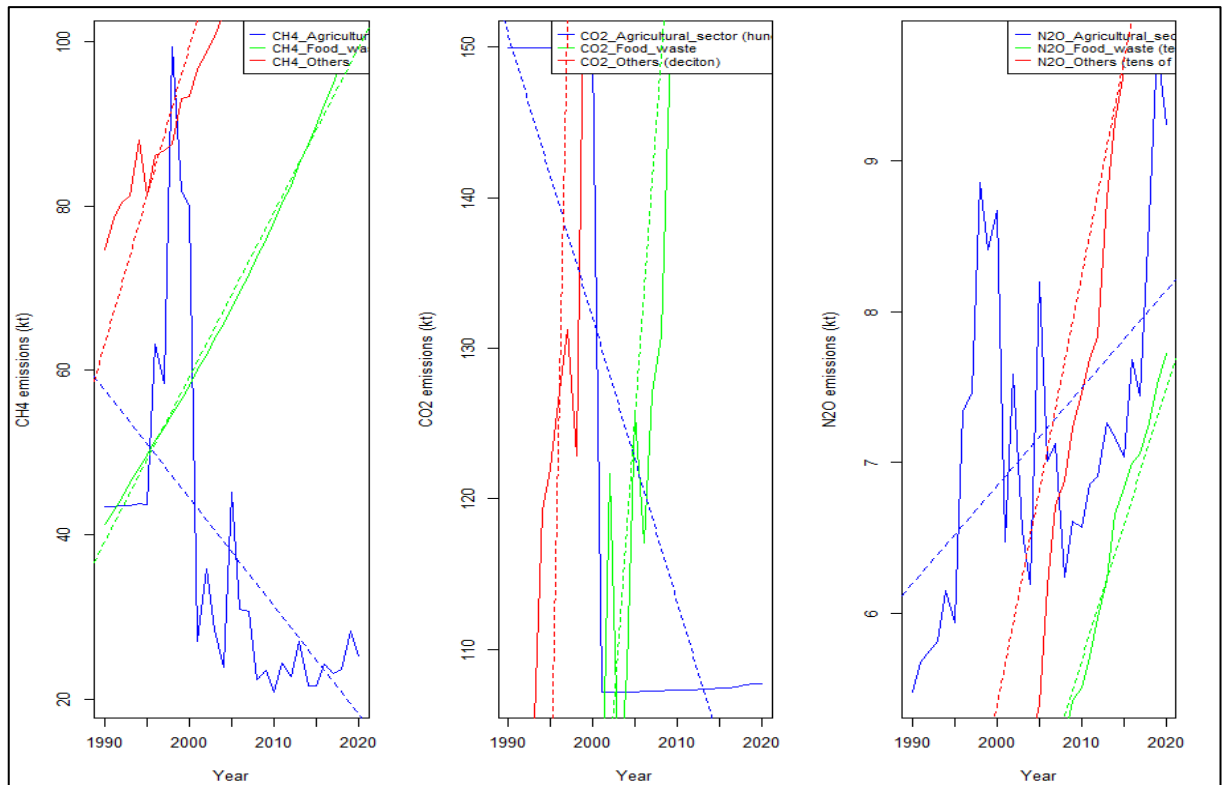


Figure 5. Air pollutant emissions by production source

4.1.3. Evolution of population density

The graph presented below illustrates the chronological progression of the population in Benin over time (figure 6). Both the rural and urban populations demonstrate a consistent upward trajectory, thereby reflecting the overall growth evident in the total population. Notably, the rural population exhibits a more pronounced upward trend compared to the urban population, and currently, the urban population is also converging with the rural population. These increases reaffirm the rapid pace of population expansion experienced by nations worldwide, particularly those within sub-Saharan Africa. This region has emerged as a potential hub for demographic surge, largely attributed to elevated fertility rates, notably in rural areas where household sizes tend to be larger (Edoun and Mongbo, 2020). This phenomenon accounts for the substantial inclination of the rural population as opposed to the urban counterpart.

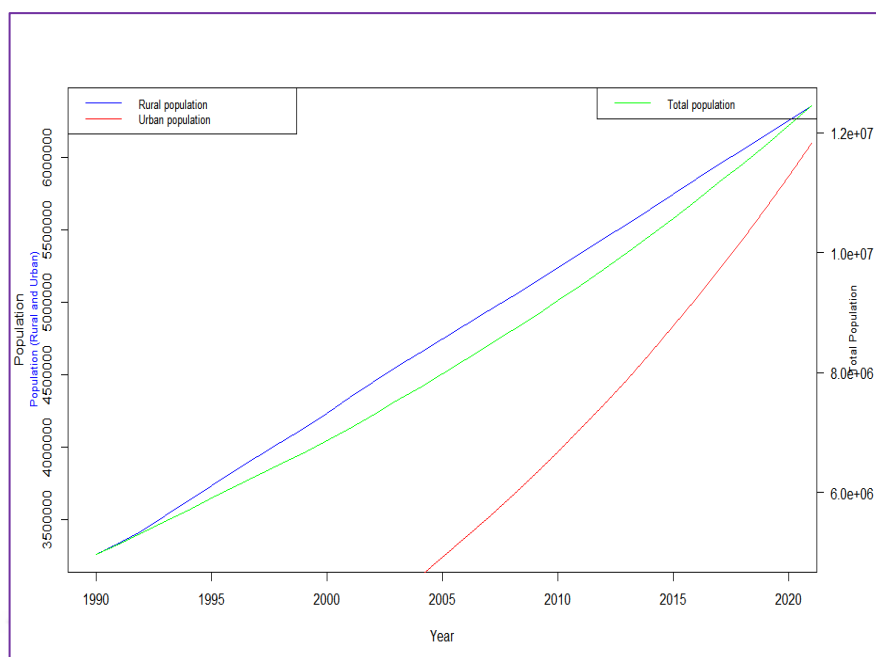


Figure 6. Chronological evolution of population density from 1990 to 2020

4.1.4. Volume of production, area sown, and quantities of fertilizers used.

Figure 7 summarizes the national evolution of production volume (in tonnes), total agricultural area (in hectares) and fertilizer quantities (in tonnes) over time. A major observation is the continued growth in production volume, particularly for maize. From 400,000 tonnes and less than 500 hectares in the 1990s, maize production increased considerably to exceed 1,600,000 tonnes on almost 1,267,159 hectares in the 2000s. These observations can be attributed to several factors. Firstly, the strategic inclusion of maize in Benin's Agricultural Sector Development Plan has played a pivotal role in promoting this crop and ensuring household food security, along with poverty alleviation efforts (PSDSA, 2017). Secondly, the exponential population growth observed both in rural and urban areas significantly contributes to increased food demand (Edoun and Mongbo, 2020). Consequently, for a staple like maize, which holds the status of the most consumed food item (Akpo, 2020; PSDSA, 2017), the rapid population increase markedly elevates the necessity for this commodity.

The subsequent graph indicates a parallel rise in the utilization of phosphate, nitrogen, and potassium (K_2O) fertilizers, particularly from the year 2015 onward. The intensive adoption of these chemical fertilizers, often in the form of NPK blends, is primarily attributed to the escalating employment of adaptive strategies by producers to enhance soil fertility levels. This becomes crucial due to the progressive soil degradation witnessed year after year (Azontondé et al., 2010). These mineral fertilizers, enhancing maize yield, consequently, amplify its production volume (Maliki et al., 2017).

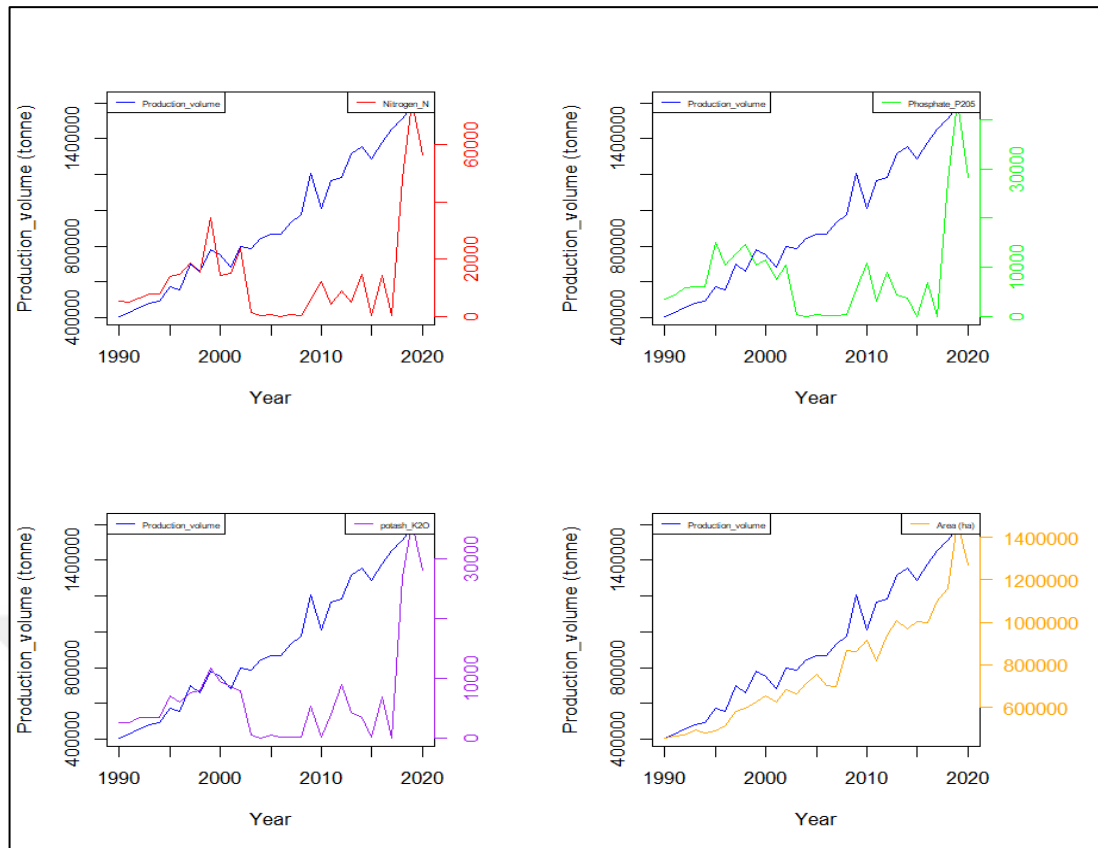


Figure 7. Maize production volume over time, area and amount of fertilizer used

4.1.5. Significance of time series for maize production volume

Considered as the variable of interest for the present study, it is essential to understand the factors exerting a significant influence on the evolution of the volume of production (figure 8). Furthermore, it is important to first verify the temporal effect at the level of this variable before exploring the other determining factors. Indeed, the analysis of the significance thresholds of the simple autocorrelation plots (ACF) shows several significant delays. These results confirm that the residual values of these variables are not independent. In other words, this suggests that the observations at time $t-1$ and those of the following years are linked.

Furthermore, the partial autocorrelation graph shows a single significant delay, thus reflecting the possibility of the existence of other determining factors in its evolution.

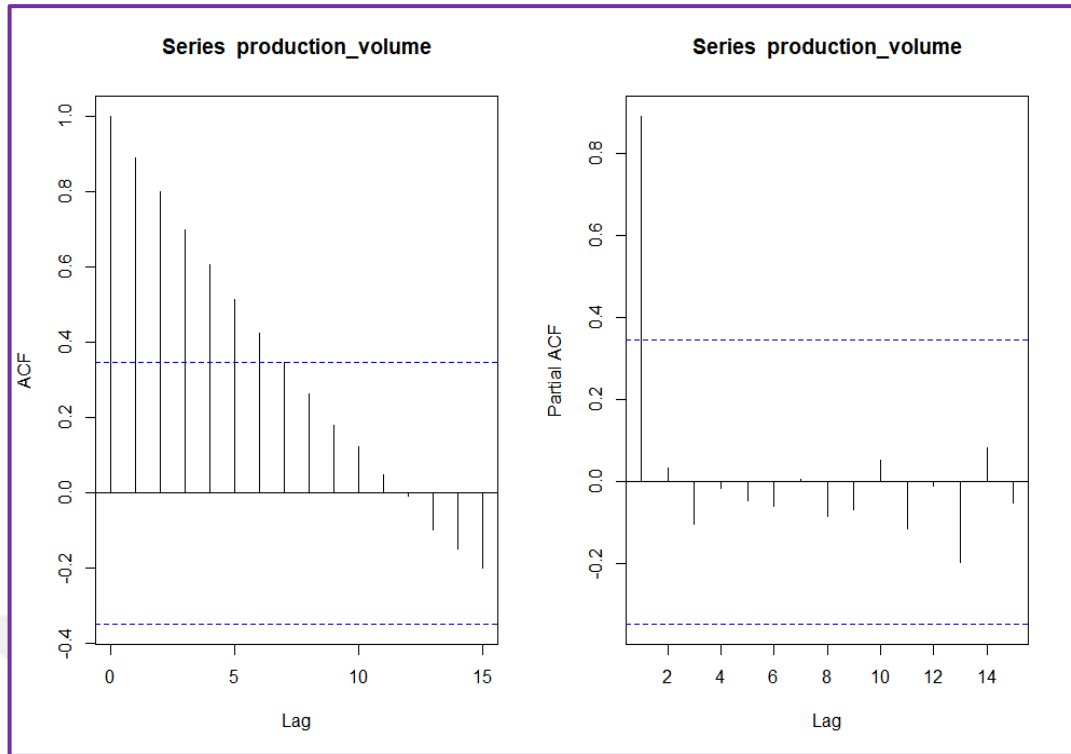


Figure 8. Autocorrelation at the level of maize production volume

4.2. Impact of climatic parameters on the volume of maize production in Benin

Analysis of the determinants of the volume of maize production

The application of the ARDL method is preceded by a careful evaluation of the stationarity of the explanatory variables considered in the model. To achieve this, three tests have been employed to scrutinize the stationarity of each distinct series corresponding to the various parameters (Table 4). These tests encompass the Augmented Dickey-Fuller (ADF) test, the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test, and the Phillips-Perron (PP) test.

The ADF test, known as the Augmented Dickey-Fuller test, evaluates the presence of a unit root in a time series, indicating non-stationarity (Kuma, 2018). Analysis of the results reveals that none of the explanatory variables demonstrate stationarity ($p > 0.05$). Similarly, the outcomes of the KPSS test align with the results for most variables, except for the data pertaining to fertilizer quantities. Specifically, the KPSS test indicates that the variable associated with fertilizer quantity is stationary, contrary to the first test ($p > 0.05$). However, results from the Phillips-Perron test, akin to the ADF test, indicate that most variables are non-stationary ($p > 0.05$), except for the production volume (dependent variable), rural population density, and maximum temperature. These variables exhibit stationary characteristics ($p < 0.05$) according to this test.

To recap, a minimum of two tests concur that all series exhibit non-stationarity. This circumstance amply justifies proceeding with differentiation, as certain studies have similarly undertaken only one or two tests to assess stationarity (Chandio et al., 2021).

Table 4. Stationarity test of the different variables studied

Settings		ADF test (Augmented Dickey-Fuller test): Dickey- Fuller (p-value)	KPSS test (Kwiatkowski- Phillips-Schmidt- Shin test): KPSS Level (p-value)	PP test (Phillips- Perron test): Z(alpha) (p- value)
Production volume (ton)		-1.1431 (0.901)	1.112 (0.010)	-22.852 (0.011) **
CH ₄	AS	-2.899 (0.226)	0.589 (0.026)	-13.720 (0.239)
	food waste	-0.810 (0.950)	1.120 (0.010)	-0.785 (0.980)
	Others	-1.340 (0.826)	1.090 (0.010)	-1.817 (0.968)
N ₂ O	AS	-2.350 (0.435)	0.398 (0.077)	-12.528 (0.320)
	food waste	-1.887 (0.616)	1.117 (0.010)	-3.175 (0.922)
	Others	-1.155 (0.897)	1.014 (0.010)	-2.118 (0.960)
CO ₂	AS	-1.476 (0.774)	0.87 (0.010)	-6.580 (0.708)
	food waste	-3.510 (0.059)	1.085 (0.010)	-14.520 (0.186)
	Others	-2.290 (0.450)	1.083 (0.010)	-5.210 (0.798)
Fertilizers	Phosphates	-1.347 (0.824)	0.210 (0.100) *	-9.930 (0.488)
	Nitrogen	-0.788 (0.952)	0.262 (0.100) *	-9.216 (0.535)
	Potash	-1.152 (0.899)	0.293 (0.100) *	-8.030 (0.613)
Population	Rural	-2.840 (0.248)	1.130 (0.010)	-21.320 (0.019)
	Urban	0.670 (0.990)	1.114 (0.010)	1.290 (0.99)
Temperature	Maximum	-2.276 (0.466)	0.835 (0.010)	-25.980 (0.010)
	Minimum	-0.100 (0.990)	0.249 (0.100)	-6.068 (0.742)
Rainfall		-0.766 (0.950)	0.356 (0.096)	-22.640 (0.010)

Significant at the 5% threshold: **; Significant at the 10% threshold: *

4.2.2 Short-term effects of climatic and social factors through the error correction model (ECM)

The selection of the optimal lagged model was guided by the Schwarz Information Criterion (SIC), ensuring the attainment of statistically significant outcomes (Table 5). The chosen model encompasses several factors, including the quantity of CO₂ derived from food waste (CO₂_Food_waste), the amount of methane resulting from food waste (CH₄_Food_waste), along with methane sourced from electricity and transportation (CH₄_Others). Additionally, the model

considers nitrogen fertilizer quantity (Nitrogen_fertilizer_N), maximum temperature (Temperature_max), rainfall (Rainfall), and the densities of rural (rural_population) and urban (urban_population) populations. Lag periods were established based on an analysis of the autocorrelation functions for each explanatory parameter.

Evaluation of the outcomes from the lagged model indicates that several variables CO₂_Food_waste, CH₄_Food_waste, maximum temperature, rainfall, and rural population density hold significant short-term sway over maize production volume. The table reveals a significant negative correlation in the short term between atmospheric pollutants like CO₂ from food waste and methane from other emission sources such as energy and transportation. The coefficients signify that a one-unit increase (1 kiloton) in their levels in the environment two years prior leads to a subsequent reduction of several tons (41,590 tons) in maize production volume two years later. Notably, while the inverse relationship is well-discussed, the converse also holds true. Crops and forests are profoundly affected by climate change and atmospheric pollutants like CO₂ and methane, given that ecosystem functioning is intrinsically linked to factors like radiation, temperature, water presence, and precipitation. These factors, which are significantly affected by air pollution, can impact ecosystems both positively (e.g., atmospheric deposition and carbon storage) and negatively, including through dysfunctions like acidification (Dossa and Miassi, 2023). Moreover, pH variations strongly correlate with waste decomposition, a process that facilitates the release of methane and CO₂ into the environment (Kelthoum and Kelthoum, 2017).

In addition to these variables, the table underscores the adverse impact of rising maximum temperatures and increased rainfall on production volume. These findings align with Adjovi *et al.* (2019), who also observed a negative influence of these climatic parameters on maize production. They specified that maize is more susceptible to climatic variability compared to other crops like sorghum or soybeans, which adapt better to warmer conditions.

Furthermore, the results reveal a significant negative association in the short term between rural population density and maize production volume at a lag period. The coefficient signifies that an increase of one individual in rural areas during the preceding year corresponds to a decrease of approximately six (06) tons of maize in the subsequent year. Although these results counter the anticipated positive effect of this factor, they can be attributed to the growing phenomenon of rural-to-urban migration, which is increasingly prevalent on a national scale. This trend reduces the agricultural population's intensity and subsequently the production volume, while amplifying the demand for agricultural products in urban areas (DGEC, 2022). This aligns with the DGEC (2022) report, emphasizing human mobility and urban migration as climate change adaptation strategies increasingly embraced by the rural population.

For the other explanatory variables, no statistically significant effect on maize production volume was observed. This might be attributed to these factors not yet reaching a threshold of substantial influence within this country's context.

Below are the estimation results of the optimal ARDL model retained:

Table 5. Estimation of short-term effects

Settings	Estimate	Std.error	t value	Pr(> t)
(Intercept)	6.30E+04	1.42E+04	4.45	0.000222 ***
L(t_C02_Food_waste_diff, -2)	-4.16E+04	1.70E+04	-2.445	0.023385 **
L(diff3_CH4_Food_waste, -2)	-2.66E+04	2.77E+04	-0.962	0.347087
L(diff2_t_CH4_Others, -2)	-6.59E+07	2.30E+07	-2.865	0.009268 ***
L(diff3_t_Nitrogen_fertilizer_N, -2)	5.96E+02	8.97E+02	0.664	0.513738
L(Temperature_max_diff, -1)	-1.51E+05	4.79E+04	-3.145	0.004886 ***
L(Rainfall_diff, -2)	-5.77E+02	1.68E+02	-3.444	0.002435 ***
L(diff2_Rural_population, -1)	-6.20E+00	2.69E+00	-2.303	0.031636 **
L(diff4_Urban_population, -2)	2.57E+00	2.28E+00	1.125	0.273482
Residual standard error	64420 on 21 degrees of freedom			
Multiple R-squared:	0.5305			
Adjusted R-squared:	0.3517			
F-statistic:	2.967 on 8 and 21 DF			
p -value	0.02178*			

Noted: *** 1% significance level; ** 5% significance level.

In the long term, as indicated in Table 6, only the increased utilization of nitrogenous fertilizers demonstrates a significant influence at the 10% significance threshold on maize production volume. In contrast, the remaining climatic parameters exhibit a lack of significant long-term impact on production volume. This observation might be attributed to the escalating adoption of new improved crop varieties available in the market, renowned for their heightened resilience to climatic adversities like limited rainfall, elevated temperatures, and emerging diseases from diverse sources (FAO, 2014). Indeed, an array of adaptation strategies is increasingly being embraced by producers to navigate the challenges posed by climate change. Among these strategies, besides deploying climate-resistant crop varieties, producers also employ adjustments to cropping calendars (such as altering sowing dates or modifying the frequency of weeding) to capitalize on the initial rainfall signals marking the onset of the rainy seasons (DGEC, 2022).

Table 6. Long-term effects of climatic factors on production volume

Settings	Estimate	Std.error	t-value	Pr(> t)
(Intercept)	-14847.4	14811.5	-1.002	0.331
L(t_C02_Food_waste_diff, -2)	26430.8	16551.3	1.597	0.130
L(diff3_t_Nitrogen_fertilizer_N, -2)	-3751.7	2092.9	-1.793	0.092*
L(Rainfall_diff, -2)	251.3	174.7	1.439	0.170

Noted: * 10% significance level.

4.2.3 Post-estimate diagnostics of the estimated error correction model (ECM)

Regarding the diagnostic tests employed to assess the validity of the estimated short-term model, it is noteworthy that the results from the Durbin-Watson (DW) and Breusch-Godfrey tests (Table 7) reveal an absence of errors autocorrelation. These test choices align with the methodology outlined by Kuma (2018). Additionally, these findings are corroborated by the graphical analysis of residuals (Figure 9). Furthermore, there is no presence of heteroscedasticity, and the errors conform to a normal distribution. Consequently, the model aligns well with the specifications stipulated by the Ramsey test (Fisher), effectively elucidating the interplay between explanatory variables and the dependent variable, without necessitating the incorporation of nonlinear terms.

Given the acceptance of the null hypothesis across all these tests, it can be deduced that this model maintains its statistical integrity. Therefore, it stands as an acceptable representation from a statistical standpoint.

Table 7. Results of short-term model diagnostic tests

Test hypothesis	Testing	Values (probability)
Autocorrelation of residuals	Durbin–Watson test	DW = 2.7074, p-value = 0.9937
Autocorrelation of residuals	Breusch-Godfrey test	LM test = 0.66156, p-value = 0.416
Heteroscedasticity	Breusch-Pagan-Godfrey Arch-test	BP=6.2314, p-value=0.6213
Normality	Jarque Bera	$X^2 = 2.3155$, p-value = 0.3142
Specification	Ramsey (Fisher)	RESET = 1.2266 p-value = 0.3155

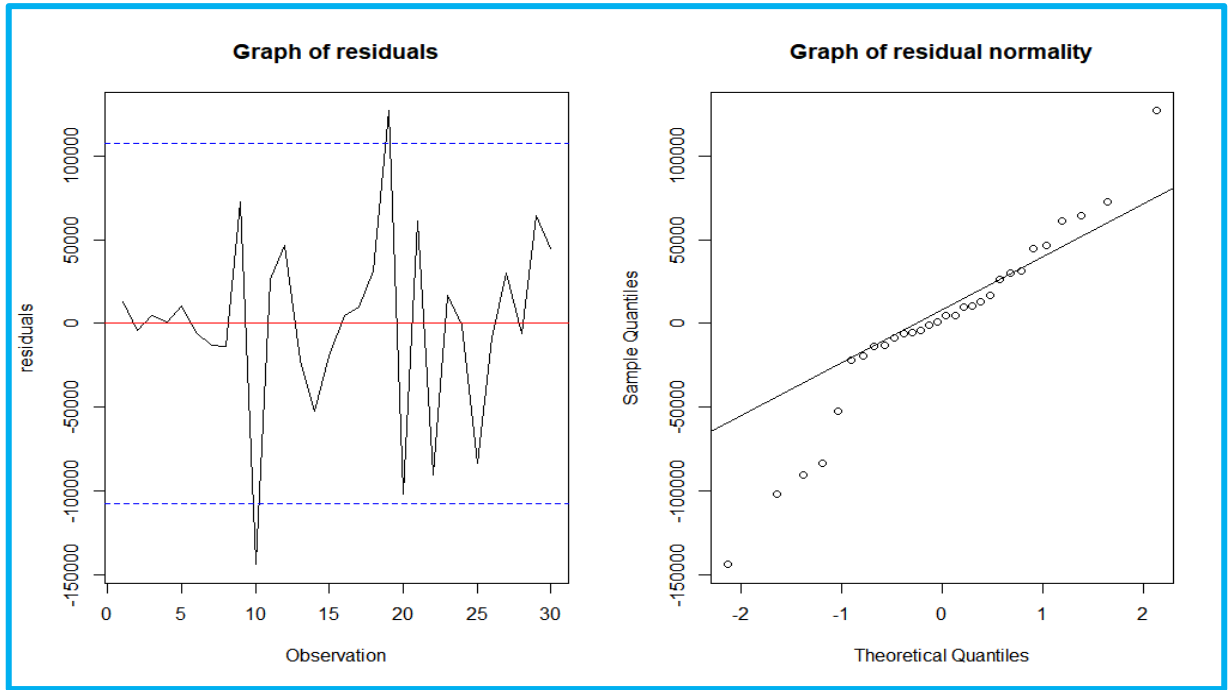


Figure 9. Autocorrelation of residuals and normality test

4.2 Prediction of maize production volume under the influence of climatic parameters

The endeavor to forecast maize production volume, influenced by significant explanatory variables, is illustrated through the subsequent graph, presenting a reasonably apt prediction (figure 10). It is worth noting that the ARDL methodology, including distributed delay models, doesn't inherently facilitate forecasting of future values for the dependent variable. This characteristic is evident in several studies that have employed this analysis method, including works by Kuma (2018), Bensbahou and Seyagh (2020), Mestiri (2022), Demirhan (2020), and Tagwi (2022).

However, for the purpose of forecasting maize production volume in upcoming years, this study employed an endogenous modeling approach, specifically the Auto Regressive Integrated Moving Average (ARIMA) type, coupled with the outcomes from the realized dynamic model (DL). This strategy aligns with the methodology utilized by Sawadogo *et al.* (2010), who employed a similar approach for predicting grain prices in Burkina Faso. While ARIMA models forecast based on previous parameter data, they don't account for the impact of exogenous variable shocks on the considered parameter (Sawadogo *et al.*, 2010). This limitation is addressed effectively by dynamic models such as the stepped-delay models utilized in this study.

To achieve this, ARIMA was employed to predict the values of influential explanatory variables that significantly impact maize production volume. These variables include CO₂ quantity from food waste, CH₄ quantity from electricity and transport sectors, maximum temperature, rainfall, and rural population density-effects that are observed prominently in the produced

dynamic model. These predicted values were then utilized to directly forecast the production volume, based on the short-term effects identified in the model estimation results.

As depicted in the prediction graph for the forthcoming years, there is an exponential growth trend in national-level production volume, even under the influence of key determining factors such as CO₂ quantity from food waste, CH₄ quantity from electricity and transport sectors, maximum temperature, rainfall, and rural population density (Figure 10). The forecasted values of explanatory variables derived from the ARIMA models indicate a gradual evolution of the various evaluated parameters. Analysis of the prediction graphs suggests that by 2030, CO₂ quantity could surpass 200 kt and potentially exceed 400 kt by 2050 in Benin. Similarly, methane is projected to surpass 200 kt by 2030, with a potential quantity approaching 400 kt by 2050. Population size could reach seven million inhabitants by 2030, aligning with forecasts from the DGEC (2022), which predicts a population increase of approximately 2.7% annually for Benin.

Regarding rainfall, a slight upward trend is evident compared to previous years, with a potential increase of at least 1000 mm by 2050 compared to the 1990s. Nonetheless, the trend in rainfall evolution appears less pronounced than the other parameters, suggesting the possibility of stable rainfall over the next decade. This outlook is echoed by Benin's Ministry of the Environment, Housing and Urban Planning, which states in its 2021 report on rainfall forecasts that there will likely be relatively consistent annual rainfall from south to north of the country until 2100, compared to the reference period of 1971 to 2000.

Lastly, maximum temperature is anticipated to experience a gradual evolution over time, consistently remaining within the range of 38°C. This temperature rise aligns with predictions made by the Ministry of the Environment (2021), which anticipates temperature increases throughout all regions of Benin by 2100, with the most significant thermal rise estimated at 3.27°C compared to the reference period of 1971-2000. This temperature increase, in turn, contributes to heightened potential evapotranspiration (ETP) and a scenario of water scarcity, ultimately impacting overall agricultural production, including maize, as highlighted by the Ministry of Environment (MEHU, 2021).

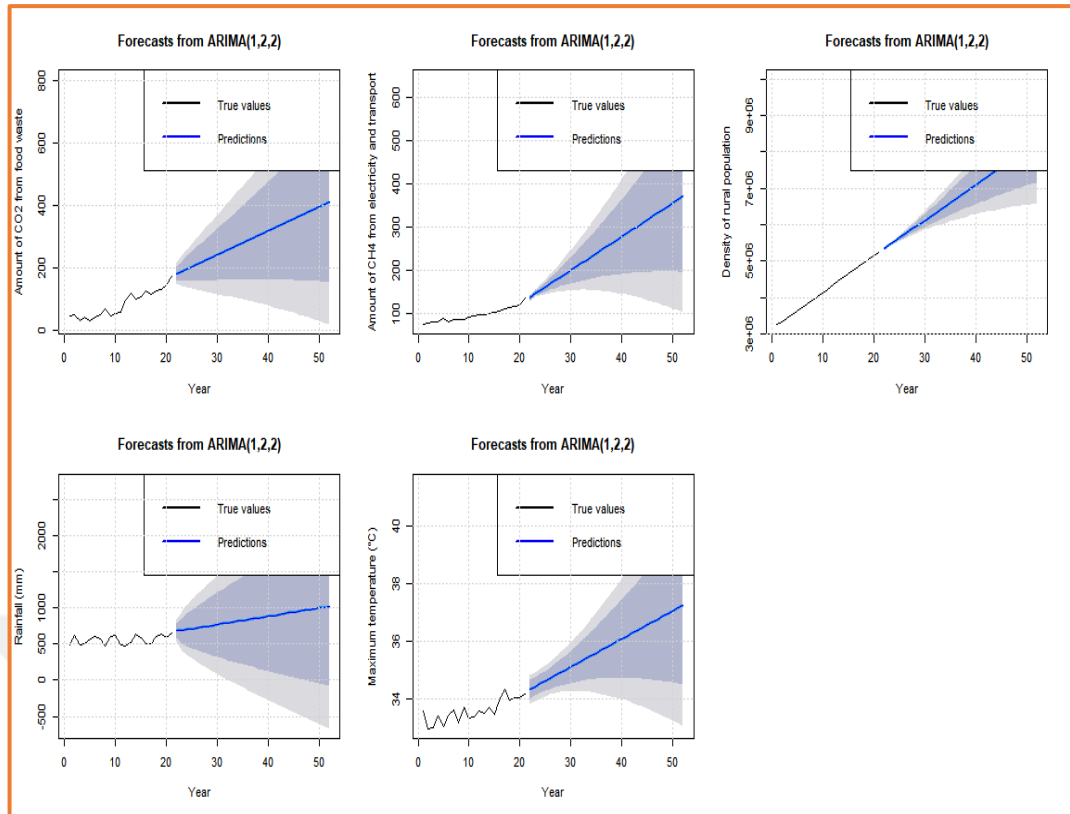


Figure 10. Predicted explanatory parameter values from ARIMA

Despite the anticipated escalation of various climatic parameters and atmospheric pollutants, along with an increase in maximum temperature according to ARIMA forecasts, there will still be a substantial rise in maize production volume over time. The results of the predictions strongly suggest a production volume surpassing threefold (4 million tons of maize) the amount produced in 2020 (approximately 1.6 million tons of maize) (Figure 11). This noteworthy production surge is primarily attributed to the projected rise in the agricultural population (rural population) in the forthcoming years, as outlined by the forecasts concerning explanatory variables, particularly the evolution of the rural population in relation to weather conditions. Consequently, despite the impact of climatic factors like atmospheric pollutants, rainfall, and maximum temperature, the maize production volume could experience a considerable increase by 2030. These findings align with certain predictions put forth in the Second National Communication regarding maize production yields in specific zones of Benin by 2025, including the extreme North-Benin zone, northern cotton-growing zone, North-Donga zone, and West-Atacora zone (MEHU, 2021). However, in other agro-ecological zones such as the southern food crop zone, barre land zone, depression zone, and fisheries zone, forecasts by MEHU (2021) indicate a considerable decline in maize yields by 2025. Nevertheless, when considering the entire national territory, a general upswing in production levels by 2025 is expected, and these predictions concur with the outcomes of the present study.

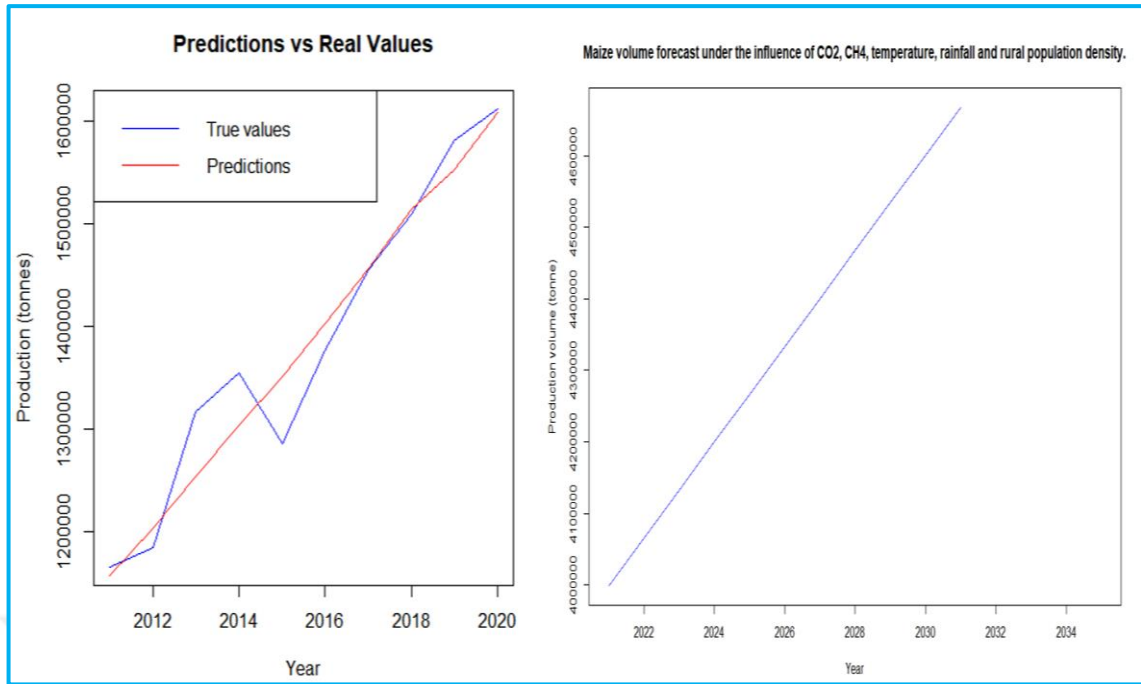


Figure 11. Predictions of maize production volume for the next ten years

4.4 Structuring based on surface area

For an adequate structuring, when analyzing the farm areas of the households studied, the grouping method is based on the size of the maize farms of the different observation units. In fact, the thresholds set for the boundaries of each maize area class are chosen by considering the total average area (β) and the median value (φ) from the various observation units. This method, also adopted by other studies such as Dossou *et al.* (2019) carried out on soybean farms, enabled three classes or categories of farms to be constituted, including: small (Minimum Area $\leq$ Area $< \varphi$), medium ($\varphi \leq$ Area $< \beta$) and large maize area farms ($\beta \leq$ Area $\leq$ Maximum Area).

As a result, we find small farms with a surface area of 1 to 3 hectares forming Group I, followed by medium-sized farms with a surface area of 3.5 to 9 hectares forming Group II units, and finally large farms with a surface area of 9 to 50 hectares (maximum surface area) forming Group III units. This group structuring will be considered in the remainder of the study to identify the various factors determining the size of the different farms within the study population.

4.4.1 Area planted by farmers

Overall, the average area sown by maize farmers is 8.87 hectares (Table 8). There is considerable variation by group category. The majority (37.39%) have an area of 3 hectares or less, with an average area of less than 2 hectares. However, a significant proportion (33%) of these producers have large farms, with an average area of around 20 hectares. The remainder cultivate an average area of 5.84 hectares. This strong interest among farmers in this crop relates to its introduction in Benin's Strategic Plan for the Development of the Agricultural Sector (PSDSA)

to promote and guarantee food security and poverty reduction (MAEP, 2018). Similarly, this crop has been recognized as the most cultivated speculation in Benin, i.e. by around 85% of producers in Benin and it constitutes the leading food product far ahead of rice and Sorghum (World Food Program (WFP), 2014 cited by Akpo, 2020). Thus, its use in the preparation of various traditional dishes by the local population and its high demand on the local market creates an economic incentive for producers to produce this crop in large quantities to meet the population's food needs (Akpo, 2020).

Table 8. Average area of farmers by group

Area		Mean $\pm$ Standard deviation (ha)	Percentage
Area	I	1.98 $\pm$ 0.74	37.39
	II	5.84 $\pm$ 1.55	29.56
	III	19.68 $\pm$ 10.94	33.04
	Total	8.87 $\pm$ 9.97	100.00

4.4.2 Gender

The gender breakdown of respondents shows that both sexes are present, regardless of the area class considered (Table 9).

However, the comparative analysis carried out shows statistically significant differences ($p < 0.05$) in the distribution of the sexes both within the survey population as a whole and within each area class. Indeed, these results show a strong predominance of men in all three groups (small, medium, and large farms), i.e. 86.95% of male producers versus 13.04% of female maize producers.

This means that maize production is still predominantly a male activity in North Benin. These results corroborate those of Yegbemey et al (2014), who found that 93% of maize farmers surveyed were male. For some, the dominance of men in the agricultural production sector is general and can be explained by the fact that women do not have farmland or access to agricultural inputs to ensure production (Herr and Muzira, 2012). In this context, they prefer to pursue other income-generating activities (Yabi et al., 2016) such as processing or trading (Hinnou, 2018).

Table 9. Distribution of producers by gender

		Gender			P (Chi-deux)
		Woman	Men	Total	
Areas	I	26.70	73.30	100.00	1.61e-05***
	II	7.35	92.60	100.00	2.01e-12***
	III	2.60	97.40	100.00	1.46e-16***
Total		13.04	86.95	100.00	0.00***

Signif. codes : '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

4.4.3 Socio-cultural groups (ethnicity)

Table 10 shows the distribution of farmers by socio-cultural group according to the different farm sizes. The table shows that the study area is highly culturally diverse, with around eleven (11) different ethnic groups.

Furthermore, whatever the farm size category considered, there is a significant dominance of producers belonging to the "Bariba" socio-cultural group, averaging 76.52% of the population studied. The other minority is mainly represented by producers belonging to the "Gando" ethnic group, averaging 10.8% of the population studied. This high representation of the Bariba is since in North Benin, this is the majority socio-cultural group, particularly in the agricultural production sector. This great dominance of the Bariba in North-Benin has also been highlighted by others during their research in North-Benin, particularly Hounzinme *et al.* (2017).

Table 10. Distribution of producers by socio-cultural group

		Social groups											Total	P
		1	2	3	4	5	6	7	8	9	10	11		
Area	I	4.65	72.10	4.65	5.81	0.00	2.33	9.30	1.16	0.00	0.00	0.00	100.00	2,29e-48***
	II	1.47	73.50	1.47	16.20	1.47	2.94	0.00	0.00	1.47	0.00	1.47	100.00	1,86e-48***
	III	0.00	84.20	1.32	11.80	0.00	0.00	1.32	0.00	0.00	1.32	0.00	100.00	6,16e-42***
Total		2.17	76.52	2.60	10.80	0.43	1.73	3.91	0.43	0.43	0.43	0.43	100.00	0,0015**

Signif. codes : '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Legend: 1= Dendi; 2 = Bariba; 3 = Nagot; 4 = Gando; 5 = Zerma ; 6 = Fon; 7 = Peulh; 8 = Ditamari; 9 = Lokpa ; 10 = Yoruba ; 11 = Idaasha

4.4.4. Religion

Although the study population is predominantly Bariba, there is a diversity of religions, particularly Islam, Christianity, and Animism. However, Muslims dominate, accounting for an average of 70% of the study population, compared with 27.83% Christian and 2.17% Animist (Table 11). These results show that agricultural production, essentially that of maize, is carried out more by Muslims. This finding could be linked to the fact that the northern zone, like the Borgou department which includes the areas of interest in this study, is characterized by a concentration of Muslim communities. This is also revealed by the exhaustive studies carried out by INSTaD (2013), ex INSAE in this department, where 69% of the population belongs to the Muslim community.

Table 11. Distribution of producers by religion

		Religion				P (Chi-deux)
		Animist	Christian	Muslim	Total	
Area	I	2.33	36.00	61.60	100.00	1.22e-10***
	II	1.47	26.50	72.10	100.00	4.47e-12***
	III	2.63	19.70	77.60	100.00	5.04e-16***
Total		2.17	27.83	70.00	100.00	0.179

Signif. codes : '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

4.4.5. Land tenure

Land is a central resource for agricultural production. It is the starting point for all agricultural production and remains one of the most vital and fundamental resources for agriculture.

However, there is significant variability in land tenure within the study population. In total, 4 different modes of land tenure were identified: inheritance, gift, purchase, and lease. However, most producers (63.04%) have access to their land through inheritance, compared with 16.52% through rental and 14.78% through purchase (Table 12).

These results corroborate those of Savi et al (2022), who first found that maize farmers in North Benin use three modes of land tenure (inheritance, gift, and lease), with inheritance predominating (90% of farmers acquired their land by inheritance).

Nevertheless, analysis of the results shows that as we move from small-area producers (I) to large-area producers (III), the proportion of producers who acquired their land through inheritance increases significantly. In other words, most farmers planting more than 10 hectares acquired their land by inheritance, i.e. 81.6% of the total, compared with only 61.8% and 47.7% respectively for medium- and small-acreage farmers. Inheritance is a common practice whereby land is passed down from generation to generation within a family. This form of tenure maintains the continuity of farms within the same family line.

Table 12. Distribution of producers by land tenure method

		Land tenure					P (Chi-deux)
		Heritage	Don	Purchase	Rental	Total	
Areas	I	47.70	9.30	20.90	22.10	100.00	5.82e-06***
	II	61.80	7.35	11.80	19.10	100.00	5.03-11***
	III	81.60	0.00	10.50	7.89	100.00	4.97-18***
Total		63.04	5.65	14.78	16.52	100.00	0.166

Signif. codes : '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

4.4.6 Marital status

An assessment of the respondents' family status shows that, ranging from small-acreage to large-acreage producers, the majority are married (90% in total) (Table 13). Only 5.21% are single, 2.6% widowed and 2.17% divorced. These results are like those of Ollabode et al (2022), who found that 95% of farmers in northern Benin were married, compared with 2.7% single. However, the results show that almost all farmers (97.4%) planting more than 10 hectares (group III) are married, some 14% more than farmers planting less than 3 hectares.

As a result, marriage is an indicator of access to resources such as farming tools, capital, agricultural knowledge passed down within the family and, above all, land, considered to be the key element in production. It's easy to understand why "inheritance" is the predominant mode of access for all three groups of producers. Thus, married producers benefit from these shared resources, particularly the land, which facilitates their commitment to maize production.

Table 13. Distribution of producers by marital status

		Marital status				Total	P (Chi-deux)
		Married	Divorced	Widower	Single		
Areas	I	83.70	2.33	4.65	9.30	100.00	2.97e-34***
	II	89.70	4.41	2.94	2.94	100.00	1.03e-32***
	III	97.40	0.00	0.00	2.63	100.00	1.46-16***
Total		90.00	2.17	2.60	5.21	100.00	0.047*

Signif. codes : '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

4.4.7 Membership of a producers' organization

As far as associative life is concerned, the results of the table below show that the majority, i.e. 93.47% of farmers in general, do not belong to any peasant organization (formal or informal) (Table 14). And whatever the group of producers considered; this proportion remains similar. Despite the various benefits of association life for producers (improved production capacity, access to services such as training, access to complementary production resources (Wokpo A., 2010), many are still unaware of the power of associations and prefer to work individually to ensure their production. These results stand in contrast to those obtained by Ollabode et al. (2017), who noted in their studies of soybean farmers in North Benin that more than half (54.5%) of them belong to an organization. This difference could no doubt be explained by the fact that soy is a commodity for which several organizations are set up to facilitate its marketing in most major production zones such as northern Benin.

However, some of them belong to groups or associations, representing around 6.52% of all farmers. For others, this diversity of lifestyles can be attributed to the specific associative needs and interests of farmers. While some seek to establish social ties and share knowledge with other farmers, others are more interested in access to technical support services or business opportunities.

These specific needs and interests influence whether farmers engage in informal or formal forms of associative life.

Table 14. Distribution of producers by PO membership

		Membership of a PO			P (Chi-deux)
		No	Yes	Total	
Areas	I	94.20	5.81	100.00	2.49e-16***
	II	91.20	8.82	100.00	1.11e-11***
	III	94.70	5.26	100.00	6.18e-15***
Total		93.47	6.52	100.00	0.000***

Signif. codes : '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

4.4.8 Literacy (local language)

The level of literacy among the maize farmers we met remains very low, below 21% for all three groups, with an average rate of 18.26% (Table 15). These results are contrary to those of Ollabodé *et al.* (2017), who found that most producers (61.8%) were literate in the local language. This difference could be explained by the fact that most producers in their soybean studies belong to producers' organizations, which enables them to benefit from certain services such as training or technical supervision requiring literacy beforehand.

Table 15. Distribution of producers by literacy level

		Literacy			P (Chi-deux)
		No	Yes	Total	
Areas	I	79.10	20.90	100.00	6.98e-08***
	II	80.90	19.10	100.00	3.52e-07***
	III	85.50	14.50	100.00	5.85e-10***
Total		81.73	18.26	100.00	0.000***

Signif. codes : '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

4.4.9 Education level

The table below shows the distribution of farmers by level of education according to the three farm groups identified. Most farmers had formal education (from primary school to university), i.e. 56.09% of all farmers, compared with 43.91% who had no formal education at all (Table 16). These results are like those of Adebiyi *et al.* (2019), who found that 54% had received formal education.

Table 16. Distribution of producers by level of education

		Education level				Total	P (Chi-deux)
		No	Primary	Secondary	University		
Areas	I	37.20	27.90	3.40	3.49	100.00	4,56e-05***
	II	42.60	23.50	29.40	4.41	100.00	0,0001***
	III	52.60	21.10	17.10	9.21	100.00	2,98e-07***
Total		43.91	24.34	26.08	5.65	100.00	0,166

Signif. codes : '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

4.4.10 Contact with a suitable structure

As in the previous analysis, we also note here that most producers surveyed (74.34) are not in contact with any extension structure or agent (Table 17). This rate remains well above that obtained by Yegbemey *et al.* (2014), who estimate that only 45% of producers are not in contact with extension agents. This difference can be attributed to the fact that these are two different groups of farmers in terms of flagship speculation. With soybean policies in place, it's only natural that producers who make soybean their main crop should be in contact with the extension agents deployed in the field to coordinate soybean projects.

In addition, the percentage of producers with agricultural contacts decreases as we move from small- to large-scale producers. In fact, around 35.5% of producers with more than 10 hectares feel they are in contact with structures specializing in supporting producers, compared with 67.6 and 88.4% respectively for medium- and small-acreage producers. Indeed, contact with structures specialized in agricultural production enables producers to benefit from several advantages, including access to agricultural inputs (improved seeds, chemical fertilizers, and others). These are just some of the resources available to ensure that the production levels of large-scale producers improve.

Table 17. Distribution of producers according to contact with a specialized structure

		Contact with a structure			P (Chi-deux)
		No	Yes	Total	
Areas	I	88.40	11.60	100.00	1.10e-12***
	II	67.60	32.40	100.00	0.0036**
	III	64.50	35.50	100.00	0.0116
Total		74.34	25.65	100.00	0.00076***

Signif. codes : '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

4.4.11 Main activity

Overall, the study population is multi-sectoral, i.e. characterized by a diversity of main activity sectors, i.e. some 9 different activities (Table 18). They include producers, stockbreeders, hunters/fishermen, craftsmen, traders, agri-food processors, active and retired civil servants and students.

Nevertheless, whatever the producer group considered, analysis of the results shows a significant predominance of agricultural producers, i.e. 73.04% of those surveyed.

Although this rate is below their rates, these results corroborate those of Savi et al. (2022) who found that, despite the existence of other sectors of activity, 97% of maize producers have agriculture as their main activity.

However, a high proportion of farmers whose main activity is farming are those cultivating more than 10 hectares, i.e. 89.5% of their workforce. In contrast, only 58.1% of smallholders consider farming to be their main activity. Others in this group of small-scale producers are involved in handicrafts, with an average proportion of 10%.

Table 18. Distribution of producers according to their main activities

		Main activity									Total	P
		1	2	3	4	5	6	7	8	9		
Area	I	58.10	4.65	4.65	18.6	8.14	2.33	2.33	0.00	1.16	100.00	3,58e-35***
	II	73.50	2.94	1.47	10.3	10.30	0.00	0.00	1.47	0.00	100.00	4,16e-33***
	III	89.50	5.26	0.00	0.00	2.63	0.00	2.63	0.00	0.00	100.00	2,51e-36***
Total		73.04	4.34	2.17	10.0	6.95	0.86	1.73	0.43	0.43	100.00	0,00049***

Signif. codes : '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Legend: 1 = Agriculture; 2 = Livestock; 3 = Hunting/Fishing; 4 = Crafts; 5 = Trade; 6 = Food processing; 7 = Active civil servant; 8 = Retired civil servant; 9 = Student

4.4.12 Secondary activity

The survey population shows that 19.6% of respondents have no secondary activity, particularly on large farms. In fact, 79.4% of producers have an additional activity apart from growing maize (Table 19).

Table 19. Distribution of producers according to secondary activities

		Secondary activity											P	
		0	1	2	3	4	5	6	7	8	9	10	Total	
Area	I	16.30	39.50	10.50	2.33	6.98	19.80	0.00	0.00	0.00	1.16	2.23	100.00	6.75e-18***
	II	19.10	26.50	20.60	4.41	8.82	10.30	2.94	0.00	0.00	0.00	1.47	100.00	2.99e-09***
	III	23.70	6.58	30.30	2.63	9.21	11.80	6.58	3.95	0.00	0.00	2.63	100.00	2.69e-12***
Total		19.60	24.78	20.00	3.04	8.26	14.30	3.04	1.30	0.00	0.43	2.17	100.00	0.00049***

Signif. codes : '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Legend: 0 =No other activity; 1 = Agriculture; 2 = Animal husbandry; 3 = Hunting/Fishing; 4 = Crafts; 5 = Trade; 6 = Food processing; 7 = Active civil servant; 8 = Retired civil servant; 9 = Student; 10 = Other

4.4.13 Access to credit

On the financial front, the analyses show that access to credit is a real concern for most farmers, i.e. 70.86% (Table 20). Although lower, this result is close to that of Ollabode et al. (2017), according to whom access to credit is still very low among producers, particularly in the commune of N'Dali, at just 18%. This is also underlined by others such as Oladéjo and Adétunji (2012) when they reveal in their studies that most agricultural producers depend essentially on personal savings from their production activities.

However, we can see that the rate of access increases as we move from small-acreage producers (14%) to large-acreage producers (39.5%). This seems logical in a context where larger acreage and access to credit have a mutual influence: access to credit enables producers to have sufficient means or resources to increase production levels, but in return the availability of large acreage reinforces the confidence of microfinance actors to grant credit to producers.

Table 20. Distribution of producers according to access to credit

		Access to credit			P (Chi-deux)
		No	Yes	Total	
Areas	I	86.00	1.00	100.00	2.29e-11***
	II	63.20	36.80	100.00	0.029*
	III	60.50	39.50	100.00	0.066
Total		70.86	29.13	100.00	0.00044***

Signif. codes : '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

4.4.14 Breakdown of farmers by age (%)

Classification by age category indicates that the majority (67.24%) of farmers are adults aged between 36 and 59, with an average age of 41.22 years (Table 21). This corroborates the findings of Adebisi et al. (2019), who report an average age of around 42. This situation reflects the fact that agricultural production remains an activity for people of relatively advanced age. It could also be partly explained by the lack of interest among young people in agricultural activities, who nowadays prefer schooling or apprenticeships in the technical field. It could also be explained by the difficulty of access to land that can be mobilized over the long term by younger population groups, or simply by the phenomenon of rural exodus to large urban centers (Balogoun et al., 2014). So, lacking the means to acquire land or the status to inherit land that could be used for production, they prefer to turn to other income-generating activities. The few in the sample are mainly to be found in the category of farmers producing 3 hectares or less, i.e. 47% of Group I farmers.

Table 21. Distribution of farmers by age group

		Age					
		<= 35	36 - 59	60+	Total	P	Mean ± Standard deviation
Area	I	47.05	52.94	0.00	100.00	4.73e-10***	36.72 ± 8,94
	II	26.47	66.17	7.35	100.00	105-08***	43.18 ± 10,20
	III	11.84	84.21	3.94	100.00	419-20***	44.56 ± 7,86
Total		29.25	67.24	3.49	100.00	2.04-31***	41.22 ± 9,64

Signif. codes : '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

4.4.15 Breakdown of producers by household size

Household size is often used as an indicator of a farm's labor availability, and therefore of an increase in unit size. Indeed, the table below shows that the overall average household size is around 8.44 (Table 22). This size is lower than that obtained by Adebisi et al. (2019), i.e. an equivalence of 11 individuals on average per household.

The table also shows that the majority (81.57%) of farmers with farms of over 10 hectares (group III) have households of between 6 and 16 individuals, and only 15.78% have households of over 17 individuals. On the other hand, the majority (56.97%) of producers with small areas (less than 3.5 hectares) have households of no more than 5 individuals, and no producer in this group has a household size of 17 individuals.

This poor performance by maize farmers in terms of productivity levels could therefore also be attributed to the lack of manpower to launch the activity. This importance of labor in production was also highlighted by Boublal (2014).

Table 22. Distribution of producers by household size

		Household size					
		<= 5.00	6.00 – 16.00	17+	Total	P	Mean ± Standard deviation
Area	I	56.97	43.02	0.00	100.00	1.31e-10***	5.17 ± 2,11
	II	26.47	72.05	1.47	100.00	4.47-12***	7.39 ± 3,15
	III	2.63	81.57	15.78	100.00	1.93-18***	13.07 ± 6,55
Total		30.00	64.35	5.65	100.00	8.72-27***	844 ± 5,48

Signif. codes : '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

4.4.16 Distribution of producers by number of farm assets (%)

Although having a large household size does not directly translate into having a large labor force without agricultural assets, the two factors influence each other significantly in certain situations.

Indeed, out of an overall average size of 8.44 individuals per household, around 7 or exactly 6.57 represent the average number of agricultural assets in the households of maize farmers (Table 23). This result corresponds to that of Ollabodé *et al.* (2017), who obtained an average number of assets of 7 per household.

However, analysis of the table shows that producers with more farm workers in their household are those who sow the largest areas. In fact, the vast majority (86.58%) of producers planting less than 3.5 hectares (group I) have fewer than 5 farm workers, while 75% of producers in group III have between 6 and 13 farm workers, while 15.78% of this same group have more than 14 farm workers.

Table 23. Distribution of producers by number of farm workers

		Number of farm workers					
		<= 5.00	6.00 – 13.00	14.00+	Total	P	Mean ± Standard deviation
Area	I	86.58	13.41	0.00	100.00	6.26e-24***	3.74 ± 1.86
	II	52.94	45.58	1.47	100.00	1.36e-07***	5.67 ± 2.42
	III	9.21	75.00	15.78	100.00	9.99e-14***	10.59 ± 5.93
Total		50.44	43.80	5.75	100.00	7.52e-18***	6.57 ± 4.81

Signif. codes : '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

4.4.17 Distribution of farmers by length of time in maize production

Finally, in terms of seniority, these are experienced farmers with several years' experience, averaging 14.53 farmers (Table 24). These results show that these farmers are as experienced as those encountered by Yegbemey et al. (2014) (21 years' experience on average) during their work in northern Benin.

In fact, although most farmers (48.03%) have been farming for less than 10 years, 36% of large-scale farmers have more than 10 years' experience, and 2.06% of them have been farming for more than 25 years. These results suggest that, like household size and assets, the number of years of experience or seniority enables farmers to improve their production levels. These experiences have enabled large-scale producers not only to find a way to expand the size of their fields, but also to fully maintain them using family labour. Such results confirm those of Yegbemey et al. (2014), who concluded that experience in agriculture enables producers to increase their technical production capacity.

Table 24. Distribution of producers according to seniority

		Years of experience in maize production					
		<= 10,00	11,00 - 24	25+	Total	P	Mean $\pm$ Standard deviation
Area	I	59.30	31.39	9.30	100.00	9.23e-08***	11.71 $\pm$ 7.72
	II	42.64	35.29	22.06	100.00	1.08e-01***	15.47 $\pm$ 10.02
	III	40.00	36.00	24.00	100.00	2.10e-14***	16.89 $\pm$ 9.85
Total		48.03	34.06	17.90	100.00	1.64e-07***	14.53 $\pm$ 9.40

Signif. codes : '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

4.5. Analysis of energy source management methods

4.5.1. Manifestation and implications of climate change

The results of the analysis of maize farmers' perceptions of the manifestations and implications of climate change reveal significant trends within the different study areas (Table 25). Across the sample, a high proportion of farmers claimed to be aware of the manifestations of climate change (98.3%). This knowledge was particularly marked in N'Dali (98.6%) and Sinendé (100%). In addition, most farmers in all communes perceive direct effects on maize production (97.4% overall). This perception is more pronounced in Sinendé (100%) and N'Dali (98.6%) than in Nikki (91.2%).

Analysis of data relating to climatic events shows significant differences between communes ($p < 0.001$). Notably, in N'Dali, a large proportion of producers have been observing events for 1 to 5 years (73.9%), while in Nikki, a significant portion have more extensive observation experience (34.6% for 6 to 10 years).

Similarly, the diversity of manifestations of climatic variations reveals significant differences between the communes studied, as shown by the results of the chi-square test ($p < 0.001$). In N'Dali, disruptions to rainfall (55.1%) and seasonal calendars (34.8%) are the most widespread manifestations, while in Nikki, farmers mainly mention disruptions to temperature levels (19.2%) and seasonal calendars (26.9%). Sinendé stands out for its high proportion of seasonal calendar disruptions (52.4%) compared to other events.



Table 25. Maize farmers' perceptions of climate change

Perception of climate change		Communes							
		N'Dali		Nikki		Sinendé		Total	
		N	%	N	%	N	%	N	%
Knowledge of CC events	Yes	69	98.60	54	94.70	103	100.00	226	98.30
	No	1	1.43	3	5.26	0	0.00	4	1.74
	Chi-deux	64.129***		43.860***				212.350***	
Demonstrations in maize production	Yes	69	98.60	52	91.20	103	100.00	224	97.40
	No	1	1.43	5	8.77	0	0.00	6	2.61
	Chi-deux	64.129***		37.120***				204.730***	
Duration (years) of event observation	[1-5]	51	73.90	30	57.70	69	67.00	150	67.00
	[6-10]	18	26.10	18	34.60	34	33.00	70	31.2
	[11-15]	0	0	4	7.69	0	0.00	4	1.79
	Chi-deux	14.840***		19.540***		11.220***		143.180***	
Type of event: Disturbance	Rain	38	55.10	28	53.80	38	36.90	104	46.40
	Temperature	6	8.70	10	19.20	11	10.70	27	12.10
	Seasonal calendars	24	34.80	14	26.90	54	52.40	92	41.10
	Other	1	1.45	0	0.00	0	0.00	1	0.40
	Chi-deux	50.250***		10.310**		27.520***		133.320***	
Consequences	Lower production yields	39	55.70	45	78.90	46	44.70	130	56.50
	Decline in water availability	31	44.30	10	17.50	54	52.40	95	41.30
	Other	0	0	2	3.51	3	2.91	5	2.17
	Chi-deux	0,7		55.050***		43,830***		108.480***	

Noted: *** 1% significance level; ** 5% significance level; * 10% significance level.

These results concur with several other studies also carried out in Benin, in which the population claims to perceive climate change through several aspects. These aspects include the decrease and irregularity of rainfall, the late or early start of the rainy season, the early cessation of rainfall and the high frequency of pockets of drought during the season (Yegbemey *et al.*, 2014; Fadina & Barjolle, 2018).

Finally, the consequences of climate change vary between communes ($p < 0.001$). In Sinendé, declining water availability (52.4%) is more frequently reported, while in Nikki, declining production yields (78.9%) predominate. However, in N'Dali, there is a more balanced distribution between the consequences observed, particularly the drop in yields (55.7%) and water availability (44.3%). These variations underline the importance of taking local realities into account when developing climate change management methods in each commune.

These consequences have also been addressed in various previous research studies (IPCC, 2014; Hartter *et al.*, 2012; Molua, 2010; Mwalusepo *et al.*, 2015). These previous works thus reinforce the recognition of the impacts of climate change on agriculture, underlining the urgency of actions and adaptations in this context.

4.5.2. Analysis of energy used

The results of the energy assessment on maize farms reveal some significant trends. Overall, the data indicate a low rate of energy use for all activities related to maize production (Table 26). On the other hand, activities such as weeding (79.6%), herbicide application (73.5%), manual ploughing (74.8%), pesticide application (90%) and transport (70.4%) show a marked similarity with predominant energy use in the 0-5 MJ/ha range (Table 2). These results reflect a common trend in these farming practices. This convergence also suggests a similarity in energy requirements for these specific activities.

Finally, some activities stand out for their different and wider energy intervals. Mechanical ploughing (54.3%) and animal-drawn ploughing (82.2%) have energy requirements of between 100-200 MJ/ha and 0-100 MJ/ha respectively (Table 26). This suggests that these two activities are the ones that require the most commitment or effort from farmers in terms of labor power. These variations highlight the heterogeneity of energy requirements in these specific farming practices, underscoring the need for targeted approaches to optimize energy efficiency in each context.

Table 26. Breakdown of energy requirements by farming activity

Energy (MJ/ha)	Grass clearing and		Weeding		
	mowing		Energies (MJ/ha)		
	N	%		N	%
0-10	85	37.00	0-5	183	79.60
10-30	116	50.40	5-15	07	3.04
30-50	16	6.96	15-30	16	6.96
> 50	13	5.65	> 30	24	10.40
Herbicide			Harvest		
0-5	169	73.50	0-15	54	23.50
5-15	37	16.10	15-30	96	41.70
15-30	20	8.70	30-50	35	15.20
> 30	4	1.74	> 50	45	19.60
Manual ploughing			Fertilization		
0-5	172	7.80	0-5	87	37.80
5-15	41	17.80	5-15	108	47.00
15-30	07	3.04	15-30	29	12.60
> 30	10	4.35	> 30	06	2.61
Pesticide treatment			Transport		
0-5	207	90.00	0-5	162	70.400
5-15	13	5.65	5-15	45	19.60
15-30	09	3.91	15-30	18	7.83
> 30	01	0.43	> 30	05	2.17
Mechanical ploughing			Animal-drawn ploughing		
0-100	77	33.50	0-100	189	82.20
100-200	125	54.30	100-200	24	10.40
200-400	15	6.52	200-500	11	4.78
> 400	13	5.65	> 500	06	2.61

The results of the average energy requirements per agricultural activity reveal significant disparities. The highest average energy requirement is observed for operations such as mechanical ploughing using farm machinery (mechanical traction), with an average of 133.02 MJ/ha. This is closely followed by operations or activities such as animal-drawn ploughing (53.04 MJ/ha) and harvesting (45.18 MJ/ha). In contrast, lower energy requirements are recorded for activities such as weeding (6.34 MJ/ha), transport (5.91 MJ/ha), herbicide application (5.66 MJ/ha), manual ploughing (4.97 MJ/ha) and pesticide treatments (1.55 MJ/ha) (Figure 12).

Comparative analysis of the means, using the Mann-Whitney test, leads to the conclusion that there are significant differences in energy expenditure between agricultural activities (Figure 12). Thus, activities whose means have the same letters are significantly identical. In fact, this pairwise comparison (Mann-Whitney test) shows that animal traction and harvesting operations do

not differ significantly in terms of energy expenditure (Figure 12). Similarly, average energy consumption for transport and herbicide application are statistically similar. The amounts of energy derived from the other activities are significantly different from each other and from the energy of the previous operations listed.

These results are partially consistent with the findings of Ruiz-Vega et al. (2015), who specify that farmers use more agricultural machinery with a greater amount of energy (11800 MJ/ha). On the other hand, other aspects, notably labor dedicated to fertilization (2212 MJ/ha) and manual plowing (64.35 MJ/ha) are significantly higher than animal traction (12.2 MJ/ha) in terms of energy quantities (Ruiz-Vega et al., 2015).

The implications of these findings for the management of farms where maize is grown are particularly relevant to the most energy-intensive farming activities, such as "mechanical traction". Careful management and optimization of energy resources, particularly for the most energy-intensive farming activities such as "mechanical traction", are therefore crucial. Firstly, these energy-intensive activities can account for a significant proportion of total production costs on maize-producing farms. By taking an attentive approach to energy consumption, producers can potentially reduce these costs, which has a direct impact on the overall profitability of these farms. This detailed understanding of energy needs by activity provides a sound basis for implementing sustainable farm management methods, thus contributing to the achievement of long-term sustainability objectives.

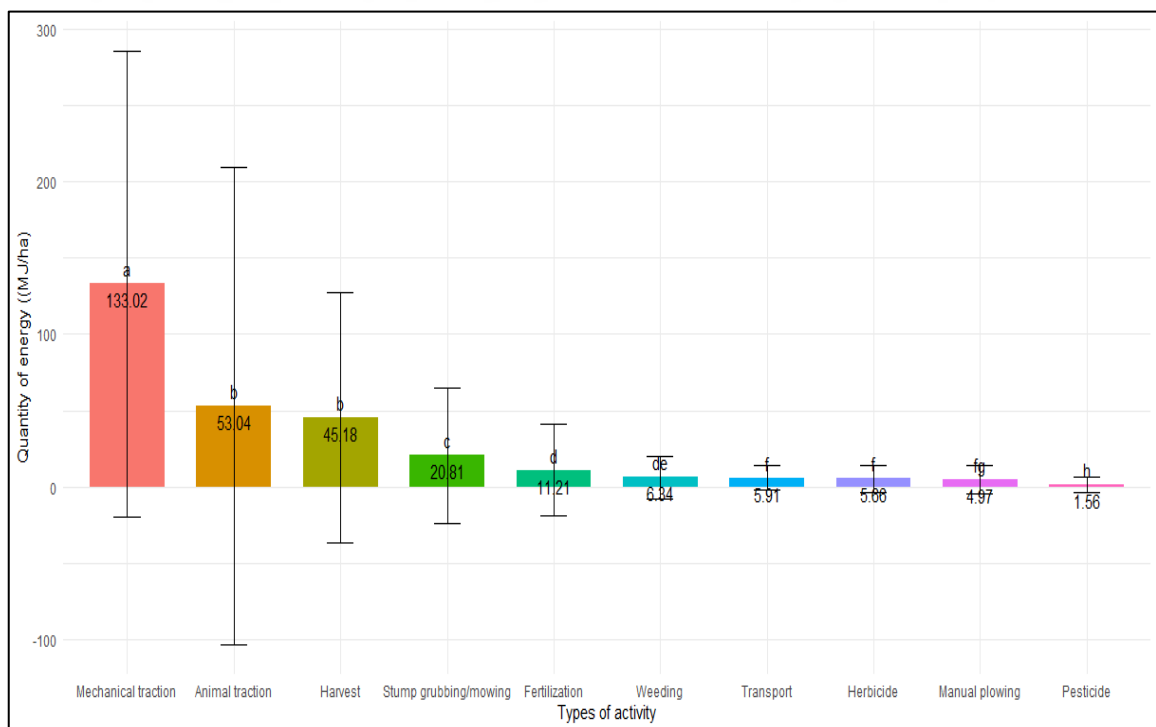


Figure 12. Comparison of average energy requirements by agricultural activity

The results for energy expenditure on agricultural inputs (chemical fertilizers, herbicides, and insecticides) reveal significant differences (Table 27). For herbicide, most producers (61.7%) used between 100 and 300 MJ/ha of energy, indicating a preference for the use of moderate quantities of herbicides. However, a considerable proportion (22.2%) were in the 300 to 500 MJ/ha range, leading to the conclusion that some farmers opt to use large quantities of herbicide to maintain their plots. In this context, farmers' interest in herbicides is not negligible. This could be attributed to the fact that, by increasing their acreage, herbicide use enables them to maintain their plots more rapidly. These results differ from the observations made by Kosemani and Bamgboye (2021) in their research, which indicates low herbicide use by farmers, representing only 3.88% of the total amount of energy used in maize production. As far as insecticides are concerned, the vast majority (93%) of producers have lower energy requirements ranging from 0 to 300 MJ/ha. It is therefore plausible that producers are seeking to minimize insecticide use, probably in response to growing concerns about negative impacts on biodiversity, human health, and water quality.

Results for the use of chemical fertilizers such as NPK (nitrogen, phosphorus, potassium) and urea show distinct patterns. Regarding NPK application, most producers (84.8%) used energy quantities more than 1000 MJ/ha, suggesting intensive use of this fertilizer. Also, for urea, a significant proportion of producers (47.4%) fell within the range of energy expenditure above 1000 MJ. These results indicate a marked preference among producers for the intensive use of chemical fertilizers, particularly NPK. This preference may be explained by producers' perception of the benefits of these fertilizers in terms of optimizing crop yields.

Similarly, the results for energy from fuel use, both for running farm machinery and for moving agricultural produce, show different trends. Indeed, a large proportion of producers (80%) show the lowest energy expenditure of between 1,000 and 1,200 MJ/ha, indicating a low dependence on fuels for their maize production. This observation highlights the low level of mechanization of farming activities on these maize farms.

Table 27. Breakdown of energy expenditure on agricultural and production inputs

Energies (MJ/ha)	Herbicide		Energies (MJ/ha)	Insecticide	
	N	%		N	%
0-100	18	7.83	0-300	214	93.00
100-300	142	61.70	300-500	05	2.17
300-500	51	22.20	500-700	10	4.35
>500	19	8.26	> 700	01	0.43
NPK			Urea		
0-300	12	5.22	0-300	14	6.09
300-600	06	2.61	300-600	21	9.13
600-1000	17	7.39	600-1000	86	37.40
> 1000	195	84.80	> 1000	109	47.40
Carburation					
1000-1200	184	80.00			
1200-1300	32	13.90			
1300-1400	07	3.04			
>1400	07	3.04			

The results of average energy expenditure for the various agricultural inputs reveal significant disparities between categories (Figure 13). At the top of the list, NPK fertilizer stands out with an average of 2238.87 MJ/ha. A multiple comparison of means using the Mann-Whitney test shows that the energy expenditure associated with NPK fertilizer differs significantly from that of other inputs (Figure 13). This trend testifies to its intensive use in agricultural practices, underlining its importance in crop fertilization, but also the energy implications associated with its application. On the other hand, urea ranks second with an average of 1172.95 MJ/ha, marking a similarity with fuel-related energy expenditure (1167.08 MJ/ha). This preference for fertilizers such as NPK and urea has also been highlighted by other researchers (Abikou et al. 2023; Yabi et al., 2016).

In contrast, other inputs such as plant protection products (herbicides and insecticides) show comparatively lower energy averages, at 286.87 and 43.13 MJ/ha respectively. This observation may be explained by farmers' preference for more traditional farming practices, such as manual weeding, rather than the intensive use of chemicals such as herbicides. The use of manual weeding may result from several considerations, including the desire to minimize environmental impacts, to ensure better crop quality or to respond to growing consumer concerns about chemical residues in agricultural products. So, despite the availability of chemical alternatives, farmers seem to be opting for more eco-responsible methods, thus having a positive impact on their overall energy requirements.

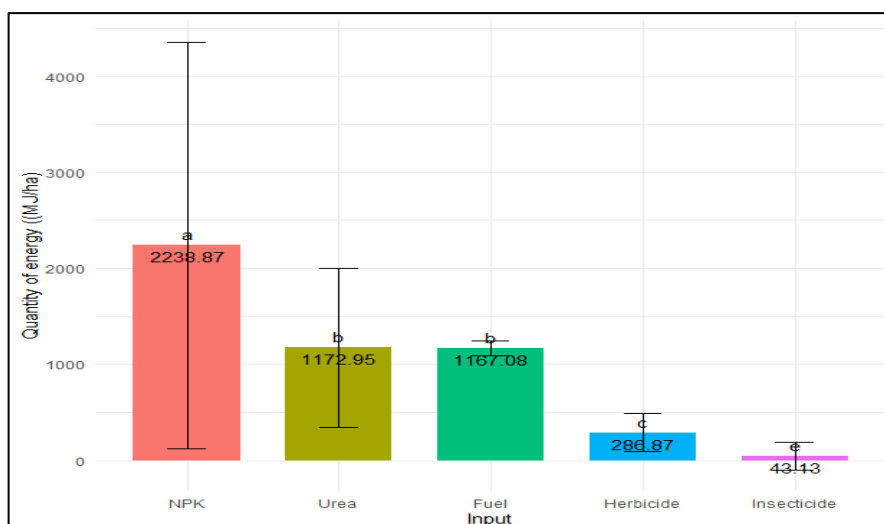


Figure 13. Comparison of energy quantities from input use

4.5.3. Comparison of energy from labor and agricultural inputs

The results of the comparison of total energy, whether derived from inputs, labor, or a combination of the two, reveal significant differences (Figure 14) (a). Indeed, all activities and the use of agricultural inputs result in an average energy expenditure of 6369.59 MJ/ha. This amount of energy is lower than that obtained in other studies carried out on maize. These include studies by Kosemani and Bamgboye, (2021) (9502 MJ/ha) in Nigeria, Canakci et al. (2005) (11366 MJ/ha) in Turkey, Lorzadeh et al. (2011) (29307 MJ/ha) in Iran and Lawal et al. (2014) (31500 MJ/ha) in Nigeria. This divergence could be linked to several factors, including variation around farming practices at the level of different farms, particularly in the use of agricultural inputs, geographical context, and level of development.

Moreover, most of this energy expenditure is attributed to agricultural inputs alone, with an average contribution of 6081.88 MJ/ha, or 94.91% of total energy (Figure 14) (b). The share of labor power in total energy remains very low (5%). This observation highlights the preponderant importance of inputs in the overall contribution to the energy requirements of maize production in Benin. Indeed, these results corroborate those of Kosemani and Bamgboye (2021), Lawal et al. (2014), Lorzadel et al. (2011). At the end of their studies, these researchers also concluded that agricultural inputs, in particular fertilizers, account for most of the energy expenditure to ensure maize production. This dominance of inputs in total energy can be explained by the increased dependence of farms on modern inputs, especially chemical fertilizers, and pesticides. These results underline the need for thoughtful, sustainable management of inputs, given their significant weight in total energy consumption.

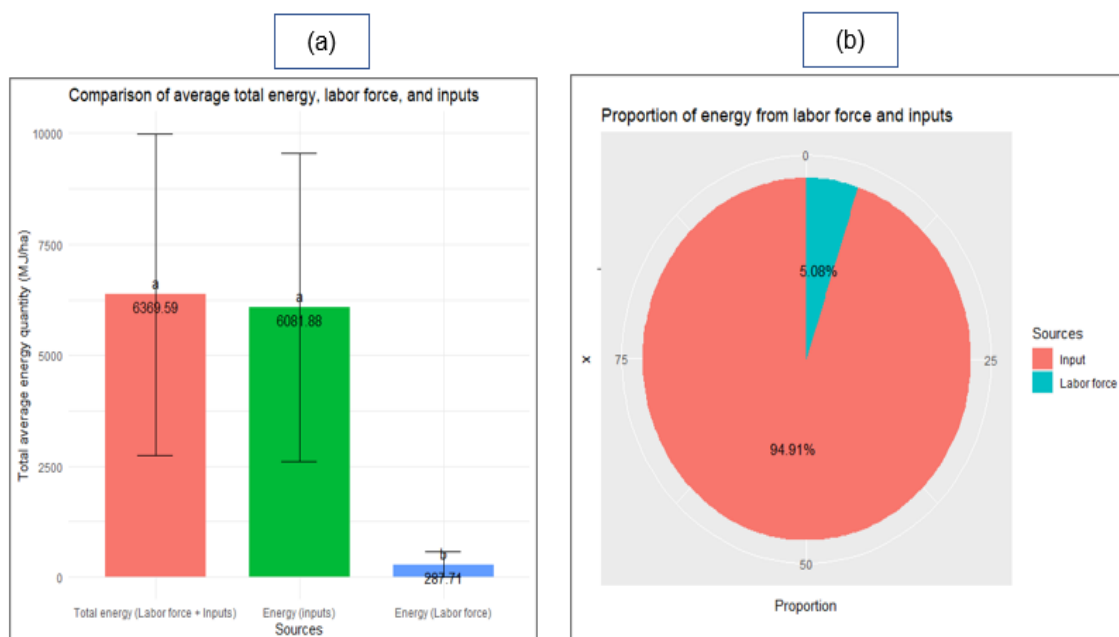


Figure 14. Comparative analysis of average total energies

4.5.4 Main management methods

Faced with the challenges posed by climate change, producers have adopted various management approaches to maintain the productivity of their farms (Table 28). Among these approaches, two major solutions emerge: increasing agricultural inputs, such as fertilizers and pesticides, and increasing the labor force. These two management approaches reflect crucial choices made by producers to mitigate the effects of climate change on maize production and guarantee the sustainability of their farming practices.

Indeed, analysis of the results reveals significant variations between the communes of N'Dali, Nikki and Sinendé (Table 28). Regarding the management methods adopted, there is a marked disparity in the increase in inputs, with a notable proportion in Nikki (61.4%) compared to N'Dali (32.9%) and Sinendé (31.1%). A similar trend can be observed in the increase of the workforce, where Sinendé has a higher adoption rate (68.9%) than N'Dali (67.1%) and Nikki (38.6%). These discrepancies highlight the diversity of approaches adopted by producers in each commune to cope with climate change (Assoumana et al., 2016; Sutcliffe et al., 2016; Gebreeyesus, 2017).

Furthermore, regarding the duration of adoption of management methods, most farmers began using these methods within the last five years (0-5years), especially in N'Dali (85.7%). In Nikki, this proportion rises to 78.9%, while in Sinendé it reaches 80.6%. These results indicate a general trend towards the relatively recent adoption of these management or adaptation methods, underlining producers' heightened awareness of recent climatic challenges.

Table 28. Change management methods and adoption times by the producers

Adaptation		Communes						Total	
		N'Dali		Nikki		Sinendé			
		N	%	N	%	N	%	N	%
Management modes	Increased inputs	23	32.90	35	61.40	32	31.10	90	39.10
	Increased workforce	47	67.10	22	38.60	71	68.90	140	60.90
	Chi-deux	0.0059**		0.112		1.8e-4***		0.00123**	
Duration (years) of management system adoption	[0-5]	60	85.70	45	78.90	83	80.60	188	81.70
	[6-10]	9	12.90	9	15.80	20	19.40	38	16.50
	> 10 years	1	1.43	3	5.26	0	0.00	4	1.740
	Chi-deux	< 2.2e-16***		1.605e-12***		5.381e-10***		< 2.2e-16***	

Noted: *** 1% significance level; ** 5% significance level; * 10% significance level.

4.6. Influence of management style on farm performance

4.6.1. Producer efficiency index

Analysis of the efficiency indices for the two groups of producers, distinguished by their climate change adaptation strategy (increased labor force or increased agricultural inputs), offers interesting insights into the performance of these approaches (Table 29). Three efficiency indices were used: Constant Scale Return (CRS) technical efficiency, Variable Scale Return (VRS) technical efficiency, and scale efficiency, which measures the relative efficiency between these two approaches. Indeed, in the context of this study, Constant Scale Return (CSR) technical efficiency highlights the constancy of maize yields with fixed inputs, while Variable Scale Return (VSR) technical efficiency reflects flexibility in adjusting inputs to optimize maize yields. Finally, scale efficiency assesses the optimal management of maize farm size in relation to an ideal size for maximizing production without wasting resources.

Regarding the group that opted to increase the labor force, the results of the comparative analysis show significant variability in these three efficiency levels. Producers with efficiency levels between 20 and 30% dominate the sample (31.43%). Thus, only 5% of farmers have an efficiency level above 90%, illustrating optimal technical management at constant yield. This indicates inefficient management in the use of inputs and available resources. However, a significant proportion of farmers (97.9%) show levels of technical efficiency at variable yield above 90%.

On the other hand, for the group that opted for an increase in agricultural inputs, a similar trend can be observed, especially regarding technical efficiency at constant yield. However, a higher proportion (15.6%) of farmers achieved technical efficiency levels of over 90% at constant yield, compared with 87.8% at variable yield. These results are in line with those obtained by Hassan et al. (2014), who report that around 55% of farmers have variable-yield efficiency levels

above 90%. This indicates, according to the indices obtained, that increasing inputs can potentially lead to better economic performance.

Analysis of the average scale efficiency indices offers further indications, with extremes ranging from 10.1% to 100% for farmers increasing labor power, and from 11.3% to 100% for those opting for increased inputs. Also, only 5% of farmers who opted for an increase in labor force showed a scale efficiency greater than 90%, compared with 18.9% for those who opted for an increase in inputs. These results underline the importance of an in-depth analysis of management methods, considering the specificities of efficiency indices, to guide producers' decisions towards more sustainable and profitable practices.



Table 29. Distribution of effectiveness levels by adaptation strategy

Management mode	Efficiency level (%)	Technical efficiency at CRS		Technical efficiency at VRS		Scale efficiency	
		Workforce	%	Workforce	%	Workforce	%
Increasing the workforce	<= 10	1	0,714	0	0.000	0	0.000
	10 < eff. <=20	31	22,143	0	0.000	32	22,85
	20 < eff. <=30	44	31,430	0	0.000	41	29,28
	30 < eff. <=40	17	12,143	0	0.000	19	13,6
	40 < eff. <=50	17	12,143	0	0.000	15	10,7
	50 < eff. <=60	8	5,710	0	0.000	9	6,43
	60 < eff. <=70	8	5,710	0	0.000	8	5,71
	70 < eff. <=80	4	2,860	2	1,43	5	3,57
	80 < eff. <=90	3	2,142	1	0,714	4	2,86
	> 90	7	5	137	97,9	7	5
	Total	140	100.000	140	100.000	140	100.00
	Minimum	9.900		78.900		10.100	
	Maximum	100.000		100.000		100.000	
Increased inputs	<= 10	0	0.000	0	0.000	0	0.000
	10 < eff. <=20	13	14.400	0	0.000	13	14.400
	20 < eff. <=30	28	31.100	0	0.000	28	31.100
	30 < eff. <=40	9	10.000	0	0.000	3	3.330
	40 < eff. <=50	10	11.110	0	0.000	16	17.800
	50 < eff. <=60	2	2.220	0	0.000	0	0.000
	60 < eff. <=70	5	5.560	0	0.000	6	6.670
	70 < eff. <=80	3	3.330	2	2.220	3	3.330
	80 < eff. <=90	6	6.670	9	10.000	4	4.440
	> 90	14	15.600	79	87.800	17	18.900
	Total	90	100.000	90	100.000	90	100.000
	Minimum	11.300		74.100		11.300	
	Maximum	100.000		100.000		100.000	

CRS= Constant Returns to Scale; VRS= Variable Returns to Scale

4.6.2. Comparative analysis of efficiency indices according to management modes

The comparative results of the averages for the three efficiency indices provide a general overview of the performance of the two management modes: increasing the labor force and increasing agricultural inputs (Figure 15). For Constant Scale Return (CSR) technical efficiency, farmers who opted for increasing inputs had a significantly higher mean (0.466) than those who chose to increase their labor force (0.367). This result leads to the conclusion that the strategy of increasing input use is more efficient in terms of optimal use of resources. On the other hand, regarding Variable Scale Return (VRS) technical efficiency, farmers who chose to increase their labor force (0.983) had a significantly higher average than farmers who increased their input quantities (0.968). This observation indicates that increasing labor power can lead to better adaptation to climate change, with performance varying according to the levels of resources available.

However, when examining scale efficiency, which measures the inefficiency associated with sub-optimal size, the group of farmers favoring an increase in inputs (0.483) performs better than those preferring to increase their labor force (0.374). These results allow us to conclude that increasing the use of agricultural inputs enables farmers to be more efficient in optimizing resources and maize production, compared with the strategy of increasing labor power. The variability in efficiency observed among labor-intensifying producers, however, highlights the challenges associated with optimal human resource management. Input intensification, on the other hand, offers a more coherent and potentially more profitable solution to these challenges. These results thus suggest that input-intensive farming practices may be a promising avenue for improving farm resilience and sustainability in the face of climatic pressures. Such conclusions are in line with the findings of several other researchers; highlighting the significant influence of inputs on agricultural production (Hassan et al., 2014).

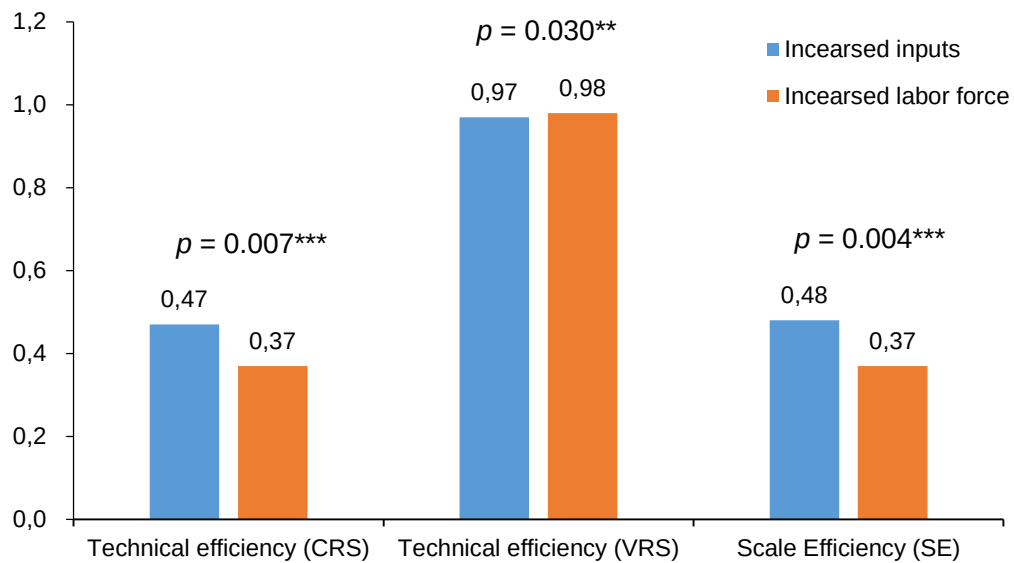


Figure 15. Comparison of average efficiency indices by management mode

** and *** represent 5% and 1% significance level, respectively

4.6.3. Determinants of farmer efficiency

Analysis of the results of the Tobit regression model highlighting the determinants of maize farmers' efficiency reveals significant trends (Table 30). The results of the three Tobit models show significant differences in terms of Pseudo R-squared. The scale efficiency model displays the lowest positive Pseudo R-squared (2.685), indicating the best fit among the three models. In contrast, the VRS technical efficiency model shows a negative Pseudo R-squared of -0.071, suggesting a less satisfactory fit compared to the constant scale efficiency (3.483) and scale efficiency (2.685) models. These results highlight variations in the ability of the models to explain the variance in the data, with the scale efficiency model showing a better fit.

Analysis of the results shows that constant yield technical efficiency (CRS) highlights several significant factors influencing maize farmers' performance. Firstly, age (-0.004) and area sown to maize (-0.008) have a negative and significant influence on this efficiency. In other words, older farmers are less efficient than younger ones. This confirms the results of Diallo and Garba (2023). Also, each additional unit of sown area (1ha) as well as production factors results in a 0.008 decrease in technical efficiency at constant returns to scale. This underlines the importance of careful management of farm size to maximize yields and thus constant efficiency. This result is at odds with the finding by Fadina and Barjolle (2018), who revealed instead a positive effect of acreage on technical efficiency.

However, the use of insecticides (0.053) and NPK fertilizers ($4.1e-05$) are associated with improved efficiency, testifying to the importance of these inputs in optimizing yields (Edison, 2021). Other determining factors include the consideration of farming as a main activity, and the number of years' experience in maize production. As a result, farmers who place central importance on farming as their main source of activity demonstrate greater efficiency, with an estimated

increase of 0.062 units. Furthermore, an additional year of experience in maize production is associated with an increase in the efficiency index (i.e. 0.005 units). Thus, the combination of professional commitment and accumulated expertise positions experienced farmers, particularly those focused on agriculture, at the top in terms of efficiency. This positive influence of experience in terms of the number of years of production has also been highlighted in other similar studies (Miassi *et al.*, 2023).

In terms of variable yield technical efficiency (VRS), on the other hand, farmers' age showed a significant influence (0.001), suggesting that relatively older farmers were more efficient than younger ones. This result suggests that the resource management skills of older producers contribute to more flexible input optimization (Abanda and Saha, 2023). Similarly, increasing maize area (0.0006) and gender (0.027) were also found to significantly influence technical efficiency at variable yields. This observation indicates that the extent of land devoted to maize and the gender of maize farmers play an essential role in the variation of technical efficiency, underlining the importance of these parameters in the context of variable-yield maize production. Indeed, the significant difference linked to gender thus highlights the superior ability of men to optimize their resources more efficiently than women. This trend could be attributed to factors such as the unequal distribution of responsibilities, differential access to resources and other socio-economic and cultural dynamics, as specified by Diallo and Garba (2023).

Thus, this relationship underlines the influence of gender dynamics on farm performance, suggesting the need to strengthen the skills of women maize producers to promote equity and empowerment of women in the agricultural sector. Finally, this technical efficiency was negatively influenced by literacy (-0.015), reflecting the fact that producer's literate in the local language is less efficient than others. This result contradicts the findings of several works according to which human capital characterized by agricultural supervision positively influences value added at the producer level in Africa (Khadimallah and Akrouf, 2017; Yakete-Wetonnoumbena and Mbetid-Bessane, 2019). This finding raises questions about local socio-educational dynamics and highlights the importance of adapting efficiency-enhancing strategies by considering specific literacy contexts.

For scale efficiency, farmer experience showed a significant influence (0.005), indicating that farmers with more experience in maize production are more efficient. This positive relationship suggests that experience acquired over the years enables producers to better manage their resources and optimize input use, leading to higher scale efficiency. Indeed, experienced farmers thus manage to develop specific skills and knowledge that enable them to make more informed farm management decisions. This finding underscores the importance of experience in improving operational efficiency, and the validity of programs aimed at building producers' skills to foster more effective farming practices. Insecticide use (0.031) was also significant, showing the impact of inputs on scale efficiency. In addition to experience, the use of insecticides (0.053) and

chemical fertilizers such as NPK (4.13e-05) are also factors with a positive and significant influence on scale efficiency. This observation suggests that farmers who employ input-intensive practices, such as the use of insecticides, chemical fertilizers, and organic matter, tend to improve their overall efficiency (Geta et al., 2013).

These results can be interpreted as a positive sign of more intensive and technologically advanced farm management. This leads to higher yields and greater efficiency on the part of producers. Similarly, a positive effect of factors such as main activity (farming) was also observed for scale efficiency. These results corroborate earlier findings for technical efficiency at constant returns to scale. Thus, individuals whose main activity is farming seem to optimize their production scale better. On the other hand, a negative influence is observed for age and area sown. Indeed, the negative relationship with the expansion of maize acreage (-0.014) suggests that producers with larger farms face specific challenges, particularly in relation to management (especially with larger fields). Furthermore, the significant gender difference (-0.005) indicates that men are less efficient than women in the context of scale efficiency. This finding can be explained by various factors such as differentiated farming practices or socio-economic dynamics. This underscores the need to understand gender nuances in the optimization of large-scale agricultural efficiency.

Putting these results together, we can conclude that age, experience, management of the area sown to maize production, use of insecticides and NPK fertilizers, are the main determinants of these different efficiency indices. These crucial factors underline the importance of strategic management of these elements to improve the overall performance of maize farms, while considering the specificities of each efficiency index.

Table 30. Determinants of maize farmers' efficiency

Variables	Technical efficiency at CRS	Technical efficiency at VRS	Scale efficiency
Age	-0,004 (0,002)*	0,001 (0,0003)***	-0,005 (0,002)*
Experience	0,005 (0,002)*	-0,0003 (0,0004)	0,005 (0,002)*
Area	-0,014 (0,002)***	0,0006 (0,0003)*	-0,014 (0,002)***
Gender (0 =F; 1 =M)	-0,033 (0,042)	0,027 (0,01)**	-0,051 (0,042)
Insecticide	0,053 (0,01)***	0,001 (0,002)	0,053 (0,009)***
NPK	4.1e-05 (8.9e-06)***	--	4.13e-05 (8.18e-06)***
Literacy	0,013 (0,036)	-0,015 (0,007)*	0,018 (0,037)
Main activity	0,134 (0,033)***	-0,007 (0,006)	0,14 (0,034)***

Table 31. Determinants of maize farmers' efficiency (devamı)

Variables	Technical efficiency at CRS	Technical efficiency at VRS	Scale efficiency
Management mode (1= labor force and 2 = inputs)	0,032 (0,031)	-0,008 (0,006)	0,036 (0,031)
Organic matter	-0,166 (0,21)	-0,025 (0,041)	-0,167 (0,212)
Const	0,471 (0,12)***	0,898 (0,23)***	0,528 (0,121)***
N		230	
Log likelihood	36,67	413,89	34,06
LR X²	102,87***	55,19***	108,54***
R2 username	3,483	-0,071	2,685

CRS: Constant Returns to Scale; VRS: Variable Returns to Scale; *,** and *** represent 10%, 5% and 1% significance level, respectively ; Standard error in brackets.

4.7. Analysis of management constraints

4.7.1. Typology of constraints

Examination of the constraints faced by maize farmers has enabled us to understand the obstacles they encounter in implementing their management methods (Figure 16). The present study looks at the typology of constraints evoked by two distinct groups of farmers, according to their strategic orientation: those who favor increasing the labor force and those who opt for increasing the volume of agricultural inputs. By examining the proportions of constraints specific to each group, as well as those prevailing on farms, we can gain a better understanding of the obstacles specific to each management approach.

Indeed, producers opting to increase the workforce identified a variety of constraints, highlighting the challenges inherent in this strategy (Figure 16) (a). The variability of proportions highlights the importance attached to access to improved varieties (36.43%), illustrating the critical need for quality seed expressed by maize farmers. Similarly, constraints linked to access to agricultural machinery (22.86%) and lack of financial means (22.86%) underline the technological and financial obstacles they face. Access to agricultural inputs (7.14%), labor (4.29%) and credit (3.57%) remain issues, but with relatively less concern.

On the other hand, farmers favoring an increase in the volume of agricultural inputs also face specific challenges (Figure 16) (b). The highest proportion concerns the lack of financial means (28.89%), underlining the crucial importance of financial resources in this strategy. Access to improved varieties (25.56%) and agricultural inputs (12.22%) remain major concerns, while access to agricultural machinery (8.89%) and the high cost of inputs (13.33%) are also significant constraints.

Taking all maize farmers together, certain constraints predominate (Figure 5) (c). Access to improved varieties (32.17%) appears to be the main concern, underlining its crucial role in the overall context of maize production. Lack of financial means (25.22%) and rainfall instability (3.04%) are also significant challenges, underlining the complexity of the conditions that maize farmers must face. In addition, constraints linked to access to farm machinery (17.39%) and agricultural inputs (9.13%) were also mentioned. All these constraints were also identified in the work of Miassi et al (2023), who placed particular emphasis on access to inputs, credit, and equipment.



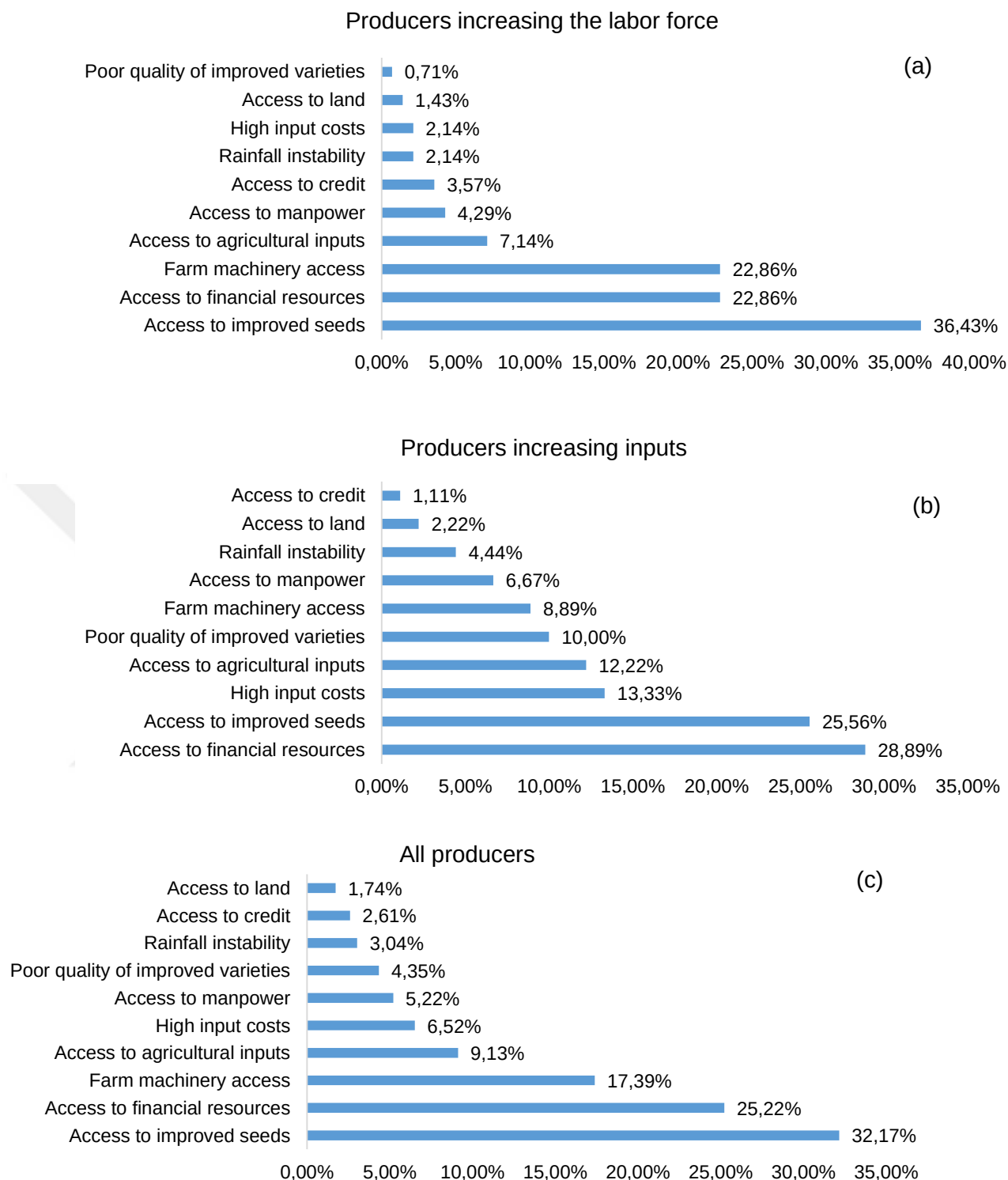


Figure 16. Typology of management constraints

4.7.2. Hierarchy of constraints

Table 31 shows a hierarchy of the different constraints listed by the two groups of maize farmers according to their adaptation strategy. In fact, this hierarchization was carried out using Kendall's concordance test, which is a ranking method based on the scores attributed to the responses. Kendall's W analysis shows that the results obtained are statistically significant at the 5% threshold.

Indeed, looking first at farmers who choose to increase labor power, it is interesting to note that access to improved varieties is ranked at the top of the list (1.728), demonstrating that these producers consider this constraint to be the most worrying. This indicates the importance attached to the genetic improvement of maize seed as part of this strategy. The second constraint identified by these farmers is the lack of financial means, with a score of 1.457. This highlights the considerable financial challenges they face, and the need to identify solutions to facilitate their access to financial resources to effectively support their farming practices. Furthermore, access to agricultural machinery ranks at the same level (1.457), underlining the technological challenges they face. Although these producers have opted for an increase in the workforce, they also place significant importance on the difficulties associated with access to agricultural inputs (1.142) and the high cost of inputs (1.043). In their view, this explains their preference for labor rather than agricultural inputs.

For farmers who opt to increase inputs, the lack of financial means (1.555) remains the primary constraint. This finding underlines the significant financial difficulties faced by these producers in implementing their strategy based on the intensive use of agricultural inputs. It is imperative to recognize the direct impact of this constraint on their ability to invest adequately in the acquisition of inputs such as fertilizers and pesticides, which can potentially affect their farm yields.

This observation underlines the importance attached by these producers to the availability of improved seeds to optimize their maize production. In addition, access to farm machinery (1,200) and farm inputs (1,244) are also highlighted as significant constraints. These results underline the need to improve accessibility to agricultural technologies and inputs, which are crucial to the success of the strategy focused on increasing inputs. However, access to credit (1.020) takes on significant importance, underlining the financial challenges faced by these producers in implementing their strategy. This result highlights the need to improve mechanisms for accessing agricultural financing to effectively support this category of producers. This would enable them to cover the costs associated with acquiring inputs and implementing more intensive farm management.

Considering all maize farmers, access to improved varieties maintains its position as a major constraint (1.643), highlighting its widespread impact on the sector. Next, lack of financial resources (1.495) also emerges as a major constraint. This confirms once again the importance of

access to agricultural financing. These results also underline the need for targeted interventions aimed at facilitating access to improved varieties and providing financial support to producers, thereby helping to strengthen the sustainability and productivity of the agricultural sector. This result corroborates with the findings of several other works that have designated the lack of financial as the major problem faced by producers in managing their farms (Sadiq *et al.*, 2019; Neema Ciza, 2023).

In addition, access to farm machinery (1.356), farm inputs (1.182), and the high cost of inputs (1.126) also remain major concerns for all maize farmers. Improving these aspects can make a significant contribution to improving the efficiency of Benin's maize farmers. This, in turn, will help increase productivity and reduce the economic constraints faced by producers. Thus, these results offer an in-depth perspective on the specific constraints perceived by producers as a function of their coping strategy, while highlighting common concerns that require particular attention in the agricultural sector studied.

Table 32. Hierarchy of constraints according to the management methods

Management constraints	Management modes					
	Increasing the workforce		Increased inputs		All producers	
	Average rank	Order	Average rank	Order	Average rank	Order
Access to improved varieties	1,728	1	1,511	2	1,643	1
Lack of financial resources	1,457	2	1,555	1	1,495	2
Farm machinery access	1,457	2	1,200	5	1,356	3
Access to agricultural inputs	1,142	4	1,244	4	1,182	4
High input costs	1,043	7	1,255	3	1,126	5
Access to manpower	1,085	5	1,133	7	1,104	6
Poor quality of improved varieties	1,010	10	1,144	6	1,060	7
Access to credit	1,071	6	1,022	10	1,052	8
Rainfall instability	1,043	8	1,055	8	1,047	9
Lack of soil	1,028	9	1,033	9	1,030	10
N	140		90		230	
Kendall's W	0,042**		0,023*		0,031**	
Chi-square	53,2		19		63,9	

** 5% significance level.

4.8. General discussion

4.8.1. Economic impact of climatic variations

The results demonstrate a steady decline in national precipitation, especially during the rainy season, from around 5,000 mm in 1990 to less than 3,500 mm in 2020. This trend is consistent with observations by other researchers, including Atchadé *et al.* (2017), highlighting changes in rainfall regimes since 1970, characterized by late or early onsets of rainfall and interruptions during peaks, with an overall decrease in annual rainfall (Atchadé *et al.*, 2017). Djenontin (2010), Dedjan (2010), and Yegbemey *et al.* (2014) also found irregular rain sequences and premature seasons influencing the perception of climate change by producers in northern Benin.

Unlike total precipitation, maximum and minimum temperatures are increasing steadily each year, a trend aligned with global observations from the IPCC and NASA that identify this rise as a major sign of climate change (IPCC, 2021). These temperature increases are strongly linked to the broader context of global warming (Badameli and Dubreuil, 2015). Producers report intensifying heat, even in shaded areas under trees, highlighting the warming trend (Dimon, 2008).

Concerning air pollutant emissions, analyzes show that methane and nitrous oxide emissions mainly come from food waste and agricultural practices, while CO₂ is mainly emitted by food waste, energy consumption (especially electricity) and transport. These results support previous research that associates CO₂ emissions with electricity and heat production, as well as energy consumption (coal and electricity), and attributes methane and nitrous oxide emissions to practices agriculture (UN, 2022; Salahuddin *et al.*, 2018; Balogan, 2021). With population growth, pollution is expected to increase alongside the expansion of production and areas of maize, the dominant crop in Benin (around 85%), playing a crucial role in the diet compared to rice and sorghum (Akpo, 2020).

In addition to the production volume of previous years, the analysis of the autocorrelation function highlights a significant association between the production volume at time $t-1$ and the following year, resulting from the accumulation of agricultural experience and the adoption of ameliorative strategies over time (Ibitola *et al.*, 2019). The ECM model confirms the significant impact of temperature and precipitation on the volume of maize production, in agreement with the findings of Adjovi *et al.* (2019) on the influence of climate indicators on maize, sorghum and soybean yields. Furthermore, a negative correlation between atmospheric pollutants (CO₂ and CH₄) and the volume of maize production is noted, supported by the work of Chandio *et al.* (2021) on the impact of CO₂ on wheat production, and supported by Casemir and Diaw (2018), highlighting the change in soil acidity and its negative impact on production yield.

The Step Lag (DL) model indicates a significant negative impact of rural population density on the volume of maize production, contradicting the positive observations of other researchers (Jouve, 2006; Cesaro, 2020). These researchers suggest that rapid population growth in

rural areas may lead to an expansion of cultivated land at the expense of grazing areas and peripheral vegetation (Jouve, 2006), although the expansion of cultivated areas is considered essential to the growth of agricultural production (Cesaro, 2020).

Forecasts indicate continued expansion in the volume of maize production over the next ten to thirty years, despite the influence of methane and the exponential growth of the urban population. These results confirm MEHU (2021) forecasts for an increase in maize production yields by 2025 in various agro-ecological zones of Benin. This growing projection of maize production volume may also be linked to the gradual increase in rural population density, often considered the most productive segment (Requier-Desjardins, 2018; Acloque *et al.*, 2017).

4.8.2. Energy management approach

The conclusions drawn from this study on the perceptions of maize farmers in northern Benin highlight a high level of awareness of climate change. Indeed, over 98% of participants surveyed claimed to have knowledge of the manifestations of this phenomenon. These results corroborate previous findings from other studies conducted both in Benin (Fadina and Barjolle, 2018; Gnangle *et al.*, 2012; Loko *et al.*, 2013) and in several other African countries (Fosu-Mensah *et al.*, 2012; Mustapha *et al.*, 2012; Muzamhindo *et al.*, 2015; Ouédraogo *et al.*, 2010). This underlines the importance of local awareness and understanding of climate change for effective adaptive management. The main changes observed are mainly associated with rainfall disturbances, including delays, early cessation and poor distribution of rainfall, as well as alterations to seasonal calendars. In addition, rising temperatures and the occurrence of extreme events such as flooding have also been noted. Similar findings have been reported in various studies conducted in Benin (Fadina and Barjolle, 2018; Houssou-Goe, 2008; Loko *et al.*, 2013), Niger (Assoumana *et al.*, 2016), Nigeria (Mustapha *et al.*, 2012; Oyekale *et al.*, 2012) and Kenya (Gebreeyesus, 2017).

Regarding the consequences of this phenomenon, the results highlight specific concerns, such as declining water availability and lower production yields. Indeed, rising temperatures, combined with rainfall disruptions, notably decreasing rainfall, exert a significant influence on decreasing yields of crops such as maize (Gebreeyesus, 2017). Thus, the delay in the onset of rainfall affects crop sowing dates and leads to poor crop performance, forcing producers to develop specific adaptations (Gebreeyesus, 2017).

Indeed, to cope with this situation, all the producers interviewed have developed adaptation strategies based on their resource management methods. This high level of strategy adoption is also highlighted by the work of Fadina and Barjolle (2018), testifying to the necessity and resilience of producers in the face of the challenges posed by climate change. Furthermore, maize farmers generally use two distinct management approaches. Some opt for intensification of agricultural inputs such as chemical fertilizers, insecticides and pesticides, while others favor increased labor, including mechanical traction, animal traction and plot maintenance. These choices reflect the

diversity of strategies adopted to cope with climatic challenges and underline the complexity of management decisions taken by producers. The intensification of agricultural inputs has been frequently mentioned in several studies as an adaptation mode increasingly adopted by producers (Assoumana et al., 2016; Gebreeyesus, 2017; Sutcliffe et al., 2016). As such, this approach aims to mitigate the negative effects of climate change (Gebreeyesus, 2017). Regarding the high rate of adoption of the management approach aimed at increasing the work force, this can be explained primarily by the success enjoyed by efforts to promote draught animals in certain countries, especially in West Africa, including Benin (Daum et al., 2023). These results confirm those obtained by Callo-Concha et al. (2012), who reported that in northern Benin, agricultural acreage is increasing thanks to the intensive use of animal traction. This trend indicates that efforts to promote draught animals have been effective and have influenced the management choices of maize producers in the region. On the other hand, this finding is not the same as that of Fadina and Barjolle (2018), who stipulate that farmers give greater preference to the use of agricultural inputs such as improved varieties, chemical fertilizers and pesticides, as well as agroforestry practices. This disparity in results could be explained by the distinct geographical context of their study, conducted in southern Benin, where production levels are relatively low compared with the north, where production is essentially concentrated (Yegbemey et al., 2014). Thus, in the context of low production in the south, producers may not feel the need to increase the labor force, particularly using mechanization or animal traction. This divergence shows that management choices can be profoundly influenced by local realities and the distinct characteristics of production zones.

However, even if most of the farm's favor increasing the work force, this does not necessarily mean that this is the most energy-intensive management method on maize farms. In fact, this was observed with a clear predominance of input use in terms of the amount of energy generated. Indeed, the results indicate that almost 95% of total energy expenditure on farms comes from the use of agricultural inputs. These results corroborate the observations of Akdemir et al. (2023), who point out that activities such as ploughing, hoeing, harvesting and transport each contribute to less than 10% of total energy consumption on maize farms. However, these results are at odds with the findings of Yilmaz et al. (2005), who indicate that the energy consumption of agricultural machinery remains higher on small farms. This disparity can be explained by changes in farming practices over time. In this respect, the results obtained reflect a paradigm shift towards approaches more focused on the use of inputs (seeds, chemical fertilizers, etc.) better adapted to the current challenges of climate change (Fadina and Barjolle, 2018). This transition to input-based management therefore influences the distribution of energy consumption on farms.

However, among these agricultural inputs, the intensive use of NPK fertilizer stands out with higher energy expenditure. This observation suggests that the management mode favoring fertilization intensification is specifically associated with the frequent use of NPK fertilizer, underlining its central role in farming practices. These results concur with the findings of several

other researchers who have also noted that, in terms of agricultural inputs, producers in North Benin use NPK more and then urea (Abikou et al. 2023; Yabi et al., 2016).

In terms of efficiency, the results underline that increasing input use leads to better optimization of resources and maize production, outperforming the strategy of increasing labor power. These results lead to the conclusion that input intensification appears to be a more coherent and potentially profitable solution for strengthening the resilience and sustainability of maize farms in the face of climatic pressures. This corroborates the findings of previous studies highlighting that maize producers' efficiency scores improve significantly with an increase in the number of agricultural inputs used (Hassan et al., 2014). According to these researchers, an increase in the quantity of inputs used significantly increases maize production. For Amaza et al. (2006), this influence of agricultural input use on producer efficiency is not limited to a single crop but can extend to all food crops. However, unlike agricultural inputs, research in other countries has highlighted that increasing labor power through farm mechanization does not significantly affect technical efficiency (Abdulai et al., 2018). This highlights the weak impact of the management mode focused on increasing labor power.

Nevertheless, it is notable that, whatever their management mode, farmers display high efficiency in variable scale yield, with an average index exceeding 96%. Although this value is significantly higher than that observed among maize farmers in Cameroon (0.429), the findings of Abanda and Saha (2023) corroborate these results. According to these researchers, farmers demonstrate greater efficiency under variable returns to scale (VRS) than constant returns to scale (CRS), with an index of technical efficiency under VRS consistently higher than that obtained under CRS.

Analysis of the determinants of these different efficiency indices highlights the strategic importance of factors such as age, experience, area under cultivation and use of agricultural inputs. Indeed, a positive influence of these different factors on most of these efficiency indices was observed. The positive influence of age on the efficiency of maize farmers was also highlighted by Abanda and Saha (2023) in Cameroon. This agreement with the results of Abanda and Saha (2023) in Cameroon therefore highlights a general trend where older producers demonstrate greater efficiency in maize production. The precision of the speculation is important in the context where these results are at odds with the findings made by other authors who have devoted their studies to rice producers (Diallo & Garba, 2023; Miassi et al., 2023). These authors stress that young people are technically more efficient than older people. This discrepancy can therefore be attributed to the peculiarities of cultures, underlining the need to adopt approaches specific to each agricultural context. Yet it is generally recognized that, over time, the experience acquired by the farmer gives him the ability to adjust and/or modify the technical production itinerary in response to parameters such as rainfall and the availability of raw materials. This also enables it to better cope with production constraints such as declining soil fertility and soil erosion (Miassi et al., 2023). This

then explains the positive effect of maize farmers' experience on their efficiencies. Similarly, the positive correlation between the use of agricultural inputs, particularly chemical fertilizers, and the efficiency of maize farmers corroborates the findings of previous research by Geta *et al.*, (2013) and Edison (2021). Finally, the positive relationship of sown area on farmer efficiency is linked to the fact that larger farmers are those who generally engage in the use of innovative strategies to cope with climate change (Fadina & Barjolle, 2018).

However, although producers are each adopting a management approach to cope with climate change, they are also encountering difficulties in adopting these approaches. Priority constraints include difficulties in accessing improved varieties, and financial and technological challenges affecting their ability to acquire agricultural inputs. Difficulties in accessing inputs and agricultural credit were also highlighted by all maize farmers.

These findings concur with several previous studies that identify lack of financing as the most relevant constraint in the agricultural context (Deressa *et al.*, 2008; Neema Ciza, 2023; Sadiq *et al.*, 2019). According to these researchers, the considerable scale of this constraint lies in its multiplier impact. Thus, limited access to credit also hinders producers' access to the resources and technologies needed to facilitate the adoption of climate change adaptation strategies (Deressa *et al.*, 2008; Sadiq *et al.*, 2019). This observation underscores the correlation between lack of finance and other challenges, highlighting the need for integrated approaches to mitigate these interrelated constraints in the agricultural context.

5. CONCLUSIONS

The results of this study indeed show an upward trend in climatic parameters such as rainfall, maximum and minimum temperature as well as the emission of atmospheric pollutants from food waste, agricultural practices, and other sources such as electricity and the transport sector. These results clearly indicate that Benin is not on the sidelines of climate change characterized mainly by global warming of the planet. Faced with this situation, agricultural producers are greatly increasing the areas sown each year for maize production to keep the total volume of production high despite situations of climate instability. Similarly, several climatic factors including temperature, rainfall, and atmospheric pollutants as well as the density of the rural population are the main parameters having a strong short-term influence on the volume of production. The predictive models carried out under the influence of temperature, which significantly influences the volume of production, predict an increase in maize production over time. However, curtailing activities that contribute to the release of atmospheric pollutants into the environment holds the potential to enhance national-level production volume by mitigating the repercussions of climatic fluctuations.

The perceptions of maize farmers in northern Benin and the effectiveness of their management methods in the face of climate change, reveals some interesting results. Indeed, rainfall disturbances, rising temperatures and seasonal calendar instabilities have a significant impact on water availability and crop yields. This encourages producers to develop diversified adaptation strategies. The diversity of management approaches adopted by producers, ranging from input intensification to labor force expansion, reflects the complexity of management decisions. The study highlights that intensification of agricultural inputs, particularly NPK fertilizer, appears to be a more coherent and potentially cost-effective solution for enhancing the resilience and sustainability of maize farms in the face of climatic pressures. However, persistent challenges, such as difficulties of access to improved varieties, financial and technological constraints, highlight the need for integrated approaches to alleviate these interrelated constraints in the agricultural context.

Determinants of producer efficiency, such as age, experience, area under cultivation and use of agricultural inputs, highlight the strategic importance of these factors. The positive results associated with age and experience are consistent with other work, while the positive influence of farm input use confirms the relevance of these practices in improving efficiency.

In the light of the results emanating from this in-depth study of the agricultural practices of maize farmers in northern Benin in the face of the challenges of climate change, several recommendations emerge. These include: train farmers on adaptive strategies to climate change, with particular emphasis on innovative techniques and best practices for coping with climatic variations; equip producers with new maize varieties resistant to the adverse effects of climate change, thus promoting more stable yields and better adaptation to changing environmental

conditions; promote farm mechanization to increase the efficiency of cultivation practices, reduce labor dependency and optimize resources, thus contributing to more sustainable agriculture; and facilitate access to agricultural inputs, focusing on mechanisms that make it easier for producers to obtain improved seeds, fertilizers and other essential inputs to maximize their productivity.



REFERENCES

- Abanda, M. C. N., & Saha, J. C. (2023). Éducation agricole et efficacité technique des producteurs de maïs au Cameroun. *Recherches et Applications en Sciences Economiques et de Gestion*, 2(1), 68-82.
- Abdulai, S., Nkegbe, P. K., & Donkoh, S. A. (2018). Assessing the technical efficiency of maize production in northern Ghana: The data envelopment analysis approach. *Cogent Food & Agriculture*, 4(1), 1512390. <https://doi.org/10.1080/23311932.2018.1512390>
- Abikou, J.M., Gouwakinnou J.Y., Chabi Sero I. & Yabi J. A. (2023). Analyse de l'Efficacité Économique des Systèmes de Culture du Riz en Bas-fonds dans la Commune de Malanville, au Nord-Bénin. *European Scientific Journal*, ESJ, 19 (10), 169. <https://doi.org/10.19044/esj.2023.v19n10p169>
- Acloque, D., Adam M., Ageron, P., Alexeeva, O., Amarouche, M., Amat-Roze J., & Amato F. (2017). Déprise. *Géoconfluences. Ressources de géographie pour les enseignants*.
- Adebiyi, K.D., Maiga-Yaleu S., Issaka K., Ayena M., & Yabi J.A. (2019). Déterminants de l'adoption des bonnes pratiques de gestion durable des terres dans un contexte de changement climatique au Nord Bénin : cas de la fumure organique.
- Adjahossou, V. N. (2014). Stratégies d'adaptation des paysans du plateau d'Allada (Bénin) aux changements climatiques. XXVIIe Colloque de l'Association Internationale de Climatologie, Dijon (France), 2014, pp. 255-259.
- Adjovi, N. R., Agboton, A., Quenum F., Miassi, Y., Dossa F.K., & Adéyèmi O. (2019). Variation climatique et production vivrière au Sud-Bénin : cas de la commune de Bohicon. *Afrique Science*, 15(2), 32-43.
- Agbossou, K. E. (2010). Rapport provisoire d'étude de vulnérabilité, impacts et adaptations de l'agriculture béninoise aux Changements Climatiques, 57p.
- Ahoyo Adjovi, N. R., Agboton, A. G., Quenum, F., Miassi, Y.E., Dossa, F.K., & Adedemi, O. (2019). Variation climatique et production vivrière au Sud-Bénin : cas de la commune de Bohicon. *Afrique Science*, 15(2), 32-43.
- Ajavon, A. Y. C., Kpatinnon, N. R., & Tente, A. H. B. (2020). Effets des changements climatiques sur la production du riz dans les départements du zou et des collines au centre du Bénin, Afrique de l'Ouest. *International Journal of Recent Advances in Multidisciplinary Research*, 7 (7), 6024-6033.
- Akcaoz, H., Ozcatalbas, O., & Kizilay, H. (2009). Analysis of energy use for pomegranate production in Turkey. *Journal of Food, Agriculture and Environment*, 7(2), 475-480. <https://www.researchgate.net/publication/25561002>
- Akdemir, Ş., Miassi, Y. E., Ismaila, I. S., Dossa, K. F., Oussou, K. F., & Zannou, O. (2023). Corn production and processing into ethanol in Turkey: An analysis of the performance of

- irrigation systems at different altitudes on energy use and production costs. *Journal of Agriculture and Food Research*, 14, 100740.
- Akpo, C. Y. (2020). Impact des semences améliorées sur la productivité du maïs au Bénin. In African Economic Research Consortium, A final report Submitted to AERC, «Biannual Research Workshop,1-26.
- Ali, C., Nadhem, M., & Hassen, T. (2011). Impact du changement climatique sur la productivité des cultures céréalières dans la région de Béja (Tunisie). *AfJARE*, 6(2): 144-154.
- Amaza, P. S., Bila, Y., & Iheanacha, A. C. (2006). Identification of factors that influence technical efficiency of food crop production in West Africa: Empirical evidence from Borno State, Nigeria. *Journal of Agriculture and Rural Development in the Tropics and Subtropics*, 107(2), 139- 147.
- Assoumana, B. T., Ndiaye, M., Puije, G. V. D., Diourte, M., & Gaiser, T. (2016). Comparative assessment of local producers' perceptions of meteorological events and adaptations strategies: Two Case Studies in Niger Republic. *Journal of Sustainable Development*, 9(3), 1-19. <http://dx.doi.org/10.5539/jsd.v9n3p118>
- Atchadé, G.A., Vissin, E. W., Gbenou P., Chabi, B.I., & Lavinon, R. (2017). Cultures de contre-saison dans la commune d'adjohoun au Bénin : entre atouts et contrainte. *Revue Ivoirienne de Géographie des Savanes*, No 2, 172-184.
- Avandé, F.L., Aboubacary, I.L, & Hinnou, L.C. (2022). Stratégies d'adaptation des riziculteurs aux effets du changement climatique dans la commune de Malanville au Bénin. *Agronomie Africaine*, 34 (3), 387 – 402.
- Avande, L. F., Aboubacary, L. I., & Hinnou, L. C. (2022). Strategies d'adaptation des riziculteurs aux effets du changement climatique dans la commune de Malanville au Bénin. *Agronomie Africaine*, 34 (3), 387-402
- Azontondé, H.A., Igué A.M., & Dagbénonbakin, G. (2010). Carte de fertilité des sols du Bénin par zone agro-écologique du Bénin. Document validé à l'INFOSEC Cotonou le 10 août 2010. Rapport final, LSSEE/CRA-Agonkanmey/INRAB/Bénin, 128 p.
- Baco, M.N., Akponikpe, P. I., Djaouga, M. M., & Egah, M. J. (2012). Documentation de la problématique et des pratiques de gestion durable de la portion du bassin du niger au benin. Partenariat National de l'Eau du Bénin. Rapport final, 1-137.
- Badameli, A., & Dubreuil, V. (2015). Diagnostic du changement climatique au Togo à travers l'évolution de la température entre 1961 et 2010, XXVIIIe Colloque de l'Association Internationale de Climatologie, Liège, 421-426.
- Balogan, K.A. (2021). Effets de la consommation d'énergie dans les transports, de l'urbanisation, des IDE et la croissance sur l'émission de CO2 dans l'UEMOA. *Revue Économie, Gestion et Société*, 1(1), 1-21.

- Balogoun, I., Saïdou, A., Ahoton, E. L., Amadji, L. G., Ahohuendo, C. B., Adebo, I. B., Babatounde, S., Chougourou, D., Adoukonou-Sagbadja, H., & Ahanchede, A. (2014). Caractérisation des systèmes de production à base d'anacardier dans les principales zones de culture au Bénin, *Agronomie Africaine*, 26(1), 10-22.
- Bamgboye, A.I., & Jekayinfa, S.O., 2006. Energy consumption pattern in palm kernel processing operations. *Agric. Eng. Int. CIGR J.* 8, 1–11. Manuscript EE05 013.
- Banker, R. D., Charnes, A. & Cooper, W. W. (1984), «Some Model for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis», in *Management Science*, 30, 1078-1092. <https://doi.org/10.1287/mnsc.30.9.1078>
- Bayala, J., Kalinganire, A., Tchoundjeu, Z., Sinclair, F., & Garrity, D. (2011). Conservation agriculture with trees in the West African Sahel. *ICRAF Occasional Paper*, No. 14.
- Behanzin, P. C., Brisso, D., Sainou, J., & Faton, D. (2018). Climate change and production of corn: Perceptions and effects on the municipality of Allada in Benin. *Environmental and Water Sciences, Public Health and Territorial Intelligence Journal*, 2(4), 106-118.
- Bellia, S. (2003). Les impacts du réchauffement climatique sur la production de blé en Beauce. *Méditerranée*, (1) 2, 103-108.
- Bensbahou A., & Seyagh I. (2020). L'émission de CO₂ et la croissance économique : cas du Maroc. *Revue Alternatives Managériales et Économiques*, 2 (4) : 505-526.
- Berre, D. (2014). Les nouveaux enjeux économiques et environnementaux des productions animales: développements méthodologiques par une approche interdisciplinaire des frontières d'efficience (Doctoral dissertation, USTL), 1-208 .
- BIPEN. (2012). Implications économiques des changements climatiques dans le secteur agricole, 115p.
- Boko, M. (1988). Climats et communautés rurales du Bénin : rythmes climatiques et rythmes de développement. Thèse de Doctorat ès d'Etat, Université de Bourgogne, Dijon, France, 601 p.
- Boublal, S. (2014). Contribution à l'étude de la réhabilitation de la palmeraie du ksar de OUARGLA (Cas de de la palmeraie de Zaoui).
- Bougma, L.A., Ouedraogo, M.H., & Sawadogo, N. (2018). Perceptions paysannes de l'impact du changement climatique sur le mil dans les zones sahéliennes et soudano sahélienne du Burkina Faso. *Afrique Science*, 14(4), 264-275.
- Bravo-Ureta, B. E., & Pinheiro, A. E. (1993). Efficiency analysis of developing country agriculture: a review of the frontier function literature. *Agricultural and resource economics Review*, 22(1), 88-101. <https://doi.org/10.1017/S1068280500000320>
- Buckles, D., Etèka A., Osiname, O., Galiba M., & Galiano, G. (2000). Plantes de couverture en Afrique de l'Ouest. Une contribution à l'agriculture durable. IITA, SG2000, CRDI, 291p.

- Callo-Concha, D., Gaiser, T., & Ewert, F. (2012). Farming and cropping systems in the West African Sudanian savanna. WASCAL research area: northern Ghana, southwest Burkina Faso and northern Benin (No.100), 1-49. ZEF working paper series. <http://hdl.handle.net/10419/88290>
- Canakci, M., Topakci, M., Akinci, I., & Ozmerzi, A. (2005). Energy use pattern of some field crops and vegetable production: a case study for Antalya Region, Turkey. *Energy Convers. Manag.* 46, 655–666. <https://doi.org/10.1016/j.enconman.2004.04.008>
- Casemir, B.H., & Diaw, A. (2018). Analysis of climate change effect on agricultural production in Benin. *Asian Journal of Agricultural Extension, Economics & Sociology*, (24):1-12
- Cesaro, J.D. (2020). Transformation des agricultures en Asie du Sud-Est : la paysannerie face aux défis de la mondialisation. *Géoconfluences*, dossier L'Asie du Sud-Est, carrefours et confins, 26p.
- Chandio, A.A., Gökmenoğlu, K.K., & Ahmad, F. (2021). Addressing the long- and short-run effects of climate change on major food crops production in Turkey. *Environmental Science and Pollution Research*, 28 (37): 51657–51673.
- Chandio, A.A., Jiang, Y., Fatima, T., Ahmad, F., Ahmad, M., & Li, J. (2022). Assessing the impacts of climate change on cereal production in Bangladesh: evidence from ARDL modeling approach. *International Journal of Climate Change Strategies and Management*, 14 (2): 125–147.
- Charnes, A. & Cooper W.W. (1962), Programming with Linear Fractional Functionals, *Naval Research Logistics Quarterly*, 9, p.181-185. <https://doi.org/10.1002/nav.3800090303>
- Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European journal of operational research*, 2(6), 429-444. [https://doi.org/10.1016/0377-2217\(78\)90138-8](https://doi.org/10.1016/0377-2217(78)90138-8)
- Chourghal, N. (2016). Impact du changement climatique sur la culture du blé dur en Algérie. Ecole Nationale Supérieure Agronomique Alger. Thèse de doctorat.181 p.
- Coelli, T. J., Rahman, S., & Thirtle, C. (2002). Technical, allocative, cost and scale efficiencies in Bangladesh rice cultivation: A nonparametric approach. *Journal of Agricultural Economics*, 53(3), 607–626. <https://doi.org/doi:10.1111/jage.2002.53.issue-3>
- Daum, T., Seidel, A., Awoke, B. G., & Birner, R. (2023). Animal traction, two-wheel tractors, or four-wheel tractors? A best-fit approach to guide farm mechanization in Africa. *Experimental Agriculture*, 59, e12 <https://doi.org/10.1017/S0014479723000091>
- Dedjan, Y.J. (2010). Changements Climatiques et évolution des périodes de semis des principales cultures dans l'Alibori : cas des communes de Malanville et de Banikoara. Thèse pour l'obtention du diplôme d'ingénieur agronome, Université de Parakou, Bénin.

- Demirhan, H. (2020). dLagM: An R package for distributed lag models and ARDL bounds testing. *PLoS ONE* 15(2): e0228812.
- Deressa, T., Hassan, R. M., & Ringler, C. (2008). Measuring Ethiopian producers' vulnerability to climate change across regional states. *Intl Food Policy Res Inst.*, 1-26.
- DGEC. (2022). Plan national d'adaptation aux changements climatiques du Bénin (PNA-Bénin), 175p.
- Diallo, M. F., & Garba, A. A. (2023). Effet des Subventions de Semences et des Engrais sur l'Efficacité Technique des Riziculteurs du Sénégal. *JLIFAD, Investing in rural people*, 1-22.
- Dimon, R. (2008). Adaptation aux changements climatiques : perceptions, savoirs locaux et stratégies d'adaptation développées par les producteurs des communes de Kandi et de Banikoara au Nord du Bénin. Thèse pour l'obtention du diplôme d'ingénieur agronome, Faculté des Sciences Agronomiques, Université d'Abomey Calavi, Bénin, 132 p.
- Djenontin, S. N. I. (2010). Vulnérabilité des ressources en eau face aux changements climatiques et stratégies endogènes de gestion développées dans le secteur agricole : cas des communes de Banikoara et Malanville (Bénin). Thèse pour l'obtention du diplôme d'ingénieur agronome, Université de Parakou, Bénin.
- Djohy, G.L., Edja, A.H., & Nouatin, G.S. (2015). Variation climatique et production vivrière : la culture du maïs dans le système agricole péri-urbain de la commune de Parakou au Nord-Benin. *Afrique Science*, 11(6) : 483–494. DOI: 10.4314/Ijbc.V10i2.27, 10(2), 779–792.
- Dossa, K. F., & Miassi, Y. E. (2023). Exploring the nexus of climate variability, population dynamics, and maize production in Togo: Implications for global warming and food security. *Farming System*, 1(100053): 1-12.
- Dossou, A. A. A., Vodouhe F., Yegbemey N.R., & Yabi J.A. (2019). Accès au crédit et performance économique et financière des exploitations de l'Union Nationale des Producteurs de Soja au Centre du Bénin. *Ann. UP, Série Sci. Nat. Agron.* Juin 2019, 9 (1):79-94.
- Dumrul, Y., & Kilicarslan, Z. (2017). Economic impacts of climate change on agriculture: empirical evidence from ardlapproach for Turkey, *Journal of Business, Economics and Finance*. No 5, 336–347.
- Edison, E. (2021). Determinants of Technical Efficiency in Smallholder Corn Crop Farming: Application of Stochastic Frontier Production Function. *International Journal of Science. Technology & Management*, 2(6), 1900-1906. <https://doi.org/10.46729/ijstm.v2i5.335>

- Edoun, G., & Mongbo, R. (2020). Les formes socioculturelles de la malnutrition des enfants de moins de cinq ans dans la commune de Karimama au Nord du Bénin. *European Scientific Journal*, (16):73-97.
- Egah, J., Baco, M. N., Lokossou, R. S., Moutouama, F. T., Akponikpè, P. B. I., Fatondji, D., Djènonatin, A. J., Tossou, C. R., & Sokpon, N. (2014). Incidence économique des techniques exogènes de conservation de l'eau et des sols au Bénin. *Bulletin de La Recherche Agronomique du Bénin*, 75, 47–57.
- Et-Touile, H., & Arib, F. (2021). Étude économétrique des impacts du changement climatique sur la sécurité alimentaire au Maroc. *African Scientific Journal*, 3, (4), 525-545.
- Fadina, A. M. R., & Barjolle, D. (2018). Producers' adaptation strategies to climate change and their implications in the Zou Department of South Benin. *Environments*, 5(1), 1-17. <https://doi.org/10.3390/environments5010015>
- FAO. (2014). Variétés de Semences Appropriées pour les Agriculteurs à Petite Échelle, 44p.
- FAO. (1995). La mise en valeur des eaux au profit de la sécurité alimentaire. Rome, (1995), 43 p.
- FAO. (2002). Food insecurity: When people must live with hunger and fear starvation. The state of food insecurity in the world 2002. FAO. Rome, Italy, 214p.
- Faye, A., Ndiaye, M., et Ndiaye, A. (2018). L'impact des changements climatiques sur les rendements des principales cultures céréalières au Sénégal. *Revue Internationale Des Economistes de Langue Française*, 3 (2), 291–306.
- Floquet, A., & Mongbo, R. L. (1998). Les producteurs en mal d'alternatives. Dégénération des terres, restructuration de l'espace agricole et urbanisation au bas Bénin.
- Fluck, R. C. (1985). Energy sequestered in repairs and maintenance of agricultural machinery. *Trans. ASAE* 28:738-744.
- Fosu-Mensah, B. Y., Vlek, P. L., & MacCarthy, D. S. (2012). Producers' perception and adaptation to climate change: a case study of Sekyedumase district in Ghana. *Environment, Development and Sustainability*, 14, 495-505. <https://doi.org/10.1007/s10668-012-9339-7>
- Gate, P., Blondlot, A., Gouache, D., Deudon, O., & Vignier, L. (2008). Impacts du changement climatique sur la croissance et le développement du blé en France. *Agronomie–Agriculture*, 15(5), 332–336.
- Gebreeyesus, K. A. (2017). Impact of climate change on the agroecological innovation of coffee agroforestry systems in Central Kenya (Doctoral dissertation, Montpellier SupAgro), 1-249.
- Geta, E., Bogale, A., Kassa, B., & Elias, E. (2013). Productivity and efficiency analysis of smallholder maize producers in Southern Ethiopia. *Journal of Human Ecology*, 41(1), 67-75. <https://doi.org/10.1080/09709274.2013.11906554>

- GIEC. (2007). Bilan 2007 des changements climatiques. Contribution des Groupes de travail I, II et III au quatrième Rapport d'évaluation du Groupe d'experts intergouvernemental sur l'évolution du climat [Équipe de rédaction principale, Pachauri, R.K. et Reisinger, A. (publié sous la direction de~)]. GIEC, Genève, Suisse, 103 p.
- GIEC. (2023). Rapport de synthèse du GIEC : les risques sont beaucoup plus élevés que dans les prévisions antérieures.
- GIEC. (2007). Résumé à l'intention des décideurs. In M.L. Parry, O.F. Canziani, J.P. Palutik of, P.J. van der Linden and C.E. Hanson, (éds.), Bilan 2007 des changements climatiques: Impacts, adaptation et vulnérabilité. Contribution du Groupe de travail II au quatrième Rapport d'évaluation. Rapport du Groupe d'experts intergouvernemental sur l'évolution du climat. Cambridge University Press, Cambridge, Royaume-Uni.
- Gnanglè, J.C., Yabi, J.A., Yegbemey, N.R., Glèlè Kakaï, L.R., & Sokpon, N. (2012). Rentabilité économique des systèmes de production des parcs à karité dans le contexte de l'adaptation au changement climatique du Nord-Bénin. *African Crop Science Journal*, 20 (2), 589 - 602
- Gnangle, P. C., Egah, J., Baco, M. N., Gbemavo, C. D., Kakaï, R. G., & Sokpon, N. (2012). Perceptions locales du changement climatique et mesures d'adaptation dans la gestion des parcs à karité au Nord-Bénin. *International journal of biological and chemical sciences*, 6(1), 136-149. <https://doi.org/10.4314/ijbcs.v6i1.13>
- Gologo, H. (2007). Place à l'adaptation, le rôle des paysans mieux formés au Bénin. IRDC-DFID. 4p.
- Gossiaux, A. (2020). Impacts économiques du réchauffement climatique : Répartition inégale des effets dans le monde et ralentissement de la croissance des pays pauvres. Université catholique de Louvain, 73 p.
- Grami, D., & Rejeb, J. B. E. N. (2015). L'impact des changements climatiques sur le rendement de la céréaliculture dans la Région du Nord-Ouest de la Tunisie (Béja). *Newmedit*, No 4, 36–41.
- Hartter, J., Stampone, M. D., Ryan, S. J., Kirner, K., Chapman, C. A., & Goldman, A., (2012). Patterns and perceptions of climate change in a biodiversity conservation hotspot. *PLoS ONE*, 7(2). <https://doi.org/10.1371/journal.pone.0032408>
- Hassan, Y. U., Abdullah, A. M., Ismail, M. M., & Mohamed, Z. (2014). Technical efficiency of maize production in Nigeria: Parametric and non-parametric approach. *Asian Journal of Agriculture and Rural Development*, 4(393-2016-23849), 281-291. <https://doi.org/10.22004/ag.econ.198408>
- Hayran, S., Dönmez, R., Karabacak, T., & Külekçi, M. (2023). The reduction of greenhouse gas emissions and energy optimization in apricot production in Turkey. *Erwerbs-Obstbau*, 65(4), 1207-1216. <https://doi.org/10.1007/s10341-022-00767-7>.

- Herr, M. L., & Muzira, T. J. (2012). Le développement des chaînes de valeur au service du travail décent (DECAV). Guide à l'usage des praticiens du développement économique, des gouvernements et des entreprises privées, BIT, 252p.
- Hinnou, C. L. (2018). Réseau social, gouvernance et innovations dans les chaînes de valeur du riz local au Bénin : Cas du département des Collines ; Thèse de Doctorat.
- Hounzinme, S.S., Teka, O. et Oumorou, M. (2017). Stratégies d'adaptation des producteurs agricoles face à la variabilité climatique dans le domaine soudanien au Bénin.
- Houssou-Goe, S. S. P. (2008). Agriculture et changement climatique au Bénin: risques climatiques, vulnérabilité et stratégies d'adaptation des populations rurales du département du Couffo (Doctoral dissertation, Département d'Économie, Socio-Anthropologie et Communication pour le développement rural (DESAC), Université d'Abomey-Calavi (UAC), Cotonou, BJ), 1-160. <http://hdl.handle.net/10625/44965>
- Ibitola, O. R., Fasakin, I. J., Popoola, O. O., & Olajide, O. O. (2019). Determinants of maize producers' productivity among smallholder producers in Oyo State, Nigeria. *Greener Journal of Agricultural Science*, 9(2): 189- 198.
- IFAD. (2010). Rapport annuel 2010. 60 p.
- INSTaD. (2013). Cahier des villages et quartiers de ville du département du Borgou (RGPH-4, 2013)
- Intergovernmental Panel on Climate Change (IPCC). (2014). Summary for policymakers. In: *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* [Field, C.B., V.R. Barros, D.J. Dokken, K.J. Mach, M.D. Mastrandrea, T.E. Bilir, M. et al. (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.
- IPCC. (2021). Summary for Policymakers. In: *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 3–32, doi:10.1017/9781009157896.001.
- Issa, M. S. (1995). Impacts potentiels d'un changement climatique dû au doublement du CO₂ atmosphérique sur l'agriculture en République du Bénin. Mémoire de DESS. Université Senghor d'Alexandrie, 113p.
- Jama, B., & Gonzalo, P. (2008). Agriculture in Africa: Strategies to Improve and Sustain Smallholder Production Systems. *Ann. N.Y. Acad. Sci. New York*, 1136, 218–232.
- Jayasooriya, S. P. (2023). Impact of Climate Change on Sovereign Risk in Asia. ADBI Working Paper 1358. Tokyo: Asian Development Bank Institute. Report. No 1348, 21 p.

- Ji, Y. B., & Lee, C. (2010). Data envelopment analysis. *The Stata Journal*, 10(2), 267-280.
<https://doi.org/10.1177/1536867X1001000207>
- Jouve, P. (2006). Transition agraire : la croissance démographique, une opportunité ou une contrainte ? *Caire info*, No 217, 43-54.
- Kabore, N. P., Ouedraogo, A., Some, L., & Millogo-Rasolodimby, J. (2015). Les facteurs déterminants de la production de céréales sèches en zone soudano-sahélienne du Burkina-Faso. *International Journal of Innovation and Applied Studies*, 11(1), 214-230.
- Kelthoum, F. M. & Kelthoum, O. (2017). Effet du traitement chimique et aérobie sur le rendement de PBM (Potentiel Biochimique Méthanogène) des déchets organiques du restaurant universitaire. *Mémoire de master*, 82 p.
- Khadimallah, A., & Akrouf, Z. (2017). Le capital humain et le renforcement de la productivité de l'agriculture en Afrique; *International Journal of Innovation and Applied Studies*, 20 (1), 234-250. <http://www.ijias.issr-journals.org/>
- Kosemani, B. S., & Bamgboye, A. I. (2021). Modelling energy use pattern for maize (*Zea mays* L.) production in Nigeria. *Cleaner Engineering and Technology*, 2, 100051.
<https://doi.org/10.1016/j.clet.2021.100051>
- Kuma, J. (2018). Modélisation ARDL, Test de cointégration aux bornes et Approche de Toda-Yamamoto : Eléments de théorie et pratiques sur Logiciel, cel-01766214. *Guide théorique et pratique*, 55p.
- Lawal, A. I., Akinoso, R., Olubiyi, M. R., & Olatoye, K. K. (2014). Embedded energy of on farm losses and energy analysis for maize production in Nigeria. *Transportation*, 62(1), 109-73.
- Loko, Y. L., Dansi, A., Agre, A. P., Akpa, N., Dossou-Aminon, I., Assogba, P., Dansi, M., Akpagana, K., & Sanni, A. (2013). Perceptions paysannes et impacts des changements climatiques sur la production et la diversité variétale de l'igname dans la zone aride du nord-ouest du Bénin. *International Journal of Biological and Chemical Sciences*, 7(2), 672-695. <https://doi.org/10.4314/ijbcs.v7i2.23>
- Lorzadeh, S.H., Mahdavidamghani, A., Enayatgholizadeh, M.R. & Yousefi, M. (2011). Agrochemical input application and energy use efficiency of maize production systems in dezfoul, Iran. *Middle East J. Sci. Res*, 9 (2), 153–156.
- MAEP. (2018). Plan Stratégique de Développement du Secteur Agricole (PSDSA) : Orientations stratégiques 2025 Plan National d'Investissements Agricoles et de Sécurité Alimentaire et Nutritionnelle PNIASAN 2017-2021, 132p.
- MAEP. (2010). Rapport annuel d'activités, 37p.

- MAEP. (2005). Politiques agricoles à travers le monde quelques exemples. Rapport de performance secteur agricole. Ministère de l'Agriculture, de l'Élevage et de la Pêche, Bénin, 5 p.
- MAEP. (2010). Rapport de performance secteur agricole. Direction de la Programmation et de la Prospective. Ministère de l'Agriculture, de l'Élevage et de la Pêche, Cotonou, Bénin, 20 p.
- MAEP. (2015). Politiques agricoles à travers le monde quelques exemples. Rapport de performance secteur agricole. Ministère de l'Agriculture, de l'Élevage et de la Pêche, Bénin, 5 p.
- MAEP. (2017). Plan Stratégique de Développement du Secteur Agricole (PSDSA) 2025 et Plan National d'Investissements Agricoles et de Sécurité Alimentaire et Nutritionnelle PNIASAN 2017 – 2021, 139p.
- MAEP. (2020). Rapport annuel d'activités, 48 p.
- Mafié, G.K. (2022). The Impact of Climate Change on Agricultural Productivity in Tanzania. *International Economic Journal*, 36 (1),129–145.
- Maiga, A., Bathily, M., Bamba, A., Mouleye, I. S., Traoré, M., & Diawara, D. S. (2022). Analysis of the Effects of Climate Change on the Income of Malian Producers. *International Journal of Business and Economics Research*, 11(3), 173–179.
- Maliki, R., Bernard, M., Padonou, E., Englehart, C., Sinsin, B.A. et Aho, N. (2017). Effet combiné de NPK et de trois différents mulch d'origine végétale sur la production maïsicole et la fertilité des sols au Sud-Bénin. *Bulletin de la Recherche Agronomique du Bénin (BRAB)*, 1025-2355, 1-17.
- Mandal, K. G., Saha, K. P., Ghosh, P. K., Hati, K. M., & Bandyopadhyay, K. K. (2002). Bioenergy and economic analysis of soybean-based crop production systems in central India. *Biomass and Bioenergy*, 23(5), 337-345. [https://doi.org/10.1016/S0961-9534\(02\)00058-2](https://doi.org/10.1016/S0961-9534(02)00058-2)
- Mani, I., Kumar, P., Panwar, J. S., & Kant, K. (2007). Variation in energy consumption in production of wheat–maize with varying altitudes in hilly regions of Himachal Pradesh, India. *Energy*, 32(12), 2336-2339. <https://doi.org/10.1016/j.energy.2007.07.004>
- MEHU. (2021). Deuxième communication nationale de la république du Bénin sur les changements climatiques. DGCC. Cotonou. Bénin, 41p.
- Mestiri, S. (2022). La modélisation ARLD en utilisant logiciel R. Unité de recherche EAS-Mahdia Faculté des sciences économiques et de gestion de Mahdia. Conférence FSGE Mahdia, 18p.

- Meul, M., Nevens, F., Reheul, D., & Hofman, G. (2007). Energy use efficiency of specialised dairy, arable and pig farms in Flanders. *Agriculture, Ecosystems & Environment*, 119 (1-2), 135-144. <https://doi.org/10.1016/j.agee.2006.07.002>
- Miassi, Y. E., Akdemir, Ş., Dossa, K. F., & Omotayo, A. O. (2023). Technical efficiency and constraints related to rice production in West Africa: The case of Benin Republic. *Cogent Food & Agriculture*, 9(1), 2191881. [10.1080/23311932.2023.2191881](https://doi.org/10.1080/23311932.2023.2191881)
- Ministère de l'Environnement, de l'Habitat et de l'Urbanisme Direction Générale de l'Environnement. (2021). Deuxième communication nationale de la république du Bénin sur les changements climatiques, 168p.
- Molua, E.L. (2010). Global climate change and vulnerability of African agriculture: Implications for resilience and sustained productive capacity. *Quarterly Journal of International Agriculture*, 49(3), 183–211. [10.22004/ag.econ.155547](https://doi.org/10.22004/ag.econ.155547)
- Mustapha, S. B., Sanda, A. H., & Shehu, H. (2012). Producers' perception of climate change in Central Agricultural Zone of Borno State, Nigeria. *Journal of Environment and Earth Science*, 2(11), 21-27.
- Muzamhindo, N., Mtabheni, S., Jiri, O., Mwakiwa, E., & Hanyani-Mlambo, B. (2015). Factors influencing smallholder producers' adaptation to climate change and variability in Chiredzi district of Zimbabwe. *Journal of economics and Sustainable Development*, 6(9), 1-9.
- Mwalusepo, S., Massawe, E. S., Affognon, H., Okuku, G. O., Kingori, S., Mburu, P. D., & Le Ru, B. P. (2015). Smallholder producers' perspectives on climatic variability and adaptation strategies in East Africa: the case of mount Kilimanjaro in Tanzania, Taita and Machakos Hills in Kenya ; 6(10), 1-10. <http://dx.doi.org/10.4172/2157-7617.1000313>
- NASA. (2023). Le réchauffement climatique constitue désormais une menace existentielle de notre temps. Consulté le 15 Mai 2023.
- Neema Ciza, A. (2023). Développement agricole, genre et sécurité alimentaire : Une analyse comparative des ménages ruraux dans les zones montagneuses du territoire de Kalehe (RDC) et du district de Rusizi (Rwanda). Doctoral thesis, ULiège - Université de Liège. ORBi-University of Liège. <https://orbi.uliege.be/handle/2268/304590>
- Niasse, M., Afouda, A., & Amani, A. (2004). Réduire la Vulnérabilité de l'Afrique de l'Ouest aux impacts du climat sur les ressources en eau, les zones humides et la désertification. *Eléments de stratégie régionale de préparation*. UICN, Gland & Cambridge, 59 p.
- OCDE. (2023). Production végétale (indicateur). doi: 10.1787/5631370e-fr (Consulté le 20 juin 2023).

- Oladejo, J.A., Adetunji, M.O. (2012). Economic analysis of maize (*Zea mays* L.) production in Oyo state of Nigeria. *Agricultural Science Research*, 2(2), 77-83.
- Ollabode, N. , Tovihoudji, P.G., Labiyi, A. I., Aihounton, G. B., Adimi, O. G., & Yabi J. A. (2017). Déterminants du rendement de soja dans la commune de N'Dali au nord Bénin, 1(1), 35-42.
- ONU. (2022). Cinq choses à savoir sur les gaz à effet de serre qui réchauffent la planète. <https://news.un.org/fr/story/2022/01/1112132>
- Ouédraogo, M., Dembélé, Y., & Somé, L. (2010). Perceptions et stratégies d'adaptation aux changements des précipitations: cas des paysans du Burkina Faso. *Science et changements planétaires/Sécheresse*, 21(2), 87-96. 10.1684/sec.2010.0244
- Oyekale, A. S., & Oladele, O. I. (2012). Determinants of climate change adaptation among cocoa producers in southwest Nigeria. *ARP. Journal of Science and Technology*, 2(1):154-168.
- Özdemir, D. (2022). The impact of climate change on agricultural productivity in Asian countries: a heterogeneous panel data approach. *Environmental Science and Pollution Research*. No 29, 8205–8217.
- Ozkan, B., Kurklu, A., & Akcaoz, H. (2004). An input-output energy analysis in greenhouse vegetable production: a case study for Antalya region of Turkey. *Biomass and Bioenergy*, 26(1), 89-95. [https://doi.org/10.1016/S0961-9534\(03\)00080-1](https://doi.org/10.1016/S0961-9534(03)00080-1)
- PSDSA. (2017). Plan Stratégique de Développement du Secteur Agricole, Orientations stratégiques 2025, Plan National d'Investissements Agricoles et de Sécurité Alimentaire et Nutritionnelle PNIASAN, 2017 – 2021 », Version finale (2017) 132p.
- Requier-Desjardins, D. (2018). Démographie, agriculture familiale et développement rural en Amérique latine. *Éléments pour un débat. Mondes en développement*, 182 (2) : 87-114.
- Ruiz-Vega, J., Mena-Mesa, N., Diego-Nava, F., & Herrera-Suárez, M. (2015). Productivity and energy efficiency of three tillage systems for maize (*Zea mayz* L.) production. *Revista Facultad de Ingeniería Universidad de Antioquia*, (76), 66-72. <https://doi.org/10.17533/udea.redin.n76a08>.
- Sadiq, M. A., Kuwornu, J. K., Al-Hassan, R. M., & Alhassan, S. I. (2019). Assessing maize producers' adaptation strategies to climate change and variability in Ghana. *Agriculture*, 9(5), 90. <https://doi.org/10.3390/agriculture9050090>
- Sakli, L. (2016). Modélisation et évaluation des vulnérabilités et des risques dans les chaînes logistiques. Thèse de Doctorat. Université d'Aix Marseille, École Doctorale mathématiques-informatique UFR Sciences. Laboratoire des sciences de l'information et des systèmes, UMR CNRS, 729 : 1-214.

- Salahuddin, M., Ali, M. I., Vink, N., & Gow, J. (2018). The effects of urbanization and globalization on CO₂ emissions: evidence from the Sub-Saharan Africa (SSA) countries. *Environ Sci Pollut Res*, 2699–2709 : 26.
- Savi, M. M. O. M., Yabi, J. A., & Sodjinou, E. (2022). Perception des variabilités climatiques des producteurs de maïs en relation avec les tendances climatiques au Nord-Bénin. *International Journal of Biological and Chemical Sciences*, 16(5), 2174-2188.
- Sawadogo, I., Kabore M., Koursangama, A. et Guissou, R. (2010). Dynamique à court terme et prévision des prix des céréales au Burkina-Faso : approche par la cointégration. In Lankoande, Dr Damien, *Quelle agriculture pour un développement durable de l'Afrique*, 657-667.
- Sutcliffe, C., Dougill, A. J., & Quinn, C. H. (2016). Evidence and perceptions of rainfall change in Malawi: Do maize cultivar choices enhance climate change adaptation in sub-Saharan Africa?. *Regional Environmental Change*, 16, 1215-1224. <https://doi.org/10.1007/s10113-015-0842-x>
- Tagwi, A. (2022). The Impacts of Climate Change, Carbon Dioxide Emissions (CO₂) and Renewable Energy Consumption on Agricultural Economic Growth in South Africa: ARDL Approach. *Sustainability*, 14. <https://doi.org/10.3390/su142416468>.
- Teteli, S. C., Padonou, E. A., & Akakpo, B. A. (2022). Priorisation des pratiques anti-érosives de conservation des sols dans la zone soudanienne au Bénin (Afrique de l'Ouest). *Tropicultura*, 3(4):1-22. DOI: 10.25518/2295-8010.2136.
- Tidjani, M. A., & Akponikpe, B. I. P. (2012). Évaluation des stratégies paysannes d'adaptation aux changements climatiques : cas de la production du maïs au Nord-Bénin. *African Crop Science Society*, 20 (2): 425–441.
- UNDP (2019). Rapport annuel 2019. Le PNUB au Bénin, 45p.
- Wokpo, A. (2010). La vie associative comme moyen d'autopromotion des communautés de base : cas des groupements agricoles de Kpélé Adeta (préfecture de Kpélé - Togo).
- Yabi, A. J., Bachabi, F. X., Labiyi, A. I., Odé, A. C., & L. R. Ayéna. (2016). Déterminants socio-économiques de l'adoption des pratiques culturales de gestion de la fertilité des sols utilisées dans la commune de Ouaké au Nord-Ouest du Bénin. *Int. J. Biol. Chem. Sci*, 10(2): 779-792.
- Yakete-Wetonnoubena, J. C. P. & Mbetid-Bessane, E. (2019). Éducation, un déterminant de la productivité agricole en République Centrafricaine. *Afrique Science*, 15(4):51-59.
- Yegbemey, R. N., Yabi, J. A., Aïhounton, G. B., Paraïso, A. (2014). Modélisation simultanée de la perception et de l'adaptation au changement climatique : cas des producteurs de maïs du Nord Bénin (Afrique de l'Ouest). *Cah. Agric.* 23 (3) : 177-187. 10.1684/agr.2014.0697

Yilmaz, I., Akcaoz, H., & Ozkan, B. (2005). An analysis of energy use and input costs for cotton production in Turkey. *Renewable Energy*, 30(2), 145-155.
<https://doi.org/10.1016/j.renene.2004.06.001>



CURRICULUM VITAE

YANN EMMANUEL SONAGNON MIASSI, obtained a bachelor's degree in agricultural economics and rural sociology from Parakou University in 2017 in West Africa in Benin. During the 2018-2019 academic year, he studied at Çukurova University's Turkish Language Learning, Research and Application Center. In September 2019, thanks to the scholarship program offered by the Turkish government, he enrolled in a master's program in the Department of Agricultural Economics at Çukurova University and then graduated in 2021. After obtaining completed his master's degree, he enrolled in the same university to obtain a Ph.D. in agricultural economics. Yann is also completing another PhD in forest economics at Laval University in Canada, where he also working as a teaching and research assistant. His previous publications focus on climate change, agricultural credit, farm economic efficiency, forest economics, food security and rural development.



APPENDICES

Appendice 1: ARDL and ARIMA models

Model 1 : Without production among the explanatory variables

Time series regression with "numeric" data:

Start = 1, End = 30

Call:

```
dynlm(formula = Production_volume_tonne_diff ~ L(t_C02_Food_waste_diff,
-2) + L(diff3_CH4_Food_waste, -2) + L(diff2_t_CH4_Others,
-2) + L(diff3_t_Nitrogen_fertilizer_N, -2) + L(diff2_Rural_population,
-1) + L(diff4_Urban_population, -2) + L(Rainfall_diff, -2) +
L(Temperature_max_diff, -1), data = data)
```

Residuals:

Min	1Q	Median	3Q	Max
-144220	-13319	2733	29360	127043

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	6.304e+04	1.417e+04	4.450	0.000222 ***
L(t_C02_Food_waste_diff, -2)	-4.159e+04	1.701e+04	-2.445	0.023385 *
L(diff3_CH4_Food_waste, -2)	-2.660e+04	2.765e+04	-0.962	0.347087
L(diff2_t_CH4_Others, -2)	-6.585e+07	2.298e+07	-2.865	0.009268 **
L(diff3_t_Nitrogen_fertilizer_N, -2)	5.957e+02	8.968e+02	0.664	0.513738
L(diff2_Rural_population, -1)	-6.199e+00	2.692e+00	-2.303	0.031636 *
L(diff4_Urban_population, -2)	2.568e+00	2.284e+00	1.125	0.273482
L(Rainfall_diff, -2)	-	5.772e+02	1.676e+02	-3.444 0.002435 **
L(Temperature_max_diff, -1)	-1.505e+05	4.785e+04	-3.145	0.004886 **

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 64420 on 21 degrees of freedom

Multiple R-squared: 0.5305, Adjusted R-squared: 0.3517

F-statistic: 2.967 on 8 and 21 DF, p-value: 0.02178

Model 2 : With production as explanatory variable

Time series regression with "numeric" data:

Start = 1, End = 30

Call:

```
dynlm(formula = Production_volume_tonne_diff ~ L(Production_volume_tonne_diff,
-2) + L(diff3_CH4_Food_waste, -2) + L(t_C02_Food_waste_diff,
-2) + L(diff2_t_CH4_Others, -2) + L(diff3_t_Nitrogen_fertilizer_N,
-2) + L(diff2_Rural_population, -1) + L(diff4_Urban_population,
-2) + L(Rainfall_diff, -2) + L(Temperature_max_diff, -1),
data = data)
```

Residuals:

Min	1Q	Median	3Q	Max
-2.513e-11	-8.990e-12	-3.394e-12	3.682e-12	5.429e-11

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	1.594e-11	6.026e-12	2.646e+00	0.0155 *
L(Production_volume_tonne_diff, -2)	1.000e+00	6.659e-17	1.502e+16	<2e-16 ***
L(diff3_CH4_Food_waste, -2)	9.674e-12	8.623e-12	1.122e+00	0.2752
L(t_C02_Food_waste_diff, -2)	-5.767e-12	5.883e-12	-9.800e-01	0.3387
L(diff2_t_CH4_Others, -2)	-4.788e-09	8.271e-09	-5.790e-01	0.5692
L(diff3_t_Nitrogen_fertilizer_N, -2)	7.619e-14	2.765e-13	2.760e-01	0.7857
L(diff2_Rural_population, -1)	1.635e-15	9.194e-16	1.779e+00	0.0905 .
L(diff4_Urban_population, -2)	-1.931e-15	7.176e-16	-2.691e+00	0.0140 *
L(Rainfall_diff, -2)	-4.092e-14	6.398e-14	-6.400e-01	0.5297
L(Temperature_max_diff, -1)	-1.234e-11	1.771e-11	-6.970e-01	0.4938

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.966e-11 on 20 degrees of freedom

Multiple R-squared: 1, Adjusted R-squared: 1

F-statistic: 5.338e+31 on 9 and 20 DF, p-value: < 2.2e-16

Model 3 : Long-term model

Time series regression with "numeric" data:

Start = 1, End = 20

Call:

```
dynlm(formula = residuals_ct ~ L(t_C02_Food_waste_diff, -2) +  
      L(t_C02_Food_waste_diff, -2) + L(diff3_t_Nitrogen_fertilizer_N,  
      -2) + L(Rainfall_diff, -2), data = data_lt2)
```

Residuals:

Min	1Q	Median	3Q	Max
-102249	-43231	4398	50775	72335

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-14847.4	14811.5	-1.002	0.331
L(t_C02_Food_waste_diff, -2)	26430.8	16551.3	1.597	0.130
L(diff3_t_Nitrogen_fertilizer_N, -2)	-3751.7	2092.9	-1.793	0.092
L(Rainfall_diff, -2)	251.3	174.7	1.439	0.170

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 61120 on 16 degrees of freedom

(0 observations deleted due to missingness)

Multiple R-squared: 0.251, Adjusted R-squared: 0.1106

F-statistic: 1.788 on 3 and 16 DF, p-value: 0.19

Model 4 : Long-term model with many variables

Call:

```
dynlm(formula = residuals_ct ~ L(diff3_N2O_Agricultural_sector,  
      -2) + L(t_C02_Food_waste_diff, -2) + L(diff3_t_Nitrogen_fertilizer_N,  
      -2) + L(Temperature_min_diff, -2) + L(diff2_Rural_population,  
      -1), data = data_lt2)
```

Residuals:

Min	1Q	Median	3Q	Max
-----	----	--------	----	-----

-105344 -23810 -361 39034 88112

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-1.494e+04	1.810e+04	- 0.825	0.423
L(diff3_N2O_Agricultural_sector, -2)	3.044e+03	6.503e+03	0.468	0.647
L(t_CO2_Food_waste_diff, -2)	2.617e+04	2.239e+04	1.169	0.262
L(diff3_t_Nitrogen_fertilizer_N, -2)	-4.071e+03	2.634e+03	-1.546	0.145
L(Temperature_min_diff, -2)	3.498e+04	7.057e+04	0.496	0.628
L(diff2_Rural_population, -1)	8.377e-01	3.282e+00	0.255	0.802

Residual standard error: 67620 on 14 degrees of freedom

(0 observations deleted due to missingness)

Multiple R-squared: 0.1978, Adjusted R-squared: -0.0887

F-statistic: 0.6904 on 5 and 14 DF, p-value: 0.6389

Appendice 2: Tobit regression results

Model 1

Tobit regression	Number of obs	=	230
	Uncensored	=	230
Limits: Lower = -inf	Left-censored	=	0
Upper = +inf	Right-censored	=	0
	LR chi2(20)	=	112.55
	Prob > chi2	=	0.0000
Log likelihood = 41.51093	Pseudo R2	=	3.8112

	ETCRS	Coefficient	Std. err.	t	P> t	[95% conf. interval]
AGE		-.0040335	.002053	-1.96	0.051	-.0080806 .0000136
SEXE		-.0419868	.0436605	-0.96	0.337	-.1280557 .0440822
TMENAGE		-.0042309	.0048564	-0.87	0.385	-.0138044 .0053425
EXP		.0055512	.0023193	2.39	0.018	.0009792 .0101232
ALPHA		.0220684	.0374006	0.59	0.556	-.0516604 .0957972
INSTR		.0146281	.016014	0.91	0.362	-.0169408 .0461969
AGRIC		.1418387	.0356103	3.98	0.000	.0716393 .2120381
CREDIT		-.0251659	.0323743	-0.78	0.438	-.0889862 .0386544
MODE		.0055166	.0131649	0.42	0.676	-.0204358 .031469

SUP	-.0133121	.0032142	-4.14	0.000	-.0196483	-.0069758
HERBI	.0016049	.0006949	2.31	0.022	.0002349	.0029748
INSEC	.0584698	.0110245	5.30	0.000	.036737	.0802026
PEST	-.0006537	.0008365	-0.78	0.435	-.0023027	.0009952
NPK	.0000404	8.62e-06	4.69	0.000	.0000234	.0000574
UREE	-.0000129	.0000293	-0.44	0.661	-.0000707	.0000449
GESTION	.03105	.0307565	1.01	0.314	-.029581	.0916809
MAOR	-.1774794	.2073842	-0.86	0.393	-.586301	.2313423
MECAN	.0211358	.068196	0.31	0.757	-.1133006	.1555722
ROTATION	-.043191	.0531192	-0.81	0.417	-.1479063	.0615243
SEMISRA	-.0369405	.0317867	-1.16	0.246	-.0996024	.0257213
_cons	.4376558	.1315793	3.33	0.001	.1782702	.6970414
-----+-----						
var(e.ETCRS)	.0408094	.0038055			.0339567	.0490451

Tobit regression

Number of obs = 230

Uncensored = 230

Limits: Lower = -inf

Left-censored = 0

Upper = +inf

Right-censored = 0

LR chi2(20) = 66.55

Prob > chi2 = 0.0000

Log likelihood = 419.57907

Pseudo R2 = -0.0861

ETVRS	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
-----+-----						
AGE	.0016127	.0003967	4.06	0.000	.0008306	.0023948
SEXE	.0313623	.0084374	3.72	0.000	.0147295	.0479951
TMENAGE	-.0000676	.0009385	-0.07	0.943	-.0019177	.0017825
EXP	-.0005964	.0004482	-1.33	0.185	-.0014799	.0002871
ALPHA	-.0165095	.0072276	-2.28	0.023	-.0307575	-.0022615
INSTR	.0031211	.0030947	1.01	0.314	-.0029796	.0092217
AGRIC	-.007006	.0068817	-1.02	0.310	-.020572	.00656
CREDIT	.0099972	.0062563	1.60	0.112	-.002336	.0223304
MODE	.0001016	.0025441	0.04	0.968	-.0049136	.0051169
SUP	.0004424	.0006211	0.71	0.477	-.000782	.0016669

HERBI	.0000855	.0001343	0.64	0.525	-.0001792	.0003503
INSEC	.0019506	.0021305	0.92	0.361	-.0022493	.0061504
PEST	.0002077	.0001616	1.28	0.200	-.000111	.0005263
NPK	-4.31e-07	1.67e-06	-0.26	0.796	-3.71e-06	2.85e-06
UREE	3.71e-06	5.67e-06	0.66	0.513	-7.46e-06	.0000149
GESTION	-.0060028	.0059437	-1.01	0.314	-.0177197	.0057141
MAOR	-.0271139	.0400768	-0.68	0.499	-.1061184	.0518906
MECAN	.0241783	.0131788	1.83	0.068	-.0018015	.050158
ROTATION	-.009998	.0102653	-0.97	0.331	-.0302342	.0102381
SEMISRA	-.0086603	.0061428	-1.41	0.160	-.0207697	.003449
_cons	.8788193	.0254276	34.56	0.000	.8286932	.9289454

var(e.ETVRS)	.001524	.0001421		.0012681	.0018316
--------------	---------	----------	--	----------	----------

Tobit regression	Number of obs	=	230
	Uncensored	=	230
Limits: Lower = -inf	Left-censored	=	0
Upper = +inf	Right-censored	=	0
	LR chi2(20)	=	118.05
	Prob > chi2	=	0.0000
Log likelihood = 38.809654	Pseudo R2	=	2.9200

EFFICACITE	Coefficient	Std. err.	t	P> t	[95% conf. interval]
AGE	-.0048134	.0020772	-2.32	0.021	-.0089083 -.0007185
SEXE	-.0618593	.0441763	-1.40	0.163	-.148945 .0252265
TMENAGE	-.0047239	.0049137	-0.96	0.337	-.0144105 .0049626
EXP	.0060962	.0023467	2.60	0.010	.0014701 .0107222
ALPHA	.0283937	.0378425	0.75	0.454	-.0462061 .1029935
INSTR	.0131751	.0162032	0.81	0.417	-.0187668 .0451169
AGRIC	.1485165	.036031	4.12	0.000	.0774877 .2195452
CREDIT	-.0325574	.0327568	-0.99	0.321	-.0971317 .0320168
MODE	.0049466	.0133205	0.37	0.711	-.0213124 .0312056
SUP	-.0134303	.0032522	-4.13	0.000	-.0198415 -.0070192
HERBI	.0015529	.0007032	2.21	0.028	.0001668 .0029391

INSEC	.0586216	.0111547	5.26	0.000	.036632	.0806111
PEST	-.0007621	.0008463	-0.90	0.369	-.0024305	.0009063
NPK	.0000412	8.72e-06	4.72	0.000	.000024	.0000584
UREE	-.0000155	.0000297	-0.52	0.602	-.000074	.000043
GESTION	.0342587	.0311198	1.10	0.272	-.0270886	.095606
MAOR	-.1744888	.2098342	-0.83	0.407	-.5881403	.2391626
MECAN	.0079002	.0690016	0.11	0.909	-.1281244	.1439248
ROTATION	-.0385171	.0537468	-0.72	0.474	-.1444694	.0674353
SEMISRA	-.0335707	.0321622	-1.04	0.298	-.0969728	.0298315
_cons	.5056963	.1331338	3.80	0.000	.2432463	.7681463

-----+-----

var(e.EFFICACITE)	.0417794	.0038959		.0347638	.0502108
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Model 2

Tobit regression	Number of obs	=	230
	Uncensored	=	230
Limits: Lower = -inf	Left-censored	=	0
Upper = +inf	Right-censored	=	0
	LR chi2(15)	=	105.65
	Prob > chi2	=	0.0000
Log likelihood = 38.059656	Pseudo R2	=	3.5775

-----+-----

ETCRS	Coefficient	Std. err.	t	P> t	[95% conf. interval]
AGE	-.0041174	.0020547	-2.00	0.046	-.0081674 -.0000675
SEXE	-.0294582	.0433829	-0.68	0.498	-.1149686 .0560521
TMENAGE	-.0036527	.004914	-0.74	0.458	-.0133384 .0060331
EXP	.0053439	.0021585	2.48	0.014	.0010892 .0095985
ALPHA	.0166283	.0372711	0.45	0.656	-.0568353 .0900919
INSTR	.0121662	.0161389	0.75	0.452	-.0196445 .0439769
AGRIC	.1417809	.0346116	4.10	0.000	.0735593 .2100024
SUP	-.0123103	.0027126	-4.54	0.000	-.017657 -.0069636
INSEC	.0577161	.0108106	5.34	0.000	.0364078 .0790244
NPK	.0000417	8.34e-06	5.00	0.000	.0000253 .0000581
GESTION	.0359936	.0309924	1.16	0.247	-.0250943 .0970814
MAOR	-.1655184	.2097522	-0.79	0.431	-.5789524 .2479155

```

MECAN | .0208732 .0690751 0.30 0.763 -.115278 .1570243
ROTATION | -.0426172 .0533546 -0.80 0.425 -.1477822 .0625478
SEMISRA | -.0329931 .0318196 -1.04 0.301 -.0957114 .0297251
_cons | .4319605 .1279307 3.38 0.001 .1798016 .6841195
-----+-----
var(e.ETCRS)| .0420527 .0039214 .0349921 .0505381
-----

Tobit regression               Number of obs   =   230
                                Uncensored =   230
Limits: Lower = -inf          Left-censored =    0
                                Upper = +inf       Right-censored =    0
                                LR chi2(15)      = 61.88
                                Prob > chi2      = 0.0000
Log likelihood = 417.24556     Pseudo R2      = -0.0801
-----+-----
ETVRS | Coefficient  Std. err.   t    P>|t|    [95% conf. interval]
-----+-----
AGE | .0015612 .0003951  3.95 0.000  .0007823  .00234
SEXE | .0293292 .0083431  3.52 0.001  .0128845  .0457739
TMENAGE | 5.27e-06 .000945  0.01 0.996  -.0018574  .001868
EXP | -.0003595 .0004151 -0.87 0.387  -.0011777  .0004588
ALPHA | -.015503 .0071677 -2.16 0.032  -.0296309  -.001375
INSTR | .0037579 .0031037  1.21 0.227  -.0023597  .0098755
AGRIC | -.0064865 .0066562 -0.97 0.331  -.0196064  .0066333
SUP | .0007851 .0005217  1.51 0.134  -.0002431  .0018134
INSEC | .0012339 .002079  0.59 0.553  -.0028639  .0053318
NPK | -1.62e-07 1.60e-06 -0.10 0.920  -3.32e-06  3.00e-06
GESTION | -.0067911 .0059602 -1.14 0.256  -.018539  .0049569
MAOR | -.0291355 .0403379 -0.72 0.471  -.108644  .0503729
MECAN | .0243633 .013284  1.83 0.068  -.0018202  .0505468
ROTATION | -.0095352 .0102607 -0.93 0.354  -.0297597  .0106893
SEMISRA | -.0077757 .0061193 -1.27 0.205  -.0198372  .0042858
_cons | .8829485 .0246026 35.89 0.000  .8344552  .9314418
-----+-----
var(e.ETVRS)| .0015553 .000145 .0012941 .0018691
-----

```

TMENAGE	-.0042039	.0049737	-0.85	0.399	-.0140074	.0055996
EXP	.0057378	.0021848	2.63	0.009	.0014314	.0100442
ALPHA	.0219382	.0377243	0.58	0.561	-.0524187	.096295
INSTR	.0103058	.0163351	0.63	0.529	-.0218917	.0425033
AGRIC	.1482583	.0350325	4.23	0.000	.0792072	.2173094
SUP	-.0126473	.0027456	-4.61	0.000	-.018059	-.0072355
INSEC	.0584338	.010942	5.34	0.000	.0368663	.0800012
NDK	.0002122	.0111065	5.61	0.000	.0002357	.0002500

```

var(e.EFFICACITE)| .0430816 .0040174          .0358482 .0517746
-----
Model 3

Tobit regression                Number of obs   =   230
                                Uncensored =   230
Limits: Lower = -inf           Left-censored =    0
                                Upper = +inf       Right-censored =    0

```

Log likelihood = 36.667393 Pseudo R2 = 3.4832

ETCRS	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
-----+-----						
AGE	-.0045199	.0020173	-2.24	0.026	-.0084957	-.0005441
SEXE	-.0329796	.0418314	-0.79	0.431	-.1154212	.049462
EXP	.0050233	.0020842	2.41	0.017	.0009157	.0091309
ALPHA	.013416	.0369981	0.36	0.717	-.0595	.086332
AGRIC	.1341645	.0334257	4.01	0.000	.068289	.2000401
SUP	-.0137363	.0022394	-6.13	0.000	-.0181497	-.009323
INSEC	.0530702	.0093255	5.69	0.000	.0346915	.071449
NPK	.000041	8.09e-06	5.08	0.000	.0000251	.000057
GESTION	.0322427	.0307685	1.05	0.296	-.028396	.0928813
MAOR	-.1669799	.2093238	-0.80	0.426	-.5795165	.2455566
cons	.471015	.1201324	3.92	0.000	.2342575	.7077726

var(e.ETCRS) | .042565 .0039692 .0354192 .0511524

Tobit regression Number of obs = 230

Uncensored = 230

Limits: Lower = -inf Left-censored = 0

Upper = +inf Right-censored = 0

LR chi2(10) = 55.19

Prob > chi2 = 0.0000

Log likelihood = 413.89957 Pseudo R2 = -0.0714

ETVRS	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
-----+-----						
AGE	.0014702	.0003913	3.76	0.000	.0006991	.0022413
SEXE	.027668	.0081133	3.41	0.001	.0116782	.0436578
EXP	-.0002846	.0004042	-0.70	0.482	-.0010813	.0005121
ALPHA	-.015563	.0071759	-2.17	0.031	-.0297053	-.0014208
AGRIC	-.0069399	.006483	-1.07	0.286	-.0197167	.0058368
SUP	.0006757	.0004343	1.56	0.121	-.0001803	.0015317
INSEC	.0007984	.0018087	0.44	0.659	-.0027662	.004363
NPK	4.29e-08	1.57e-06	0.03	0.978	-3.05e-06	3.13e-06

Log likelihood = 34.05806

Pseudo R2 = 2.6849

EFFICACITE	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
AGE	-.0052497	.0020404	-2.57	0.011	-.0092708	-.0012285
SEXE	-.051269	.0423087	-1.21	0.227	-.1346512	.0321133
EXP	.0053234	.002108	2.53	0.012	.0011689	.0094779
ALPHA	.0183397	.0374202	0.49	0.625	-.0554083	.0920876
AGRIC	.1404296	.0338071	4.15	0.000	.0738025	.2070568
SUP	-.0141916	.0022649	-6.27	0.000	-.0186553	-.0097279
INSEC	.0535514	.0094319	5.68	0.000	.0349629	.0721398
NPK	.0000413	8.18e-06	5.05	0.000	.0000252	.0000574
GESTION	.0369336	.0311195	1.19	0.237	-.0243969	.0982641
MAOR	-.16771	.2117121	-0.79	0.429	-.5849534	.2495334
_cons	.5287481	.121503	4.35	0.000	.2892893	.768207
var(e.EFFICACITE)	.0435418	.0040603			.036232	.0523263