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Demand, use and impacts of climate services for agriculture in northern Côte d'Ivoire

Titre en français : Demande, utilisation et impacts des services climatiques pour l'agriculture au nord de la Côte d'Ivoire

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Executive Summary

This CIFRE PhD thesis, funded by the French Development Agency (AFD), is structured in three chapters and focuses on climate services (CS) from the perspective of demand, use, and impact among farmers in northern Côte d'Ivoire. Climate services refer to the provision of weather and/or climate information to support informed decision-making among users. Two of the three chapters are based on survey data collected in cooperation with the private operator Ivoire Coton and in co-supervision with local consultants (CIRES and Hervé Kakou).

Chapter 1 examines the relative value of integrating local forecasting knowledge (LFK) into climate services through a discrete choice experiment involving 285 farmers. The chapter begins by documenting LFK present in northern Côte d'Ivoire and assessing farmers' perceptions of its reliability. Although farmers tend to place greater trust in LFK compared to available scientific forecasts, I show that the inclusion of LFK is not a decisive factor in choosing one climate service over another. Instead, the primary criteria influencing farmers' preferences are the cost of the service and access to oral information (via radio or a cooperative focal point). Only older farmers show a marked preference for climate services that incorporate LFK. These findings suggest that public policy should prioritize low-cost, orally delivered scientific forecasts in this region. Nonetheless, additional research is needed to explore the complementarities between CS and LFK, especially in light of farmers' continued reliance on, and trust in, local knowledge in this region.

Chapter 2 employs an experimental approach involving 313 farmers to assess: (i) how farmers' maize sowing decisions respond to dry spell forecasts; (ii) the effect of such forecasts on potential harvests; and (iii) the individual factors that influence farmers' decisions. The experiment asks each participant to divide their maize sowing between an "early and risky" period—subject to a probability of dry spell occurrence—and a "late" period, which guarantees lower but certain yields. Forecasts of dry spells are randomly assigned across five hypothetical agricultural seasons and compared to a no-forecast scenario. I find that farmers adjust their strategies in accordance with the forecasts, leading to higher expected harvests relative to a no-forecast baseline. Sowing decisions are also shaped by previous decisions and past exposure to dry spell shocks. In addition, individual characteristics—such as locus of control, adaptability, and past experiences of crop loss—significantly influence how farmers interpret and respond to forecast probabilities. From an operational perspective, these findings underscore the value of probabilistic formats in communicating weather information to farmers with limited literacy.

Chapter 3 presents a systematic review of the methodologies used to evaluate the ex post impacts of climate services in agriculture. The extent to which evaluators can control farmers' access to climate services introduces different challenges: (i) spillover effects in control groups, and (ii) selection bias in both access to and use of information. Instrumental variable approaches can help mitigate contamination effects, though further research is needed to quantify their magnitude. To avoid selection bias, distinct measurement strategies should be employed depending on whether the evaluation concerns access or actual use. Most quantified impacts to date have focused on yields and farm management, while cash crops, livestock, and social and environmental outcomes remain underexplored.

This thesis concludes that individual heterogeneity plays a central role in shaping the demand for, use of, and impact of climate services. Overall, the findings support the need to consider farmers' individual characteristics to maximize the potential benefits of such services.

Résumé Exécutif

Cette thèse CIFRE, financée par l'Agence Française de Développement (AFD), s'intéresse aux services climatiques (SC) à travers le prisme de la demande, l'utilisation et l'impact auprès des agriculteurs du nord de la Côte d'Ivoire. Les SC se définissent comme tout service diffusant des informations météorologiques ou climatiques visant à guider les usagers dans leurs prises de décision. Deux des trois chapitres reposent sur des données d'enquêtes collectées en coopération avec l'opérateur privé Ivoire Coton et en co-supervision avec des consultants locaux (CIRES, et Hervé Kakou).

Le **Chapitre 1** mesure la valeur relative de l'intégration des savoirs prévisionnels locaux (SPL) dans les SC par une expérimentation de choix mise en œuvre auprès de 285 agriculteurs. Ce chapitre commence par inventorier ces savoirs au nord de la Côte d'Ivoire et la perception des agriculteurs de leur fiabilité. Malgré une confiance plus élevée accordée aux SPL comparés aux prévisions scientifiques accessibles localement, l'intégration de ces savoirs n'est pas déterminante pour faire le choix d'un SC plutôt qu'un autre. Le premier critère de choix est le coût du service, puis, la diffusion orale (radio, coopérative). Seuls, les plus âgés, ont une préférence pour des SC intégrant des SPL. Les décideurs doivent donc privilégier dans cette région des SC oraux et ce, à moindre coût. Toutefois, de plus amples recherches pourraient être mises en œuvre sur la complémentarité des SC et des SPL dans cette zone, compte tenu de la confiance toujours importante accordée par les populations à ces savoirs.

Le **Chapitre 2** utilise une approche expérimentale auprès de 313 agriculteurs pour évaluer : i) l'ajustement de leurs décisions de semis de maïs en réponse à une prévision de pause sèche, ii) l'impact de cette prévision sur les récoltes potentielles et iii) les facteurs qui influencent leur prise en compte de l'information. Chaque agriculteur répartit ses semis entre une période « précoce et risquée », associée à une probabilité de pause sèche, et une période de semis « tardive », qui garantit des rendements faibles mais certains. Les prévisions communiquées aux agriculteurs varient aléatoirement sur cinq saisons et les choix sont comparés à un scénario sans prévision. Les résultats montrent que les agriculteurs adaptent leurs stratégies en fonction de la prévision, ce qui améliore les récoltes espérées par rapport à une situation sans prévision. Leur choix de semis sont également influencés par les choix précédents et les chocs passés. Les caractéristiques individuelles telles que le locus de contrôle, la volonté d'adaptation et les pertes passées influencent la manière dont les agriculteurs perçoivent et réagissent à la prévision. Ces résultats soulignent le potentiel des formats probabilistes pour communiquer des prévisions à des agriculteurs peu lettrés.

Le **Chapitre 3** propose une revue méthodologique des évaluations ex post des impacts des SC en agriculture. En fonction du contrôle exercé par l'évaluateur sur l'accès au SC, différents problèmes émergent : i) les effets de contamination dans le groupe de contrôle et ii) les biais de sélection pour l'accès et l'utilisation de l'information. Des variables instrumentales permettent de contrôler les effets de contamination parmi les agriculteurs, mais des recherches supplémentaires pourraient être menées pour quantifier leur étendue. Des méthodologies de mesure distinctes doivent être employées en fonction de l'impact mesuré pour éviter les biais de sélection. Les impacts quantifiés se concentrent actuellement sur les rendements et la gestion de l'exploitation. Les cultures de rente, l'élevage et les impacts sociaux et environnementaux sont moins étudiés.

Cette thèse conclue à l'influence majeure de l'hétérogénéité individuelle sur la demande, l'utilisation et l'impact des SC et appuie la nécessité de tenir compte des individualités des agriculteurs afin de maximiser les bénéfices potentiels des SC.

Contents

List of figures

List of tables

Introduction Générale

En Afrique de l'Ouest, la variabilité croissante de la distribution temporelle des précipitations représente une menace d'envergure pour les ménages agricoles (Basse et al., 2024; Gaetani et al., 2020). Cette tendance se matérialise notamment dans le nord de la Côte d'Ivoire par une hausse de la fréquence et de la longueur des pauses sèches à l'intérieur de la saison des pluies, ainsi que par la recrudescence d'épisodes de pluies intenses (Boko-Koiadia Adjoua et al., 2016; Dekoula et al., 2018, 2019). L'agriculture étant principalement pluviale, ces changements ont des conséquences néfastes sur les cultures locales, occasionnant des pertes de récoltes et, in fine, un risque grandissant d'insécurité alimentaire (Roudier et al., 2011; Sultan et al., 2013, 2019).

Dans ce contexte, fournir aux agriculteurs des services climatiques (SC) leur permettant d'anticiper ces chocs météorologiques et d'adapter leurs décisions apparait essentiel. Inscrits à l'agenda international du développement (Accord de Paris, article 7, alinéa c; Objectif de développement durable 13, cible 13.3), les SC se définissent comme tout service (applications, bulletins radio, sms etc.) comprenant des prévisions météorologiques de court-terme (1 à 15 jours), saisonnières (tendance sur 3 mois) ou encore des projections climatiques (jusqu'à un siècle) visant à guider les usagers dans leurs prises de décisions.

Cette thèse se concentre ici sur la question de la demande, de l'utilisation et de l'impact des services climatiques pour les agriculteurs du nord de la Côte d'Ivoire. Afin de mieux comprendre la demande locale, nous explorons, dans un premier temps, les préférences pour les SC à travers une expérimentation de choix auprès de 245 agriculteurs du nord de la Côte d'Ivoire. Ce premier chapitre accorde une attention particulière à la valorisation de l'intégration des savoirs locaux dans les SC. Ces savoirs étant encore peu documentés en Afrique de l'Ouest (Nyadzi, 2021a), cette thèse se propose également d'inventorier les connaissances des agriculteurs en la matière. Dans un second temps, nous nous intéressons à la question de l'utilisation et de l'impact des prévisions météorologiques à travers une approche expérimentale. Cette approche a pour objectif de tester, auprès de 313 agriculteurs, l'adaptation des semis de maïs en réponse à une prévision de pause sèche. Nous mesurons ici, l'impact de cette prévision météorologique sur les rendements potentiels et explorons les facteurs qui influencent la prise de décision des agriculteurs. Enfin, la question de la quantification des impacts des SC en agriculture est analysée au cours d'un troisième chapitre consacré à une revue méthodologique et systématique des évaluations quantitatives publiées dans la littérature scientifique. Ce chapitre, contrairement aux précédents, est bâti à partir d'expériences existantes dans différentes géographies du monde.

Cette thèse CIFRE, financée par l'Agence Française de Développement (AFD), s'inscrit en cohérence avec les activités opérationnelles de l'institution dans la région dont deux projets, relatifs au renforcement de la direction nationale de la météorologie (SODEXAM) et à celui de la filière cotonnière. La collecte des données utilisées dans deux des chapitres de thèse a été réalisée en coopération avec l'opérateur privé Ivoire Coton qui a permis l'accès aux producteurs de coton encadrés par ses agents. Les deux enquêtes de terrain ont été financées par l'AFD, et reposent sur un travail minutieux de collecte supervisé avec des consultants locaux (CIRES, et Hervé Kakou), et en discussion avec la SODEXAM pour la pertinence des recherches.

A travers cette introduction générale, nous tacherons, en amont des chapitres précédemment énoncés, de : i) contextualiser la demande de SC en Côte d'Ivoire, ii) mettre en valeur le cadre analytique commun qui traverse l'ensemble de ces travaux de recherche, avant de, iii) donner une vue d'ensemble des trois chapitres qui composent cette thèse et de leurs principales contributions à la littérature et aux politiques publiques.

La demande en services climatiques en Côte d'Ivoire

Comme ailleurs sur le continent, des barrières à l'accès et à l'utilisation des services climatiques existent en Côte d'Ivoire (Antwi-Agyei et al., 2015, 2021; Carr et al., 2020; Hansen, 2002; Lemos et al., 2012; Nkiaka, 2019). Un moyen de communication (téléphone mobile, smartphone, radio ou télévision) et un réseau de qualité sont nécessaires pour accéder à l'information. Les langues dans lesquelles sont diffusées les prévisions peuvent ne pas être comprises par les populations. Outre la langue, ce peut-être la formulation scientifique ou les horaires de diffusion qui freinent l'utilisation des informations. Enfin, l'agriculteur n'est pas toujours en mesure de changer de comportement suite à la réception d'une prévision en raison d'une méconnaissance des stratégies d'adaptation possibles et également, de l'impossibilité de réunir avant la survenue de l'évènement météorologique les moyens matériels et humains nécessaires (Makaudze, 2005; Sanfo et al., 2022). Ces barrières à l'accès et à l'utilisation des SC sont liées à des inégalités de revenu mais aussi au genre et/ou au contexte ethnique (Carr & Onzere, 2018; Diouf et al., 2020; Gumucio et al., 2020). Des caractéristiques individuelles peuvent donc être à l'origine d'une certaine hétérogénéité de la demande en services sur un même territoire.

De plus en Côte d'Ivoire, les prévisions scientifiques diffusées ne sont pas toujours précises en raison du faible maillage de stations météorologiques sur le territoire et au manque de ressources pour la collecte et le traitement de données. Ce problème est commun à de nombreux pays du continent. (Africa Adaptation Initiative, 2023). De fait, les services agrométéorologiques actuels sont souvent limités à l'échelle nationale ou régionale. Or, une offre de services ciblés sur les besoins locaux est essentielle pour « *faire la différence entre des réponses de survie (« copying responses ») et des réponses d'adaptation informées* » (GIEC, 2022). La SODEXAM fait donc actuellement l'objet de plusieurs projets de renforcement de capacité pour améliorer la performance de ses modèles de prévisions dont le projet VIGICLIMM financé par l'AFD et des programmes spécifiques axés sur la demande des régions du nord sont en cours d'élaboration avec le Programme Alimentaire Mondiale (PAM).

Enfin, la demande en services climatiques s'inscrit également dans un contexte où les savoirs prévisionnels locaux et les consultations mystiques sont toujours une source d'information majeure pour la prise de décision des agriculteurs (Nyadzi, 2021b; Roncoli, 2006; Roncoli et al., 2002). Les savoirs prévisionnels locaux (SPL) désignent ici *« les indicateurs environnementaux observés localement par les populations pour élaborer des prévisions météorologiques de court-terme et saisonnières* (Gbangou, 2021). Ces savoirs continuent de bénéficier d'une certaine légitimité, parfois supérieure aux prévisions scientifiques, et sont utilisés en source principale ou complémentaire aux SC existants (Ebhuoma & Simatele, 2019).

La valeur économique des services climatiques et l'influence de l'hétérogénéité individuelle

La valeur économique d'un service climatique peut être mesurée sous deux angles complémentaires (Vaughan et al., 2019), d'une part, à travers le consentement à payer pour ce service auprès des utilisateurs potentiels et, d'autre part, par la valorisation des impacts de ce SC. Ces deux méthodes sont explorées au cours des différents chapitres de cette thèse. Le consentement à payer pour un service intégrant des savoirs prévisionnels locaux est estimé dans le Chapitre 1 dans le cadre d'une expérimentation de choix. Cette méthode permet d'obtenir des préférences entre les attributs d'un service (moyens de diffusion, inclusion des savoirs etc.) et leurs variations (radio, sms etc.), mais également, le consentement à payer des individus pour chaque composante. Cette méthode est actuellement peu utilisée dans le domaine des SC (Prasada, 2020; Tesfaye et al., 2019, 2023). Ensuite, dans le Chapitre 2, une approche expérimentale, permet de mesurer la valeur d'une prévision de pause sèche par son impact sur les récoltes potentielles. A notre connaissance, à quelques exceptions près - comme des ateliers de recherche participative menés avec des agriculteurs sénégalais (Roudier et al., 2014) et une expérience de gestion de barrages hydrauliques basée sur des prévisions saisonnières (Crochemore et al., 2021) les études expérimentales de ce type sur les SC sont encore peu répandues. Enfin, dans le Chapitre 3, nous nous intéressons aux méthodes utilisées pour quantifier les impacts des SC en agriculture, à travers une revue systématique qui mettra en lumières les principales métriques et leurs résultats, ainsi que les problèmes méthodologiques émergents et leurs solutions. Jusqu'à présent, aucune revue de l'impact des services climatiques ex-post n'a été faite en mettant l'accent sur les méthodes utilisées.

L'hétérogénéité individuelle est le deuxième concept au cœur des analyses menées dans cette thèse. Cette question revêt une importance cruciale dans la construction d'une offre de SC adaptée au contexte local et permettant de réaliser leur plein potentiel en matière d'adaptation. Une offre de SC individuelle « à la carte » est régulièrement recommandée par la littérature (Carr et al., 2020; Hansen, 2002; Lemos et al., 2012; Warner et al., 2022). Cette thèse permet d'appuyer ces recommandations par des preuves empiriques concrètes sur l'importance des caractéristiques individuelles pour la demande, l'utilisation et l'impact des

SC, et ce, sur un territoire encore jamais étudié par cette littérature. Le Chapitre 1 traitera de l'influence de l'hétérogénéité individuelle sur la demande en services. L'utilisation d'un estimateur Mixed Logit permet de mesurer l'hétérogénéité de la demande des agriculteurs pour l'intégration des savoirs prévisionnels locaux dans les SC. Le Chapitre 2 étudie l'influence des caractéristiques individuelles sur l'interprétation d'une probabilité de pauses sèches lors de la décision de semer le maïs. Ce chapitre met en valeur des concepts novateurs sur l'utilisation et l'impact des SC comme le locus de contrôle, l'auto-efficacité ou encore la volonté d'adaptation des agriculteurs (Bandura, 1977; Burnham & Ma, 2017; Rotter, 1966) et liées à la perception du risque réel de pauses sèches (sévérité et fréquence des pertes passées) (Grothmann & Patt, 2005). Enfin, le Chapitre 3 souligne l'importance de certaines caractéristiques individuelles sur l'impact d'un service. Ce dernier Chapitre met également en valeur l'impact supérieur obtenu grâce aux formations sur l'utilisation des SC.

Vue d'ensemble des chapitres et principales contributions

Chapitre 1 : « Local Forecasting Knowledge in Climate Services: A Choice Experiment». Après avoir inventorié les savoirs prévisionnels locaux au Nord de la Côte d'Ivoire auprès de 285 agriculteurs, et vérifié la volonté des agriculteurs à contribuer à des services hybrides, ce chapitre mesure la valeur relative de l'intégration de ces savoirs aux SC par une expérimentation de choix. L'estimation du modèle mixed-logit démontre en moyenne que leur intégration n'est pas déterminante pour le choix d'un service climatique, à l'exception des populations âgées qui y accordent toujours une grande importance. Les agriculteurs regardent en premier le coût du service, et en second l'accès à une information orale (radio, personne ressource de la coopérative) pour choisir un SC. Ces résultats contribuent ainsi à la littérature économique sur l'hybridation des savoirs dans le domaine des services climatiques. Ils contribuent à la mesure des préférences et de la valeur des SC en utilisant une expérimentation de choix, une méthode peu utilisée dans ce domaine et ce, avec des estimateurs avancés.

En matière de recommandations, les décideurs doivent considérer que les cotonculteurs enquêtés accordent plus d'importance au moyen de diffusion de l'information qu'à l'intégration des savoirs locaux dans l'offre de SC. Toutefois, de plus amples recherches pourraient être mises en œuvre sur la complémentarité des SC et des savoirs locaux dans cette zone, compte tenu de la confiance toujours importante accordée par la population à ces savoirs, en particulier chez les plus âgés.

Chapitre 2 : "Forecasts in the field: Could a dry spell probability shift farmers' sowing behaviour? » Par une approche expérimentale auprès de 313 agriculteurs, nous : i) évaluons l'ajustement des décisions de semis de maïs des agriculteurs en réponse à une prévision de pauses sèches, ii) mesurons l'impact d'une prévision sur les récoltes potentielles et iii) explorons les facteurs qui influencent la prise en compte de l'information. Inspiré du protocole de Gneezy et Potters (1997), il est demandé à chaque agriculteur de répartir ses semis de maïs entre une période « précoce et risquée » - associée à une probabilité de pause sèche - et une période de semis « tardive », qui garantit des rendements plus faibles mais certains. En cas de pause sèche, tout le maïs semé pendant la période à risque est entièrement perdu. Les prévisions de pauses sèches communiquées aux agriculteurs varient de manière aléatoire sur cinq saisons et les choix en termes de semis sont comparés à chaque période à un scénario sans information. La séquence de cinq saisons est répétée deux fois afin d'évaluer l'influence sur les choix de semis de l'exposition antérieure à une même probabilité. Les résultats montrent que les agriculteurs adaptent leurs stratégies à la prévision reçue, ce qui améliore les récoltes espérées par rapport à une situation sans information. Les choix des agriculteurs sont également influencés par les décisions de semis antérieures et par leur exposition passée à une pause sèche. Des caractéristiques individuelles telles que le locus de contrôle, la volonté d'adaptation et l'expérience de pertes réelles de maïs modulent de manière significative les réponses à une prévision de pauses sèches.

Ce chapitre contribue à la littérature sur les effets des services climatiques sur la prise de décision agricole en introduisant un modèle individuel innovant. L'expérience est à la fois facilement compréhensible et reproductible parmi les populations rurales peu instruites. D'un point de vue opérationnel, les résultats soulignent le potentiel de l'utilisation du format probabiliste pour communiquer des informations météorologiques aux agriculteurs peu alphabétisés et la nécessité d'adapter les services climatiques aux profils individuels pour en obtenir les bénéfices maximums.

Chapitre 3 : "Quantifying ex-post impacts of climate services for farmers: a methodological review". 914 articles ont été passé en revue, et 15 articles ont été sélectionnés pour analyser les méthodes de quantification des impacts des SC en agriculture. Deux principaux problèmes méthodologiques émergent : i) les effets de contamination dans le groupe de contrôle et ii) des biais de sélection différents pour la mesure de l'accès et de l'utilisation de l'information. Les approches fondées sur des variables instrumentales permettent de contrôler les effets de contamination. Des méthodologies de mesure distinctes doivent être employées en fonction de l'impact mesuré (accès ou utilisation) pour éviter les biais de sélection. En matière de résultats, les estimations réalisées jusqu'à présent se concentrent sur les rendements et les variables de gestion de l'exploitation et font apparaitre un effet positif. Les cultures de rentes sont moins étudiées, de même que l'élevage, et les impacts sociaux et environnementaux. Cette étude met également en évidence la collaboration interdisciplinaire croissante dans les évaluations ex-post de SC.

Ce chapitre contribue principalement à la littérature sur les métriques utilisées pour l'évaluation des impacts des services climatiques en agriculture en mettant en évidence les points d'attention méthodologiques et les zones d'ombres de la littérature actuelle en matière d'impacts évalués.

Références de l’introduction

Africa Adaptation Initiative (AAI). 2023. State of Adaptation in Africa Report 2023.

Antwi-Agyei, P., Dougill, A. J., & Abaidoo, R. C. (2021). Opportunities and barriers for using climate information for building resilient agricultural systems in Sudan savannah agro-ecological zone of north-eastern Ghana. *Climate Services*, *22*, 100226. https://doi.org/10.1016/j.cliser.2021.100226

Antwi-Agyei, P., Dougill, A. J., & Stringer, L. C. (2015). Barriers to climate change adaptation : Evidence from northeast Ghana in the context of a systematic literature review’. *Climate and Development*, *7*(4), 297-309. https://doi.org/10.1080/17565529.2014.951013.

Bandura, A. (1977). Self-efficacy : Toward a unifying theory of behavioural change. *Psychological Review*, *84*(2), 191-215. https://doi.org/10.1037/0033-295X.84.2.191

Basse, J., Camara, M., Diba, I., & Diedhiou, A. (2024). Projected Changes in Dry and Wet Spells over West Africa during Monsoon Season Using Markov Chain Approach. *Climate*, *12*(12), Article 12. https://doi.org/10.3390/cli12120211

Boko-Koiadia Adjoua, N., Cissé, G., Koné, B., & Séri, D. (2016). Variabilité Climatique Et Changements Dans L’environnement À Korhogo En Côte D’ivoire : Mythes Ou Réalité ? *European Scientific Journal, ESJ*, *12*(5), 158. https://doi.org/10.19044/esj.2016.v12n5p158

Burnham, M., & Ma, Z. (2017). Climate change adaptation : Factors influencing Chinese smallholder farmers’ perceived self-efficacy and adaptation intent. *Regional Environmental Change*, *17*. https://doi.org/10.1007/s10113-016-0975-6

Carr, E. R., Goble, R., Rosko, H. M., Vaughan, C., & Hansen, J. (2020). Identifying climate information services users and their needs in Sub-Saharan Africa : A review and learning agenda. *Climate and Development*, *12*(1), 23-41. https://doi.org/10.1080/17565529.2019.1596061

Carr, E. R., & Onzere, S. N. (2018). Really effective (for 15% of the men) : Lessons in understanding and addressing user needs in climate services from Mali’. *Climate Risk Management*, *22*, 82-95. https://doi.org/10.1016/j.crm.2017.03.002.

Crochemore, L., Cantone, C., Pechlivanidis, I. G., & Photiadou, C. S. (2021). How Does Seasonal Forecast Performance Influence Decision-Making? Insights from a Serious Game. *Bulletin of the American Meteorological Society*, *102*(9), E1682-E1699. https://doi.org/10.1175/BAMS-D-20-0169.1

Dekoula, C. S., Kouame, B., N’goran, E. K., Yao, F. G., Ehounou, J.-N., & Soro, N. (2018). Impact De La Variabilité Pluviométrique Sur La Saison Culturale Dans La Zone De Production Cotonnière En Côte d’Ivoire. *European Scientific Journal, ESJ*, *14*(12), 143. https://doi.org/10.19044/esj.2018.v14n12p143

Dekoula, C. S., Kouame, B., N'Goran, K. E., Ehounou, J.-N., Yao, G. F., Kassin, K. E., Kouakou, J. B., N'Guessan, A. E. B., & Soro, N. (2019). Variabilité des descripteurs pluviométriques intrasaisonniers à impact agricole dans le bassin cotonnier de Côte d'Ivoire : Cas des zones de Boundiali, Korhogo et Ouangolodougou. *Journal of Applied Biosciences*, *130*(1), 13199. https://doi.org/10.4314/jab.v130i1.7

Diouf, N. S., Ouedraogo, M., Ouedraogo, I., Ablouka, G., & Zougmoré, R. (2020). Using Seasonal Forecast as an Adaptation Strategy : Gender Differential Impact on Yield and Income in Senegal. *Atmosphere*, *11*(10), 1127. https://doi.org/10.3390/atmos11101127

Ebhuoma, E. E., & Simatele, D. M. (2019). "We know our Terrain" : Indigenous knowledge preferred to scientific systems of weather forecasting in the Delta State of Nigeria'. *Climate and Development*, *11*(2), 112-123. https://doi.org/10.1080/17565529.2017.1374239.

Gaetani, M., Janicot, S., Vrac, M., Famien, A. M., & Sultan, B. (2020). Robust assessment of the time of emergence of precipitation change in West Africa. *Scientific Reports*, *10*(1), 7670. https://doi.org/10.1038/s41598-020-63782-2

Gbangou, T. (2021). Harnessing Local Forecasting Knowledge on Weather and Climate in Ghana : Documentation, Skills, and Integration with Scientific Forecasting Knowledge'. *Weather, Climate, and Society*, *13*(1), 23-37. https://doi.org/10.1175/WCAS-D-20-0012.1.

Grothmann, T., & Patt, A. (2005). Adaptive capacity and human cognition : The process of individual adaptation to climate change. *Global Environmental Change*, *15*(3), 199-213. https://doi.org/10.1016/j.gloenvcha.2005.01.002

Gumucio, T., Hansen, J., Huyer, S., & Van Huysen, T. (2020). Gender-responsive rural climate services : A review of the literature. *Climate and Development*, *12*(3), 241-254. https://doi.org/10.1080/17565529.2019.1613216

Hansen, J. W. (2002). Realizing the potential benefits of climate prediction to agriculture : Issues, approaches, challenges. *Agricultural Systems*, *74*(3), 309-330. https://doi.org/10.1016/S0308-521X(02)00043-4

IPCC, 2022: Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change

Lemos, M. C., Kirchhoff, C. J., & Ramprasad, V. (2012). Narrowing the climate information usability gap. *Nature Climate Change*, *2*(11), 789-794. https://doi.org/10.1038/nclimate1614

Makaudze, E. (2005). *Do seasonal climate forecasts and crop insurance matter for smallholder farmers in Zimbabwe ? Using contingent valuation method and remote sensing applications*. The Ohio State University.

Nkiaka, E. (2019). Identifying user needs for weather and climate services to enhance resilience to climate shocks in sub-Saharan Africa'. *Environmental Research Letters*, *14*(12), 123003. https://doi.org/10.1088/1748-9326/ab4dfe.

Nyadzi, E. (2021a). Indigenous knowledge and climate change adaptation in Africa : A systematic review. *CAB Reviews: Perspectives in Agriculture, Veterinary Science, Nutrition and Natural Resources*, *16*(029). https://doi.org/10.1079/PAVSNNR202116029

Nyadzi, E. (2021b). Techniques and skills of indigenous weather and seasonal climate forecast in Northern Ghana'. *Climate and Development*, *13*(6), 551-562. https://doi.org/10.1080/17565529.2020.1831429.

Prasada, D. V. P. (2020). Climate-Indexed Insurance as a Climate Service to Drought-Prone Farmers : Evidence from a Discrete Choice Experiment in Sri Lanka. In W. Leal Filho & D. Jacob (Éds.), *Handbook of Climate Services* (p. 423-445). Springer International Publishing. https://doi.org/10.1007/978-3-030-36875-3_21

Roncoli, C. (2006). Ethnographic and Participatory Approaches to Research on Farmers' Responses to Climate Predictions. *Climate Research*, *Vol. 33*, 81-99. http://dx.doi.org/10.3354/cr033081

Roncoli, C., Ingram, K., & Kirshen, P. (2002). Reading the Rains : Local Knowledge and Rainfall Forecasting in Burkina Faso. *Society & Natural Resources*, *15*(5), 409-427. https://doi.org/10.1080/08941920252866774

Rotter, J. B. (1966). *Rotter's Internal-External Control Scale*

Roudier, P., Muller, B., d'Aquino, P., Roncoli, C., Soumare, M., Batté, L., & Sultan, B. (2014). The role of climate forecasts in smallholder agriculture : Lessons from participatory research in two communities in Senegal. *Climate Risk Management*, *2*, 42-55. https://doi.org/10.1016/j.crm.2014.02.001

Roudier, P., Sultan, B., Quirion, P., & Berg, A. (2011). The impact of future climate change on West African crop yields : What does the recent literature say? *Global Environmental Change*, *21*(3), 1073-1083. https://doi.org/10.1016/j.gloenvcha.2011.04.007

Sanfo, S., Salack, S., Saley, I. A., Daku, E. K., Worou, N. O., Savadogo, A., Barro, H., Guug, S., Koné, H., Ibrahim, B., Rojas, A., Raimond, C., & Ogunjobi, K. O. (2022). Effects of customized climate services on land and labor productivity in Burkina Faso and Ghana. *Climate Services*, *25*, 100280. https://doi.org/10.1016/j.cliser.2021.100280

Sultan, B., Defrance, D., & Iizumi, T. (2019). Evidence of crop production losses in West Africa due to historical global warming in two crop models. *Scientific Reports*, *9*(1), 12834. https://doi.org/10.1038/s41598-019-49167-0

Sultan, B., Roudier, P., Quirion, P., Alhassane, A., Muller, B., Dingkuhn, M., Ciais, P., Guimberteau, M., Traore, S., & Baron, C. (2013). Assessing climate change impacts on sorghum and millet yields in the Sudanian and Sahelian savannas of West Africa. *Environmental Research Letters*, *8*(1), 014040. https://doi.org/10.1088/1748-9326/8/1/014040

Tesfaye, A., Hansen, J., Kagabo, D., Birachi, E., Radeny, M., & Solomon, D. (2023). Modeling farmers' preference and willingness to pay for improved climate services in Rwanda. *Environment and Development Economics*, *28*(4), 368-386. https://doi.org/10.1017/S1355770X22000286

Tesfaye, A., Hansen, J., Kassie, G. T., Radeny, M., & Solomon, D. (2019). Estimating the economic value of climate services for strengthening resilience of smallholder farmers to climate risks in Ethiopia : A choice experiment approach. *Ecological Economics*, *162*, 157-168. https://doi.org/10.1016/j.ecolecon.2019.04.019

Vaughan, C., Hansen, J., Roudier, P., Watkiss, P., & Carr, E. (2019). Evaluating agricultural weather and climate services in Africa : Evidence, methods, and a learning agenda. *WIREs Climate Change*, *10*(4). https://doi.org/10.1002/wcc.586

Warner, D., Moonsammy, S., & Joseph, J. (2022). Factors that influence the use of climate information services for agriculture : A systematic review. *Climate Services*, *28*, 100336. https://doi.org/10.1016/j.cliser.2022.100336

Chapter 1: Local Forecasting Knowledge in Climate Services: A Choice Experiment

1.1. Introduction

In several regions of Sub-Saharan Africa, seeing ants heading in the same direction is often considered an indicator of rain within the next days (Gbangou, 2021; Paparrizos et al., 2023; Roncoli et al., 2002). Rural populations still employ this type of local forecasting knowledge alongside climate services (CS) to anticipate weather events and guide agricultural decision-making (Antwi-Agyei et al., 2015, 2021; Mafongoya & Ajayi, 2017; Nyadzi, 2021b). Climate services encompass a wide range of scientific forecasts, including short-term, seasonal, and long-term projections, and have been shown to make a positive difference on farm outcomes (Roudier et al., 2016; Yegbemey et al., 2023). To be fully effective, climate services must be perceived by users as credible, relevant, and legitimate, and they must respond to one or more specific needs (Carr et al., 2020; Carr & Onzere, 2018; Cash et al., 2003). However, in some regions, local knowledge is regarded as more reliable and legitimate than scientific forecasts (Ebhuoma & Simatele, 2019). This raises important questions about how to design climate services that resonate with users' preferences. In this chapter, we explore farmers' interest in hybrid climate services that provide both scientific and local forecasts, using a choice experiment conducted in northern Côte d'Ivoire.

Local Forecasting Knowledge (LFK) refers in this chapter to environmental indicators locally observed by populations to generate short-term and seasonal weather forecasts (Gbangou, 2021). LFK focuses on field observations and relates to biodiversity (e.g., phenological stages of plants, animal behaviours) or abiotic elements (e.g., cloud patterns, stars, temperature, and wind observations). This definition deliberately excludes spiritual knowledge, although spiritual and observational knowledge are not always distinct, either within communities or in the literature (D. Nakashima et al., 2018; Nyadzi, 2021a; Roncoli et al., 2002; Roncoli, 2006). Local knowledge is part of a generational heritage and specific to a particular geographic location (Mutasa, 2015). Nonetheless, it is dynamic, evolving through innovation, intercultural exchange, and intergenerational transmission (Dudgeon & Berkes, 2003; D. J. Nakashima et al., 2012; Trogrlić, 2020). In West Africa, especially in Francophone countries, LFK remains under-documented (Nyadzi, 2021a). This chapter provides the first known inventory of LFK in northern Côte d'Ivoire

Recent years have seen a growing number of experiments combining scientific and local knowledge within hybrid climate services (Gbangou, 2021; Masinde et al., 2018; Nyadzi et al., 2020; Paparrizos et al., 2023). These studies, largely conducted by climate scientists, highlight how LFK can improve forecast accuracy and promote the uptake of innovations among rural populations. For instance, Nyadzi et al. (2020) show that the combination of scientific and local forecasts in Ghana can enhance user acceptance and result in more reliable outcomes than either source alone. However, this literature to date has not addressed whether the integration of LFK influences farmers' choices between climate services, nor has it established an economic valuation of this knowledge.

Choice experiments, which are increasingly used to inform public policy (Kotu et al., 2022; Owuor et al., 2019; Wang et al., 2021), are particularly well-suited to addressing this research gap. By presenting respondents with a series of hypothetical choices, these experiments provide insights into preferences for specific service components, such as the type of forecast, the inclusion of LFK, or the preferred delivery channel (e.g., radio vs. SMS). They also enable the estimation of willingness to pay for each component. While most studies assessing user preferences for climate services have relied on contingent valuation methods (Amegnaglo et al., 2017; Donkoh, 2019; Makaudze, 2005; Zongo et al., 2015), the use of choice experiments in this climate services is growing (Prasada, 2020; Rahaman & Iqbal, 2021; Tesfaye et al., 2019, 2023). To our knowledge, no study has yet used this method to evaluate preferences for LFK integration into climate services.

This chapter contributes to literature in three main ways. First, it provides the first systematic inventory of local forecasting knowledge in northern Côte d'Ivoire, a region where such knowledge has not previously been documented. Second, it offers empirical evidence on farmers' preferences for the integration of LFK into climate services, using a choice experiment, a method not previously applied to this question. Third, it quantifies the relative importance of LFK compared to other service attributes (such as type of forecasts and dissemination mode), thereby generating policy-relevant insights for the design of user-centered climate services in West Africa.

Our findings indicate that a large share of farmers possess local forecasting knowledge, which they generally regard as more reliable than scientific forecasts. However, in choosing a climate service, farmers primarily consider the price, followed by the mode of dissemination, particularly oral channels like the radio, while the integration of LFK is not, on average, a decisive factor, except among older individuals.

The chapter is organized as follows: Section 2 presents the context of this Chapter. Section 3 describes the choice experiment design. Section 4 provides a sample analysis. Section 5 catalogs the local forecasting knowledge. Section 6 details the econometric framework. The results are provided in Section 7 and are discussed in Section 8. Section 9 concludes.

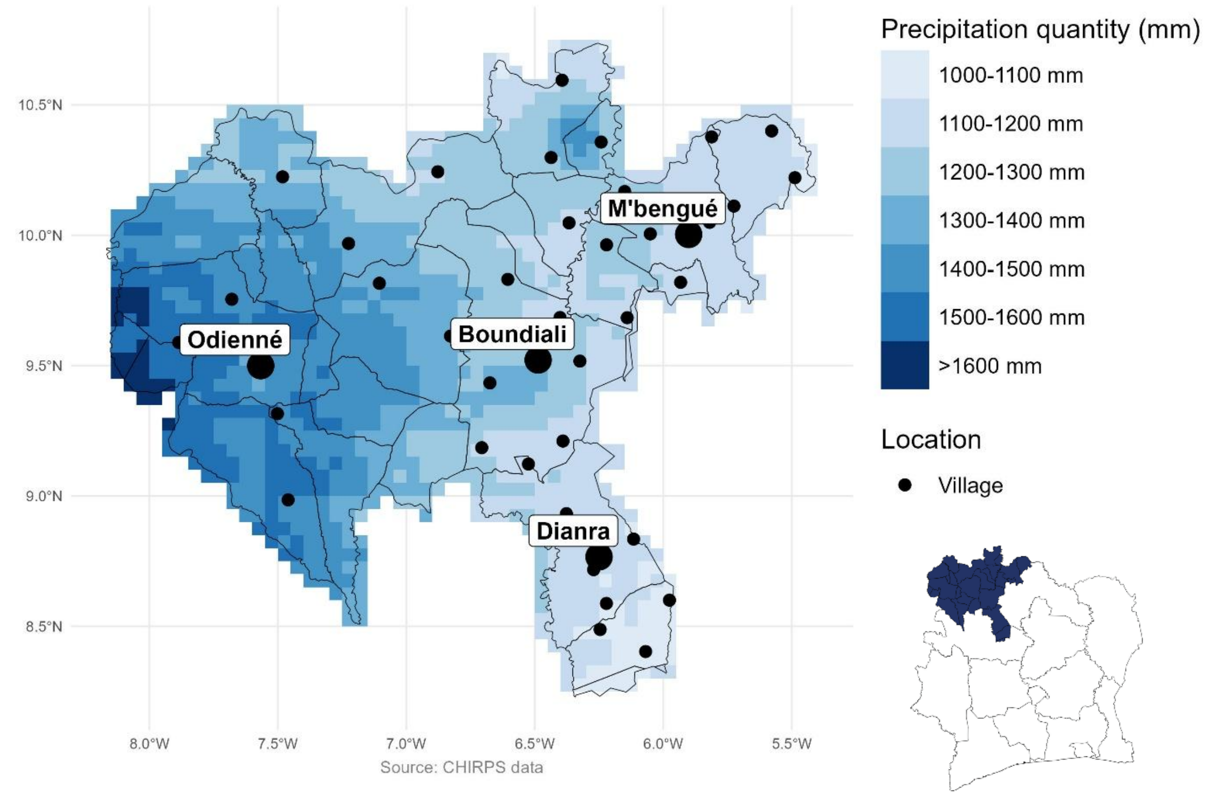
1.2. Context

The study area is located in northwestern Côte d'Ivoire, near the borders with Mali and Guinea. For this research, the company Ivoire Coton provided access to its farmer database in the area for survey purposes. Figure 1.1 displays the geographical distribution of the 40 surveyed localities in the region. Agriculture is almost entirely rainfed there, meaning that farms are highly dependent on rainfall patterns (Dekoula et al., 2018a).

The climate in the study area is classified as tropical transitional (Sudano-Guinean) and is characterized by a unimodal rainfall pattern. It consists of a dry season from November to April and a rainy season from May to October. Figure 1.1 presents the average annual rainfall over the past ten years, along with its spatial distribution. Like much of West Africa, the region is experiencing changes linked to climate change, particularly in rainfall distribution (Gaetani et al., 2020; Basse et al., 2024). Both scientific and local observations indicate a trend toward shorter rainy seasons, a decrease in total accumulated rainfall and the number of rainy days, as well as an increase in wind intensity (Boko-Koiadia Adjoua et al., 2016; Dekoula et al., 2018, 2019).

In terms of climate service provision, the national meteorological agency, SODEXAM, is the primary producer and disseminator of climate services in the area and in all Côte d'Ivoire. The country’s network of meteorological stations is sparse, with only one station located in the study area, in Odienné. Despite being limited in spatial precision and generally tailored to national or regional scales, SODEXAM offers a diverse array of agro-climatic services. These include short-term forecasts (ranging from 1 to 10 days), seasonal forecasts, and early warning alerts. These services are made available upon request through digital channels such as email and the internet or disseminated on a regular basis via more traditional media like radio and television.

Figure 1.1 - Annual average precipitation quantity in the studied area



Notes: The map above, based on CHIRPS data (Funk et al., 2015), shows the annual average precipitation amount over the 2014–2023 period in the Ivoire Coton area, with a spatial resolution of 0.05 × 0.05 degrees. It highlights geographical disparities in annual average precipitation amounts across the surveyed localities.

1.3. Experimental design

1.3.1. Choice experiment

The choice experiment method (or discrete choice modelling) originates from conjoint analysis (Louviere & Hensher, 1982; Louviere & Woodworth, 1983) , which itself is grounded in the value theory (Lancaster, 1966). The aim of a choice experiment is to reveal individuals' preferences regarding a good or service,in this case: *"Which of the available climate services is best suited to farmers?"*,based on the characteristics that define those services. This method and its various applications are thoroughly detailed in the work of Ben-Akiva et al., (2019). In a choice experiment, the characteristics of a good or a service are grouped into broad categories known as attributes (e.g., dissemination method), each of which includes different levels (e.g., radio, SMS, etc.). Combined in this way, attributes and their levels form alternatives. Here, each alternative represents a climate service.

Participants are then presented with a series of choices. For each choice task, respondents indicate their preferred alternative, that is, the climate service they favour. Each selection implicitly reflects the trade-offs they are willing to make among the different attributes presented. Experimental designs are used to construct choice surveys in such a way that the attributes are uncorrelated, allowing for unbiased estimation of the parameters (Hoyos, 2010) . Ultimately, this method allows to:

i) Estimate the contribution of each attribute, and its levels, to individuals' overall utility by establishing relative preferences.
ii) Derive individuals' willingness to pay (WTP) for changes in attribute levels, by converting marginal utility estimates into monetary units when price is included as one of the attributes.

1.3.2. Choice of attributes

The selection of attributes for this experiment (see *Table 1.1*) was informed by a literature review and discussions with Ivoire Coton, the interprofessional cotton organization (InterCoton), and meteorologists from SODEXAM. It was subsequently revised following a pilot survey conducted in April 2022 with 22 cotton farmers in the village of Marabadiassa. Based on this pilot, we replaced the attribute *"reliability»,* which consistently emerged as the primary driver of the demand, with the attribute *"means of service delivery"*, whose relative importance appeared to be less obvious. This finding regarding reliability is consistent with the results of Ouedraogo et al. (2022), who show, for example, that reliability is the most important factor of the CS demand for farmers in Ghana, Niger, and Senegal. We also remove the attribute "agricultural advice," as it caused confusion among farmers. Respondents had difficulty distinguishing this attribute from the regular visits of the farm advisor from the cotton company. Finally, given the extreme price sensitivity observed, the price range was narrowed to between 4,500 and 6,000 FCFA. Relative to the daily wage of an agricultural worker (approximately 2,000 FCFA, according to an interview with InterCoton in 2023), the proposed costs for climate services remain quite low, as it represents an annual price.

Table 1.1 - Attributes and levels of attributes

Attributes	Levels
Type of forecast	- Short term (1 to 3 days) - Seasonal forecasts

LFK	- Not included - Included
Mean of dissemination	- Radio - Mobile application - SMS - Cooperative contact person
Annual price (in FCFA)	- 4500 - 5000 - 5500 - 6000

The forecast type refers to the preference for either short-term or seasonal weather information:

- Rainfall expected in the coming days and alerts for extreme events
- Start and end dates of the rainy season, as well as dry spells within the season

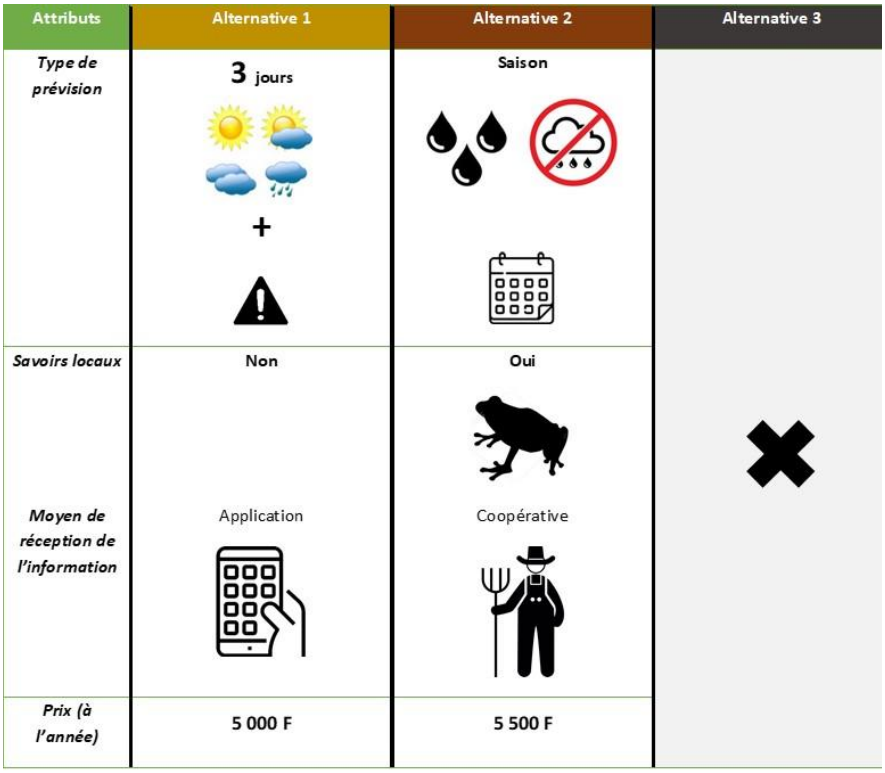
The levels for the "type of forecast" attribute were informed by the findings of Ingram et al. (2002), who studied farmers in the cotton-growing regions of southwestern Burkina Faso, a setting with climatic and agricultural conditions similar to those in our study area. The LFK attribute is presented as a comparative forecast, reflecting the average expectations of local knowledge holders within a geographic area close to the farmer. Finally, the selected payment vehicle is an annual deduction made by the cotton company at the time of harvest, a mechanism already familiar to farmers, as it is commonly used for paying for cotton inputs.

1.3.3. Survey design

Once the attributes were defined, a full factorial design would have resulted in 2 × 2 × 4 × 4 = 64 choice sets. We therefore opted for a fractional factorial design using only a specified subset, or "fraction", of the full factorial combinations. We used the *support.CEs* package (Aizaki, 2012) with a rotation design to reduce the number of choice sets to 16. The survey was not divided into blocks, in order to avoid loss of statistical information. The orthogonality property is respected, ensuring balance across attributes and levels and allowing for the estimation of parameters across all levels. Maintaining orthogonality helps avoid multicollinearity issues and minimizes estimation errors.

For each of the 16 choice cards, the farmer selects alternative 1, 2, or 3. The third alternative represents the "opt-out" option, that is, *"I choose neither of the two climate services presented in alternative 1 and 2. I prefer to stick with the status quo."* The inclusion of a status quo or opt-out option assumes the existence of a baseline CS corresponding to the first level of each attribute: short-term forecasts, disseminated by radio, and without LFK. This assumption is considered realistic, as short-term forecasts are daily broadcasted by local radio stations in the study area, according to SODEXAM.

Figure 1.2. - Example of a choice card presented to respondents



Notes: The choice card above shows: (1) a CS consisting of short-term forecasts, without local forecasting knowledge, delivered via mobile application for an annual cost of 5,000 FCFA (Alternative 1); (2) a service consisting of seasonal forecasts, incorporating local forecasting knowledge, delivered by a cooperative contact person for an annual cost of 5,500 FCFA (Alternative 2); or (3) opting for neither of these two services (Alternative 3).

1.3.4. Sample selection

Survey data were collected in May 2022 from 285 farmers. The sampling method was as follows: in consultation with Ivoire Coton, we selected 10 localities from each of the company's four geographic divisions (M'Bengué, Dianra, Odienné, and Boundiali). The localities were chosen to ensure both spatial dispersion within each division, so as to capture climatic heterogeneity, and variation in proximity to main roads, used here as a proxy for market access. Approximately 7 farmers were surveyed per locality. Respondents were randomly selected from Ivoire Coton's farmer lists using Excel's random function (Alea). One exception was made for women: when women were listed in a given locality, they were systematically included in the sample.

1.4. Sample analysis

1.4.1. Demographic and farming statistics

The sample is composed of 96.5% men. This reflects the limited number of women listed in the farmer rosters provided by Ivoire Coton. This imbalance can be explained by the near-monopoly of men over cotton cultivation in Côte d'Ivoire, due to several factors, including ethnic norms (Carranza & Donald, 2017; Bassett, 2002). The average age of surveyed farmers is 42.7 years, with the majority belonging to the Sénoufo (56.5%) or Malinké (34.4%) ethnic groups.

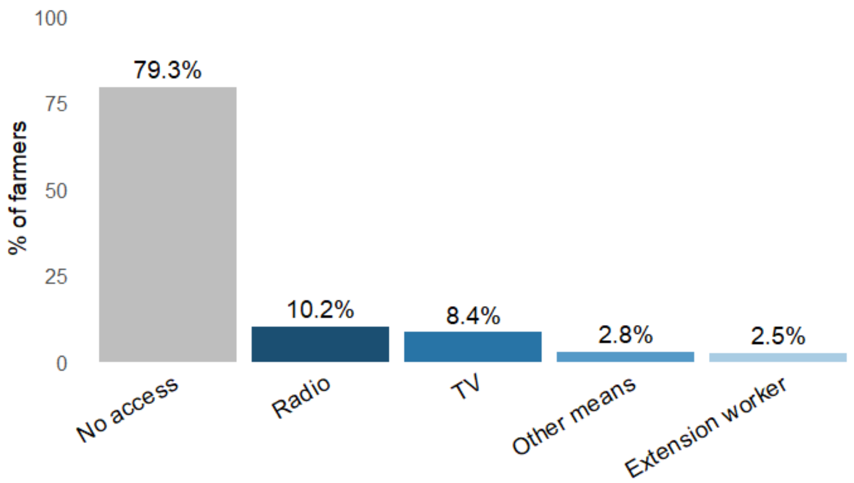
Households are intergenerational families with an average size of 13.1 members (including the farmer), of whom 5.3 work on the farm. Almost all farmers use animal traction (97.8%). The average farm size is 15.1 hectares, mostly non-irrigated (only 4 farmers reported irrigation), with around 3.4 different crops per farm. On average, 5.5 hectares are dedicated to cotton cultivation. In addition to cotton, the main crops grown are maize (96.8%), rice (86.7%), groundnuts (66.7%), and cashew (62.1%). Only 12.3% of farmers grow yams. Besides crop farming, 36.1% of farmers also engage in livestock rearing (cattle, small ruminants, and poultry). The majority, 66.3%, own their land, either through customary or legal arrangements.

Almost all farmers in our sample (284 out of 285) reported agriculture as their household's main source of income. For 84.6% of respondents, cotton is the primary income source, followed by cashew (11.3%) and rice (2.8%). Approximately one in ten households (9.8%) also reported having a non-agricultural source of income.

1.4.2. Access to CS

A total of 91.9% of surveyed farmers reported needing weather information for their agricultural activities, yet only 20.7% have access to scientific forecasts (SF). Among those with access, 79.7% receive short-term forecasts (1 or 2 days), 22% up to one week, and only 6.8% receive seasonal forecasts. The sample reveals significant geographical disparities: in 16/40 villages, no farmer reported having access to SF, whereas in some villages, up to 71.4% of farmers reported access. Farmers primarily receive forecasts via radio and television, with other sources including word of mouth and information from agricultural advisors.

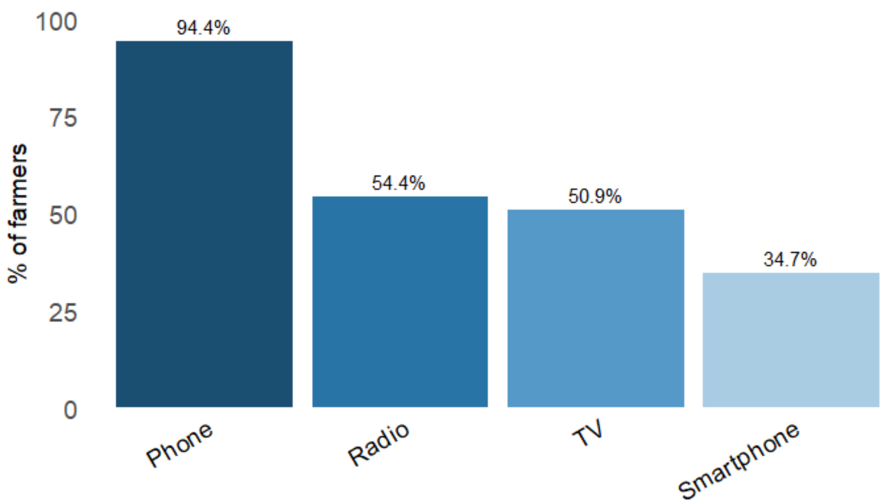
Figure 1.3 - Means of accessing scientific forecasts



Notes: The graph shows the distribution of farmers' access to scientific forecasts by source of access, expressed as a percentage of the total sample.

Yet, one in two farmers owns a radio and/or a television. Nearly all respondents have a phone, and for one-third of them, it is a smartphone. However, levels of formal education are low: 81.7% have never attended school, and only 14 farmers have reached the secondary level. Only 22.8% of farmers speak French, compared to 93.3% who speak Dioula and 61.0% who speak Sénoufo.

Figure 1.4. - Means of communication owned by farmers



Notes: The graph shows the percentage of farmers owning each means of communication, relative to the total sample.

1.5. Inventory of Local Forecasting Knowledge

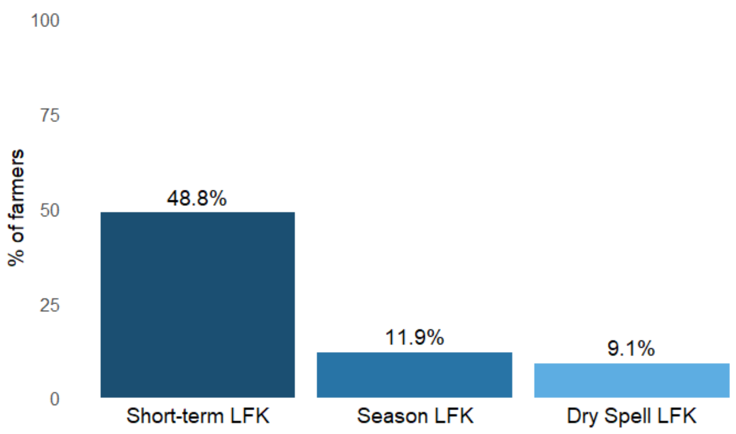
This section aims to assess the presence of local forecasting knowledge, how its reliability is perceived by the surveyed population, and the willingness to contribute, an essential condition for its potential integration into climate services. A more detailed inventory of this knowledge is provided in *Appendix 1.C* of this chapter.

A prior literature review, combined with insights from the pilot survey, guided the inventory of local forecasting knowledge toward three main areas: (i) rainfall forecasting during the rainy season; (ii) determining the characteristics of the season (start, end, and total amount of rainfall); and (iii) intra-rainy season dry periods. Since the term “drought” may be understood differently by scientists and farmers, and even among farmers themselves (Salite, 2019). we chose to use the expression “dry periods within the rainy season”. In this sample, 100% of LFK holders expressed willingness to contribute to the development of forecasts combining scientific and local knowledge.

1.5.1. Identification of Local Forecasting Knowledge

A total of 53.1% of farmers in our sample reported holding at least one form of local forecasting knowledge (LFK), and 22% of them also have access to scientific forecasts. However, such knowledge remains relatively scarce since only 1 in 5 farmers (19.6%) reported knowing at least two LFK indicators, and just 1 in 10 (8.8%) knows three or more LFK indicators. Most of the LFK reported relates to short-term forecasts predicting rainfall (48.8%), a proportion consistent with the existing literature (Elia et al., 2014; Zuma-Netshiukhwi et al., 2013). Only 11.9% reported seasonal LFK, and 9.1% cited LFK forecasting intra-season dry spells. These less common forms of knowledge are predominantly held by the older half of the population surveyed: 80.8% of those familiar with dry spells LFK and 67.6% of those with seasonal LFK are over the age of 42.

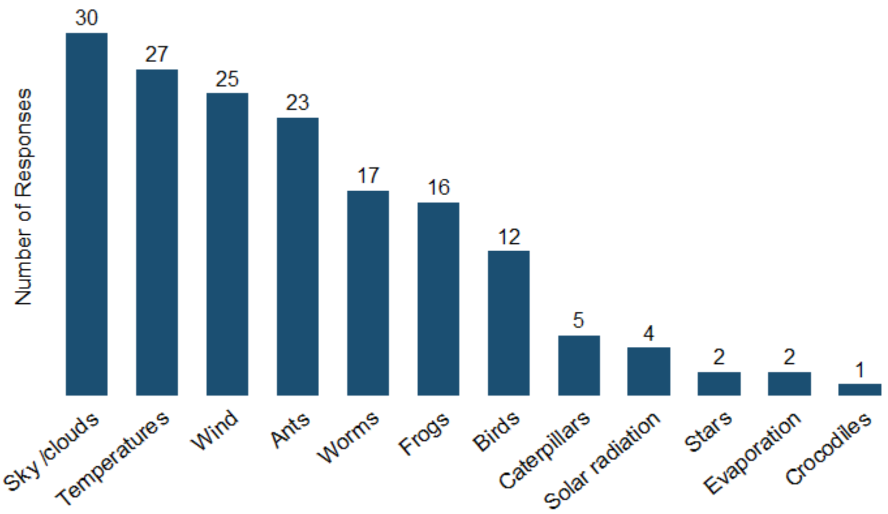
Figure 1.5 - Number of farmers holding LFK by type of knowledge held



Notes: The graph shows the percentage of farmers holding each type of LFK, relative to the total sample.

Most short-term indicators are used for forecasts ranging from 0 to 3 days. Some indicators serve both seasonal and short-term forecasting purposes, depending on the observation period and the specific features being interpreted. For example: "*When driver ants (magnan ants) move in a line toward the east, it means it will rain within a day*"[1] and *"When driver ants are often in the field, it indicates high rainfall amount during the rainy season".* LFK related to wind patterns also appears to be closely linked to the progression of the monsoon in Côte d'Ivoire, as many respondents refer to southwesterly winds. This is consistent with the annual progression of the rainy season, which follows the penetration path of the Harmattan wind, with a south-west to north-east gradient (Dekoula et al., 2018b).

Figure 1.6 - Indicators of a rainfall in the coming days (0 to 3 days)



Notes: The graph shows the short-term rainfall indicators mentioned by respondents, ranked by number of citations.

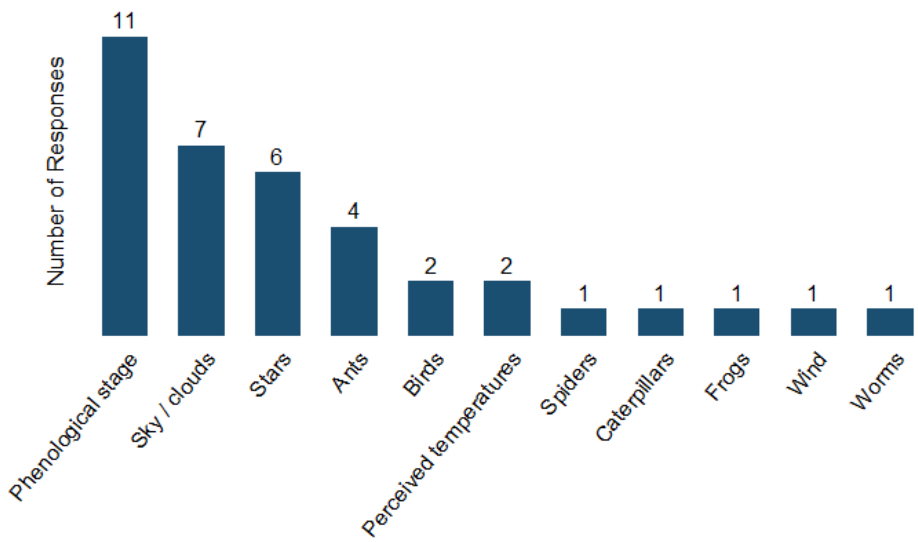
The most commonly cited short-term indicators mainly relate to sky conditions (clouds, sunlight, etc.), perceived heat, wind, and animal behaviours. These observations are consistent with the literature (Gbangou, 2021; Nyadzi et al., 2021). Reports of earthworms, ants carrying their eggs in a line, and the croaking of toads are also in line with findings from West African studies (Agbodan et al., 2020). However, some indicators appear to be more specific to the study area, such as the observation of certain birds or caterpillars, which would require further biological identification of the species. Farmers often use physical characteristics and local names to describe them. For example: "*There is a bird with a red neck, called gnamatoutou."*

For seasonal indicators, the responses were fewer in number but more diverse. The most frequently cited indicator was plants' phenological stages (flowering, fruiting), assessed both qualitatively and quantitatively (e.g., number of fruits). For instance: *"If the néré trees*

[1] All verbatims in this chapter have been translated from French by the author

have a lot of fruits, there will be a lot of rain in the coming season." This finding is consistent with the work of Roncoli et al. (2002) and Makwara (2013).

Figure 1.7 - Indicators used to forecast the rainy season characteristics



Notes: The graph shows the seasonal forecasting indicators cited by respondents, ranked by number of citations.

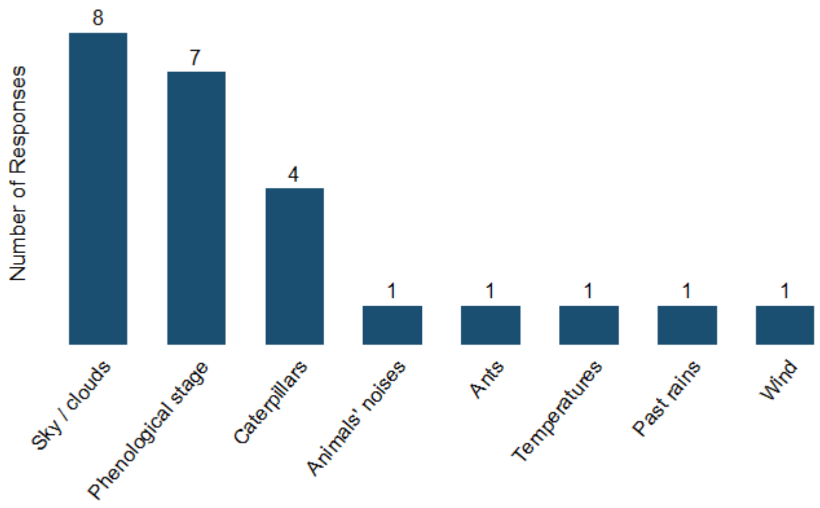
The seasonal LFK collected here, in line with the typology proposed by Gbangou et al. (2021), enables the forecasting of:

- The start of the rainy season
- The end of the rainy season
- The duration of the rainy season
- The amount of rainfall in the upcoming season

However, it remains very difficult to determine whether some forms of seasonal indicators are truly used as forecasting indicators or whether they serve instead as temporal markers. This is particularly the case for indicators related to the start or end of the season, which refer to the position of stars and constellations or to the phenological stages of trees. Agbodan et al. (2020), however, highlight that vegetation indicators can be both temporal markers and forecasting indicators as climatic factors, such as relative humidity and minimum temperature, play a major role in plant phenology.

For intra-season dry periods, the number of responses was also limited (24 in total). Once again, sky conditions and plant observations were the most frequently mentioned types of indicators. The forecasts refer to dry spells lasting from one day to three weeks or even one month, depending on the indicator. Two indicators appear to be relatively more commonly cited: the presence of a hairy caterpillar and the flowering of a tree locally known as Gatjon or Katjon.

Figure 1.8 - Indicators used to forecast dry periods

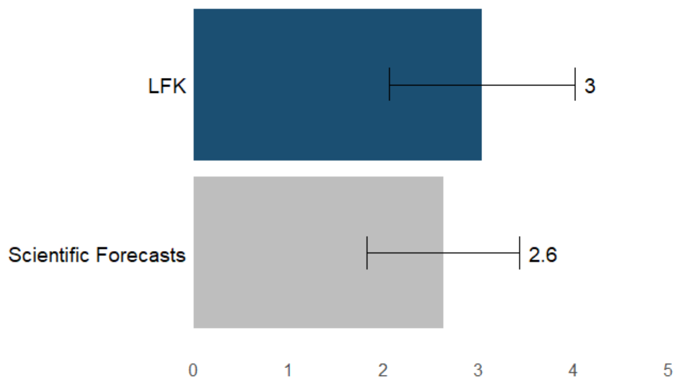


Notes: The graph shows the indicators used to forecast dry periods cited by respondents and ranked by number of mentions.

1.5.2. LFK reliability perception

Although there is considerable variation across individuals (see *Figure 1.9*), on average, farmers place greater trust in LFK than in scientific forecasts. Nevertheless, the trust levels for LFK and scientific forecasts are relatively close and, in both cases, remain moderate.

Figure 1.9 - Farmers' trust in weather information by forecast source



Notes: The graph shows the average level of trust farmers place in LFK and scientific forecasts, measured on a scale from 1 (low) to 5 (high). Standard deviations are represented by horizontal lines.

Trust in LFK also varies depending on the type of forecast. Indicators related to seasonal rainfall amounts, intra-season dry periods, and short-term rainfall are considered the most reliable (see *Table 1.2*).

Table 1.2 - Perceived reliability of LFK by type of forecast

Perceived Reliability of LFK From 1 = *"Low"* to 5 = *"High"*	**Statistics**				
	Mean / 5	***Median***	***Min***	***Max***	***n***
LFK on short-term rainfalls	3	3	1	4	164
LFK on the rainy season characteristics	2,9	3	1	4	37
Start of the rainy season	2,9	3	1	4	17
End of the rainy season	2,2	2	1	4	4
Amount of rainfall	3,4	4	1	4	15
Length of the season	2,2	2	1	4	4
LFK on dry periods	3,1	3	2	4	24

Although the question was not directly asked, some farmers spontaneously reported combining multiple indicators for short-term forecasts. While the number of such cases is relatively low (6), on average these combinations are perceived as more reliable (3.3) than individual short-term indicators. These findings are consistent with Nyadzi (2021), who notes the reliability of forecasts increases when multiple indicators are combined.

Over time, LFK related to dry periods appears to exhibit greater stability. In contrast, short-term and seasonal knowledge is reported to have experienced a more pronounced decline in perceived reliability. 53% of farmers blame climate change for the decline in reliability, echoing the findings of Shaffer (2014). Climates changes are perceived to negatively affect indicators based on animal behaviour: *"Since the weather itself has changed, animals no longer behave as they used to. I think they are tired of these changes too."* Farmers also believed that changes disrupt the interpretation of indicators related to wind and sky appearance, making them less reliable: *"Climate change causes things to happen that shouldn't. Sometimes the sky turns black, and you think rain is coming, but nothing happens, it just passes with the wind."* This perception discourages farmers from sharing their forecasts, particularly due to the fear of losing credibility if the prediction fails. *"You see certain signs, and then the rain doesn't come. That makes a man look like a liar. So, when you see the sign, you're forced to keep it to yourself, or risk being called a liar."*

31.5% of respondents believe that their lack of knowledge about how to interpret the indicators contributes to reducing LFK reliability. Local forecasting knowledge is not systematically documented, and the death of older generations gradually diminishes both the number of available indicators and their associated interpretations. *"Those who truly mastered this knowledge are now rare."* Salite (2019) links this decline in the number of indicators known by younger generations to a breakdown in transmission. Currently, the transmission of LFK across generations is, on average, rated as low by our sample (2 out of 5 in terms of quality). Elders are said to pass on their knowledge less frequently, partly due to the perceived decline in the reliability of indicators: *"The forecasts are not very reliable, so we're even afraid to talk* *about them with our children." "Sometimes, when you want to share something that the elders used to say, people respond, 'That's outdated now.'"* For some, this decline is also linked to a broader disinterest in traditional customs: "*The transmission of knowledge between generations is losing its value."* However, others believe that the transmission remains important in their communities.

Other explanations of LFK reliability decline include environmental changes, such as the scarcity of some insects, birds, and plants, that farmers do not necessarily link to climate change. Some respondents also mention mystical causes, such as the population's failure to observe traditional taboos.

1.6. Econometric Framework and Model Specifications

The analysis of the choice experiment data is based on random utility theory (McFadden, 1973). For every choice s, this theory assumes that farmer i seeks to maximize their utility U_{ij} by selecting alternative j from among several (hypothetical, climate service) options. Each choice is driven by the individual's preferences for the attribute levels characterizing each alternative. By revealed preferences, alternative $j = 1$ is preferred to $j = 2$ if and only if $U_{i1} > U_{i2}$.

The indirect (latent) utility of farmer$i$ for alternative$j$ is specified as follows:

$$U_{ijs} = ASC + \sum_{k=1}^{K} \beta_k X_{ijks} + \varepsilon_{ijs} \tag{1}$$

Where:

- $i \in \{1, \dots, 285\}$ denotes individuals
- $k \in \{1, \dots, 4\}$ denotes attributes
- $s \in \{1, \dots, 16\}$ denotes choice cards (per individual)
- $j \in \{1,2,3\}$ denotes the alternatives presented in each choice card s
- ASC (Alternative Specific Constant) is a constant that captures preferences for the opt-out (status quo) option, here defined as a free service consisting of short-term forecasts delivered via radio, without integration of LFK;
- X_{ijks} is a vector composed of four attributes describing alternative *j* : (i) type of forecast, (ii) integration of LFK, (iii) delivery mean, and (iv) price;
- $\varepsilon_{ijs}$is a random error term assumed to be independently and identically distributed (i.i.d.).

Delivery methods are coded as dummy variables for "SMS," "mobile application," and "cooperative," with the value 0 corresponding to the status quo ("radio"). Accordingly, the utility function of alternative$j$ for choice situation s by individual i is expressed as follows:

For $j = 1,2$ (non-status quo alternatives):

$$U_{ijs} = ASC + \beta_1 season_{js} + \beta_2 LFK_{js} + \beta_3 SMS_{js} + \beta_4 appli_{js} + \beta_5 coop_{js} + \beta_6 price_{js} + \varepsilon_{ijs} \quad (2)$$

For $j = 3$ (opt-out alternative):

$$U_{i3s} = ASC + \varepsilon_{i3s} \quad (3)$$

Following Kotu et al. (2022), we estimated three models to identify the most suitable one for capturing preference heterogeneity within the target population (Greene & Hensher, 2003): (i) the Multinomial Logit Model (MNL), (ii) the Mixed Logit Model (MIXL), and (iii) the Latent Class Logit Model (LC).

The Multinomial Logit (MNL) model is commonly used as a baseline in choice experiments. It assumes homogeneous preferences across individuals and the Independence of Irrelevant Alternatives (IIA). In practical terms, this means that farmers' preferences are assumed to depend solely on the available combinations of attribute levels. By contrast, the Mixed Logit (MIXL) and Latent Class (LC) models relax this assumption by allowing preferences to be influenced by observable or unobservable individual characteristics. The MIXL model accounts for individual-level heterogeneity in preferences, while the LC model segments the population into latent classes, each with distinct preference structures. The Hausman/McFadden test confirms the presence of preference heterogeneity, suggesting that the MNL model is not the most appropriate model for these data (p-value = 1.67e-16).

The selection between MIXL and LC is based on a comparison of the log-likelihood values and the Bayesian (BIC) and Akaike (AIC) information criteria. The preferred model is the one that minimizes these criteria. In our case, the MIXL model demonstrates the best overall performance. However, a five-class Latent Class (LC) model slightly outperforms the MIXL. Due to the limited sample size, we opted to retain a two-class LC model for the comparison with MIXL. Indeed, when moving to a three-class specification, one class represented only 7% of the sample, equivalent to just 20 farmers. Regression results comparing the MNL, MIXL, and LC models are presented in *Appendix 1.A* of this chapter.

The MIXL model extends the MNL framework by allowing for continuous heterogeneity in individual preferences. Under the MNL model, the probability that farmer i chooses alternative l among j alternatives in choice set s is given by:

$$P_{ils} = \frac{e^{\beta X_{ils}}}{\sum_{j=1}^{3} e^{\beta X_{ijs}}} \quad (4)$$

Unlike the MNL model, which assumes fixed coefficients across all individuals, the MIXL model allows these coefficients to vary according to a specified distribution. Thereby, it offers greater flexibility in capturing preference heterogeneity (Greene & Hensher, 2003; McFadden & Train, 2000; Train, 2001).

The probability that farmer i chooses alternative l among j alternatives in choice set s, under the MIXL model, is given by:

$$P_{il} = \int \frac{e^{\beta\prime X_{ils}}}{\sum_{j=1}^{3} e^{\beta\prime X_{ijs}}} f(\beta' \vee \theta) d\beta' \quad (5)$$

The MIXL model is a random parameters logit model with continuous heterogeneity distributions. When β'_{ik} is unobserved, it is assumed to vary across the population according to a continuous density function f), where θ denotes the parameters of this distribution. In line with most applications of the MIXL model, we assume that the parameters follow a multivariate normal distribution $\beta'_{ik}\ MVN(\beta \vee \Sigma)$, with the exception of the price parameter, which is assumed to follow a log-normal distribution $ln\left(\beta'^{price}_{ik}\right) N(\mu \vee \sigma^2)$.

The log-normal distribution is appropriate when a coefficient is known to have the same sign for all decision-makers, in this case, negative for price (Train, 2001). However, to ensure that the price coefficient remains negative for each individual, we specify the distribution using a transformation of the form $-exp\ (Y)$ where $Y\ N(\mu \vee \sigma^2)$. Accordingly, β'_i can be expressed as follows:

$$\beta'_i = \overline{\beta} + Lw_i \quad (6)$$

Where:

- w_i is a vector of random variables that follows a normal distribution for all attributes, except for the price attribute, which follows a log-normal distribution;
- $L$is the lower triangular Cholesky factor of the variance–covariance matrix Σ, such that $LL^{\top} = V(\beta'| \quad |i) = \Sigma$. If the off-diagonal elements of $L$are zero, the coefficients are independently and normally distributed.

The marginal willingness to pay (MWTP) for a given attribute level is subsequently derived by dividing the estimated coefficient of the non-monetary variable by the estimated coefficient of the monetary variable: $\frac{\alpha_{nm}}{\alpha_m}$. Confidence intervals are then computed using the Krinsky and Robb (1986) simulation method, which relies on the estimated means and variance-covariance matrix.

Observable heterogeneity can also be incorporated into the MIXL model by including individual characteristics that influence the mean of the random preference parameters.

In that case, β'_i becomes:

$$\beta'_i = \overline{\beta} + \delta z_i + Lw_i \quad (7)$$

Where z_i is a set of Scharacteristics of individual i that influence the mean of the preference parameters, and δ is a $K \times S$ matrix of additional preference parameters.

In this context, we assume that the preference for the integration of LFK, z_i, is potentially influenced by the following variables:

- age_i : age of the farmer
- edu_i : level of formal education

- $dist_i$: distance in kilometers to the nearest market (*used as a proxy for isolation*)
- $crops_i$: number of crops cultivated aside from cotton
- $farm \quad i$: total number of hectares cultivated (*used as a proxy for wealth*)
- LFK_i : number of local forecasting indicators of which the farmer is aware
- cs_{access_i} : access to climate services

We assume that isolated farmers have less access to CS and rely more on LFK. Thus, they could have different preferences for LFK integration. Crop diversification could also be a factor of heterogeneity in preferences since the more crops they cultivate, the more specific forecasts they need. Finally, the intuition in including the number of LFK held by farmers, is that the more LFK they hold by themselves the less they need CS that integrate LFK.

Thus, the equation explaining the probability of choosing a service as a function of the preference for the integration of LFK is as follows:

$$\beta'_{i,LFK} = \overline{\beta} + \delta_1 age_i + \delta_2 edu_i + \delta_3 dist_i + \delta_4 crops_i + \delta_5 farm \quad i + \delta_6 LFK_i + \delta_7 cs_{access_i} + L_{LFK} w_{i,LFK} \tag{8}$$

with $\delta =)$ denoting the estimated parameters associated with the observable individual characteristics included in the model.

1.7. Results

1.7.1. Mixed Logit Model (MIXL)

The results of the Mixed Logit model (see *Table 1.3*) indicate that farmers are generally favourable to new climate services beyond those currently available. The Alternative Specific Constant has a negative coefficient, suggesting a clear preference for selecting Alternatives 1 or 2 over Alternative 3 (the status quo). Among the attributes, price is the primary determinant of farmers' choices. The means of dissemination is the second most important attribute for choosing a CS. Farmers also show a preference for services containing seasonal forecasts. All attributes are statistically significant except for the integration of Local Forecasting Knowledge (LFK). While the coefficient for LFK is positive, it suggests that, relatively to other attributes, the integration of LFK is not a decisive factor in farmers' choice of climate services.

Price sensitivity is negative and large, indicating that price is the most important attribute in farmers' selection of a climate service. The standard deviation suggests, however, that there are varying levels of sensitivity within the population. Even though the least price-sensitive individuals still exhibit a strongly negative coefficient. As anticipated from the sample analysis, characterized by low levels of formal education, farmers show a strong preference for oral dissemination methods. In this model, each dissemination method is compared to the radio. The preferred dissemination channel in our study area is through a liaison person within the cooperative, followed by radio, mobile applications, and SMS. The latter two are strongly rejected compared to the status quo. It is worth recalling that smartphone penetration is only one-third of the surveyed population whereas almost all the farmers own basic mobile phones. Notably, the high standard deviations suggest that a segment of the population may favor technology-based dissemination methods (SMS, application), while others strongly prefer oral channels (radio and cooperative). A Mixed Logit model including education as a covariate confirms this intuition (see *Appendix 1.B*). Farmers exhibit also a preference for seasonal information, with limited divergence of opinion as evidenced by the relatively low standard deviation. However, the small coefficient value indicates that this attribute is not a key driver in the choice of climate service.

Table 1.3 - Mixed Logit (MIXL) model results

	Mixed Logit Model (MIXL)	
Attributes	Mean	Std. Dev
ASC	-1.54^{***}	
	(0.11)	
Seasonal forecasts	0.23^{***}	0.67^{***}
	(0.11)	(0.16)
LFK	0.02	0.03^{***}
	(0.10)	(0.17)
SMS	-2.26^{**}	6.72^{***}
	(0.33)	(0.53)
Mobile application	-1.91^{***}	3.33^{***}
	(0.22)	(0.15)
Cooperative	2.45^{***}	8.47^{***}
	(0.31)	(0.66)
Price	-4.75^{***}	1.33^{***}
	(0.08)	(0.15)
AIC	5242.38	
BIC	5325.91	
Log Likelihood	-2608.19	
Num. obs.	4560	

Notes: ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively. Standard errors are reported between parentheses.
The Alternative Specific Constant (ASC) is the preference for alternative 1 or 2 rather than alternative 3 i.e. the "Statu quo" option.

Table 1.4 presents the previous results in terms of willingness to pay (WTP). WTP reflects the average marginal valuation across individuals for a given attribute. Beyond the price of the service itself, the most influential factor is the dissemination method: farmers are willing to pay up to 500 FCFA more (deducted by the cotton company at the time of harvest) for information delivered through the cooperative, and up to 475 FCFA less for information received via SMS compared to radio. The type of forecast and the integration of local forecast knowledge are relatively neutral factors in terms of farmers' willingness to pay.

Table 1.4 - Willingness to pay in CFA francs for each variation in climate service attributes

Atributes	WTP	2.5% Confidence Interval	97.5% Confidence Interval
Seasonal forecasts	49	4	95
LFK	4	-38	45
SMS	-475	-612	-337
Mobile application	-403	-500	-310
Cooperative	516	393	632

Notes: Willingness to pay for each attribute is expressed in CFA francs and rounded to the nearest unit. Confidence intervals are calculated using the Krinsky and Robb (1986) method.

1.7.2. Mixed Logit Model (MIXL) with covariates

Table 1.5 demonstrates the robustness of the model when covariates are included. It is worth noting an increase in the absolute value of most coefficients, except for the preference for information delivery via cooperatives, which decreases. The standard deviations for the dissemination channels also vary more substantially. Although the average preference for LFK integration across the sample is not statistically significant, there are subgroups for whom this attribute matters in the selection of climate services. The results show that older farmers are more likely to view the integration of LFK positively when choosing among climate service options. Conversely, farmers who are geographically more isolated (i.e., further from markets) tend to reject the integration of LFK. The other covariates also do not show significant effects.

Table 1.5 - Results of the MIXL model with covariates

Attributes	Mean	Std. Dev.	LFK Covariates
ASC	-1.43^{***}	–	
	(0.11)		
Seasonal forecasts	0.49^{***}	0.04^{***}	
	(0.10)	(0.18)	
LFK	0.72	0.52^{***}	
	(0.54)	(0.12)	
Age			0.02^{**}
			(0.01)
Education level			-0.15
			(0.17)
Distance to the market (km)			-0.44^{***}
			(0.09)
Number of cultivated crops			0.10
			(0.11)
Land cultivated (ha)			-0.20
			(0.23)
Number of LFK held			-0.04
			(0.10)
Access to climate services			-0.01
			(0.01)
SMS	-3.00^{***}	9.11^{***}	
	(0.42)	(0.67)	
Mobile application	-2.81^{***}	5.99^{***}	
	(0.33)	(0.53)	
Cooperative	1.47^{***}	6.54^{***}	
	(0.27)	(0.43)	
Price	-4.85^{***}	1.04^{***}	
	(0.08)	(0.06)	
AIC		5027.48	
BIC		5155.56	
Log Likelihood		-2493.74	
Number of observations		4560	

Notes: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are shown in parentheses.
The Alternative Specific Constant (ASC) refers to the preference for alternatives 1 or 2 compared to the status quo (alternative 3).

When expressed in terms of willingness to pay (WTP) (see *Table 1.6*), the results for the significant covariates indicate only a moderate interest in the integration of local forecast knowledge (LFK). Specifically, older farmers would be willing to pay on average only 5 CFA francs more for a climate service that integrates LFK-based forecasts, while more isolated farmers would be willing to pay approximately 90 CFA francs less for such a service.

Table 1.6 - Willingness to pay in CFA francs for a climate service integrating local forecast knowledge (LFK)

Covariate	**WTP**	**2.5% Confidence Interval**	**97.5% Confidence Interval**
Age	5	2	8
Formal education level	-30	-97	41
Distance to the market (km)	-91	-130	-53

Number of cultivated crops	21	-26	64
Land cultivated (ha)	-42	-138	48
Number of LFK held	-9	-49	31
Access to CS	-3	7	2

Notes: Willingness to pay for each attribute is expressed in CFA francs and rounded to the nearest unit. Confidence intervals are calculated using the Krinsky and Robb (1986) method.

1.8. Discussion

LFK remain highly prevalent in our study area. Most farmers surveyed reported knowing at least one local forecasting indicator, whereas only one in five reported having access to scientific forecasts. These local forms of knowledge primarily concern the short-term occurrence of rainfall. Knowledge related to dry spells and seasonal forecasts appears to be less common and is mostly held by the older half of the sample. This observation supports farmers' perception of the poor transmission of knowledge across generations (Salite, 2019). The passing of elder generations gradually reduces the number of known indicators and their associated interpretations. Yet, the combination of multiple indicators is precisely what helps reduce the likelihood of error in forecasting upcoming weather events (Nyadzi et al., 2020). One-third of LFK holders specifically mentioned that the decreasing reliability of their forecasts was due to their limited understanding of the indicators and their interpretations. Farmers also attribute this decline in reliability to environmental changes, such as the disappearance of insects, birds, and plant species, that affect bio-indicators, as well as climate change, which particularly compromises the reliability of abiotic indicators (e.g., wind direction, sky appearance, etc.). These findings are consistent with the work of Gbangou (2021), Roncoli et al. (2002), and (Shaffer, 2014). However, on average, LFK is perceived as more reliable than scientific forecasts, a result also observed by Ebhuoma and Simatele (2019) in their study in Nigeria. All farmers interviewed in our study expressed willingness to collaborate with national meteorological services for the development of hybrid forecasting systems. Nevertheless, the surveyed populations do not appear to fully acknowledge the risk of error associated with forecasts derived from LFK, which may pose reputational risks for farmers who share them.

Price and the mode of dissemination are the main determinants of farmers preferred CS. Farmers also show a preference for services that include seasonal forecasts, but this preference is less pronounced. Interestingly, the high level of trust placed in LFK is not reflected in the value farmers put in the integration of LFK into a climate service. While some farmers prefer CS with the inclusion of LFK, on average it does not appear to be a decisive factor in farmers' choices of climate services in northern Côte d'Ivoire. That said, more vulnerable farmers tend to rely more heavily on local knowledge because it is free (Salite, 2019). Once such knowledge is acquired, access to information is immediate, unlike scientific forecasts that require a specific channel for dissemination. A further reason why farmers do not show strong preferences for LFK in CS is that many farmers consult designated “local forecasting experts” and, in most cases, provide compensation for these services, either in kind or in CFA francs (Chapter 2). As a result, the prospect of paying for climate services that integrate local knowledge may be perceived by some farmers as a form of double payment. This perception is particularly relevant given that the LFK component in our choice experiment, aligned with existing pilot initiatives, was based on collaboratively developed forecasts involving local farmers themselves. However, the experts whom farmers consult in practice may not be farmers and so would not be included in such processes.

Nevertheless, there is some heterogeneity in preferences regarding the integration of local forecasting knowledge. Older respondents in the sample appear to value the inclusion of LFK in climate services more positively, reflecting the interest and perceived legitimacy of such knowledge within part of the population. In contrast, the most geographically isolated farmers tend to oppose their integration. While these groups have slightly less access to formal climate services, they do not necessarily hold greater LFK. It is therefore difficult to attribute this rejection to a specific factor. However, their limited access to scientific forecasts may lead to heightened expectations in scientific forecasting.

The findings regarding the importance of the means of delivery, primarily reflect a local context in which farmers still have limited access to weather forecasts, low literacy levels, and a limited penetration of smartphones in the region. Their main priority, therefore, is to receive forecasts through accessible and low-cost channels. These preferences are, then, constrained and reflect broader barriers to access and use climate services (Antwi-Agyei et al., 2021; Carr et al., 2020). Oral dissemination channels, namely, radio and local cooperatives, are, on average, the most preferred among farmers. However, the high standard deviations observed in the data indicate considerable heterogeneity in preferences, with a notable interest in SMS and mobile applications among individuals with higher levels of formal education, as highlighted in Donkoh’s (2019) study in Ghana. These preferences, for oral dissemination channels, seasonal forecast information, and sensitivity to price are consistent with findings from the West African context (Amegnaglo et al., 2017; Ouédraogo et al., 2018) and from Rwanda (Tesfaye et al., 2023). However, they diverge from conclusions drawn in Ethiopia (Tesfaye et al., 2019), underscoring the importance of local context in interpreting the results.

1.9. Conclusion

This chapter has highlighted the active presence of LFK in northern Côte d’Ivoire. All LFK holders expressed willingness to collaborate with meteorologists to integrate their knowledge into hybrid climate services. These forms of knowledge are primarily related to short-term forecasts and, to a lesser extent, to seasonal forecasts and dry spells forecasts. They are mostly held by older farmers and are, on average, perceived as more reliable than scientific forecasts. However, this perceived reliability is declining due to a reduction in the availability of indicators, linked mainly to environmental changes, and a weakening of intergenerational knowledge transmission.

The choice experiment shows that, on average, the integration of LFK is not a decisive factor in farmers' selection of a climate service. However, the limited access to climate services in the study area, combined with low levels of formal education and limited smartphone penetration, tends to constrain farmers' preference. Nevertheless, the results reveal heterogeneity in preferences. LFK emerges as a selection criterion for older farmers. These findings thus contribute to the multidisciplinary literature on the hybridization of climate services through the application of rigorous quantitative methods.

Public policies must prioritize expanding access to scientific forecasts, as this remains the primary concern for local populations. To this end, efforts should focus on diversifying dissemination channels, particularly oral ones, to reach illiterate and geographically isolated populations more effectively. Beyond radio, the widespread availability of basic mobile phones (in contrast to smartphones) opens the possibility of using voice mailboxes accessible via phone calls. Although the use of cooperative-based intermediaries to disseminate forecasts is highly valued by farmers, it entails a reputational risk. This concern already exists with LFK as farmers engage implicitly their reputation in the forecasts they share. Therefore, any deployment of climate services must be accompanied by training to increase awareness of forecast uncertainty. Moreover, further research could be carried out in this region to better identify the complementary use of scientific and local knowledge as the farmers keep trusting LFK but, with the exception of old ones, don't necessary value their integration into climate services.

Reference of Chapter 1

Agbodan, K. M. L., Akpavi, S., Amegnaglo, K. B., Akodewou, A., Diwediga, B., Koda, D. K., Batawila, K., & Akpagana, K. (2020). Savoirs locaux sur les marqueurs temporels en zone guinéenne au Togo. *BASE*, 248-261. https://doi.org/10.25518/1780-4507.18799

Aizaki, H. (2012). Basic Functions for Supporting an Implementation of Choice Experiments in R. *Journal of Statistical Software, Code Snippets*, *50*(2), 1-24. https://doi.org/10.18637/jss.v050.c02

Amegnaglo, C. J., Anaman, K. A., Mensah-Bonsu, A., Onumah, E. E., & Amoussouga Gero, F. (2017). Contingent valuation study of the benefits of seasonal climate forecasts for maize farmers in the Republic of Benin, West Africa. *Climate Services*, *6*, 1-11. https://doi.org/10.1016/j.cliser.2017.06.007

Antwi-Agyei, P., Amanor, K., Hogarh, J. N., & Dougill, A. J. (2021). Predictors of access to and willingness to pay for climate information services in north-eastern Ghana : A gendered perspective. *Environmental Development*, *37*, 100580. https://doi.org/10.1016/j.envdev.2020.100580

Antwi-Agyei, P., Dougill, A. J., & Stringer, L. C. (2015). Barriers to climate change adaptation : Evidence from northeast Ghana in the context of a systematic literature review'. *Climate and Development*, *7*(4), 297-309. https://doi.org/10.1080/17565529.2014.951013.

Ben-Akiva, M., McFadden, D., & Train, K. (2019). Foundations of Stated Preference Elicitation : Consumer Behaviour and Choice-based Conjoint Analysis. *Foundations and Trends® in Econometrics*, *10*(1-2), 1-144. https://doi.org/10.1561/0800000036

Boko-Koiadia Adjoua, N., Cissé, G., Koné, B., & Séri, D. (2016). Variabilité Climatique Et Changements Dans L'environnement À Korhogo En Côte D'ivoire : Mythes Ou Réalité ? *European Scientific Journal, ESJ*, *12*(5), 158. https://doi.org/10.19044/esj.2016.v12n5p158

Carr, E. R., Goble, R., Rosko, H. M., Vaughan, C., & Hansen, J. (2020). Identifying climate information services users and their needs in Sub-Saharan Africa : A review and learning agenda. *Climate and Development*, *12*(1), 23-41. https://doi.org/10.1080/17565529.2019.1596061

Carr, E. R., & Onzere, S. N. (2018). Really effective (for 15% of the men) : Lessons in understanding and addressing user needs in climate services from Mali'. *Climate Risk Management*, *22*, 82-95. https://doi.org/10.1016/j.crm.2017.03.002.

Cash, D. W., Clark, W. C., Alcock, F., Dickson, N. M., Eckley, N., Guston, D. H., Jäger, J., & Mitchell, R. B. (2003). Knowledge systems for sustainable development. *Proceedings of the National Academy of Sciences*, *100*(14), 8086-8091. https://doi.org/10.1073/pnas.1231332100

Dekoula, C. S., Kouame, B., N'goran, E. K., Yao, F. G., Ehounou, J.-N., & Soro, N. (2018). Impact De La Variabilité Pluviométrique Sur La Saison Culturale Dans La Zone De Production Cotonnière En Côte d'Ivoire. *European Scientific Journal, ESJ*, *14*(12), 143. https://doi.org/10.19044/esj.2018.v14n12p143

Dekoula, C. S., Kouame, B., N'Goran, K. E., Ehounou, J.-N., Yao, G. F., Kassin, K. E., Kouakou, J. B., N'Guessan, A. E. B., & Soro, N. (2019). Variabilité des descripteurs pluviométriques intrasaisonniers à impact agricole dans le bassin cotonnier de Côte d'Ivoire : Cas des zones de Boundiali, Korhogo et Ouangolodougou. *Journal of Applied Biosciences*, *130*(1), 13199. https://doi.org/10.4314/jab.v130i1.7

Donkoh, S. A. (2019). Farmers' willingness-to-pay for weather information through mobile phones in northern Ghana. *Ghana Journal of Science, Technology and Development*, *6*(2), 19-36. https://doi.org/10.47881/166.967x

Dudgeon, R. C., & Berkes, F. (2003). Local Understandings of the Land : Traditional Ecological Knowledge and Indigenous Knowledge. In H. Selin (Éd.), *Nature Across Cultures* (Vol. 4, p. 75-96). Springer Netherlands. https://doi.org/10.1007/978-94-017-0149-5_4

Ebhuoma, E. E., & Simatele, D. M. (2019). "We know our Terrain" : Indigenous knowledge preferred to scientific systems of weather forecasting in the Delta State of Nigeria'. *Climate and Development*, *11*(2), 112-123. https://doi.org/10.1080/17565529.2017.1374239.

Elia, E., Mutula, S., & Stilwell, C. (2014). Use of Indigenous knowledge in seasonal weather forecasting in the semi-arid central Tanzania. *South African Journal of Libraries and Information Science*, *80*, 18-27. https://doi.org/10.7553/80-1-180

Gbangou, T. (2021). Harnessing Local Forecasting Knowledge on Weather and Climate in Ghana : Documentation, Skills, and Integration with Scientific Forecasting Knowledge'. *Weather, Climate, and Society*, *13*(1), 23-37. https://doi.org/10.1175/WCAS-D-20-0012.1.

Greene, W. H., & Hensher, D. A. (2003). A latent class model for discrete choice analysis : Contrasts with mixed logit. *Transportation Research Part B: Methodological*, *37*(8), 681-698. https://doi.org/10.1016/S0191-2615(02)00046-2

Hoyos, D. (2010). The state of the art of environmental valuation with discrete choice experiments. *Ecological Economics*, *69*(8), 1595-1603.

Kotu, B. H., Oyinbo, O., Hoeschle-Zeledon, I., Nurudeen, A. R., Kizito, F., & Boyubie, B. (2022). Smallholder farmers' preferences for sustainable intensification attributes in maize production : Evidence from Ghana. *World Development*, *152*, 105789. https://doi.org/10.1016/j.worlddev.2021.105789

Lancaster, K. J. (1966). A New Approach to Consumer Theory. *Journal of Political Economy*, *74*(2), 132-157. https://doi.org/10.1086/259131

Louviere, J. J., & Hensher, D. A. (1982). DESIGN AND ANALYSIS OF SIMULATED CHOICE OR ALLOCATION EXPERIMENTS IN TRAVEL CHOICE MODELING. *Transportation Research Record*.

Louviere, J. J., & Woodworth, G. (1983). Design and Analysis of Simulated Consumer Choice or Allocation Experiments : An Approach Based on Aggregate Data. *Journal of Marketing Research*, *20*(4), 350. https://doi.org/10.2307/3151440

Mafongoya, P. L., & Ajayi, O. O. C. (2017). *Indigenous knowledge systems and climate change management in Africa*. CTA.

Makaudze, E. (2005). *Do seasonal climate forecasts and crop insurance matter for smallholder farmers in Zimbabwe ? Using contingent valuation method and remote sensing applications*. The Ohio State University.

Masinde, M., Mwagha, M., & Tadesse, T. (2018). Downscaling Africa's Drought Forecasts through Integration of Indigenous and Scientific Drought Forecasts Using Fuzzy Cognitive Maps. *Geosciences*, *8*(4), 135. https://doi.org/10.3390/geosciences8040135

McFadden, D., & Train, K. (2000). Mixed MNL models for discrete response. *Journal of Applied Econometrics*, *15*(5), 447-470. https://doi.org/10.1002/1099-1255(200009/10)15:5<447::AID-JAE570>3.0.CO;2-1

Mutasa, M. (2015). Knowledge apartheid in disaster risk management discourse : Is marrying indigenous and scientific knowledge the missing link? *Jàmbá: Journal of Disaster Risk Studies*, *7*(1), 10 pages. https://doi.org/10.4102/jamba.v7i1.150

Nakashima, D. J., Galloway McLean, K., Thulstrup, H.D., Ramos Castillo, A., & Rubis, J.T. (2012). *Weathering uncertainty : Traditional knowledge for climate change assessment and adaptation*. UNESCO ; UNU-IAS.

Nakashima, D., Krupnik, I., & Rubis, J. T. (Éds.). (2018). *Indigenous Knowledge for Climate Change Assessment and Adaptation* (1re éd.). Cambridge University Press. https://doi.org/10.1017/9781316481066

Nyadzi, E. (2021a). Indigenous knowledge and climate change adaptation in Africa : A systematic review. *CAB Reviews: Perspectives in Agriculture, Veterinary Science, Nutrition and Natural Resources*, *16*(029). https://doi.org/10.1079/PAVSNNR202116029

Nyadzi, E. (2021b). Techniques and skills of indigenous weather and seasonal climate forecast in Northern Ghana'. *Climate and Development*, *13*(6), 551-562. https://doi.org/10.1080/17565529.2020.1831429.

Nyadzi, E., Werners, S., Biesbroek, R., & Ludwig, F. (2020). *Combining Indigenous and Scientific Forecast for Improved Climate Services in Ghana* [Other]. pico. https://doi.org/10.5194/egusphere-egu2020-22322

Ouédraogo, M., Barry, S., Zougmoré, R., Partey, S., Somé, L., & Baki, G. (2018). Farmers' Willingness to Pay for Climate Information Services : Evidence from Cowpea and Sesame Producers in Northern Burkina Faso. *Sustainability*, *10*(3), 611. https://doi.org/10.3390/su10030611

Owuor, M. A., Mulwa, R., Otieno, P., Icely, J., & Newton, A. (2019). Valuing mangrove biodiversity and ecosystem services : A deliberative choice experiment in Mida Creek, Kenya. *Ecosystem Services*, *40*, 101040. https://doi.org/10.1016/j.ecoser.2019.101040

Paparrizos, S., Dogbey, R. K., Sutanto, S. J., Gbangou, T., Kranjac-Berisavljevic, G., Gandaa, B. Z., Ludwig, F., & van Slobbe, E. (2023). Hydro-climate information services for smallholder farmers : FarmerSupport app principles, implementation, and evaluation. *Climate Services*, *30*, 100387. https://doi.org/10.1016/j.cliser.2023.100387

Prasada, D. V. P. (2020). Climate-Indexed Insurance as a Climate Service to Drought-Prone Farmers : Evidence from a Discrete Choice Experiment in Sri Lanka. In W. Leal Filho & D. Jacob (Éds.), *Handbook of Climate Services* (p. 423-445). Springer International Publishing. https://doi.org/10.1007/978-3-030-36875-3_21

Rahaman, M. M., & Iqbal, Md. H. (2021). Willingness-to-pay for improved cyclone early warning services across coastal Bangladesh : Application of choice experiment. *International Journal of Disaster Risk Reduction*, *61*, 102344. https://doi.org/10.1016/j.ijdrr.2021.102344

Roncoli, C. (2006). Ethnographic and Participatory Approaches to Research on Farmers' Responses to Climate Predictions. *Climate Research*, *Vol. 33*, 81-99. http://dx.doi.org/10.3354/cr033081

Roncoli, C., Ingram, K., & Kirshen, P. (2002). Reading the Rains : Local Knowledge and Rainfall Forecasting in Burkina Faso. *Society & Natural Resources*, *15*(5), 409-427. https://doi.org/10.1080/08941920252866774

Roudier, P., Alhassane, A., Baron, C., Louvet, S., & Sultan, B. (2016). Assessing the benefits of weather and seasonal forecasts to millet growers in Niger. *Agricultural and Forest Meteorology*, *223*, 168-180. https://doi.org/10.1016/j.agrformet.2016.04.010

Salite, D. (2019). Traditional prediction of drought under weather and climate uncertainty : Analyzing the challenges and opportunities for small-scale farmers in Gaza province, southern region of Mozambique. *Natural Hazards*, *96*(3), 1289-1309. https://doi.org/10.1007/s11069-019-03613-4

Shaffer, L. J. (2014). Making Sense of Local Climate Change in Rural Tanzania Through Knowledge Co-Production. *Journal of Ethnobiology*, *34*(3), 315-334. https://doi.org/10.2993/0278-0771-34.3.315

Tesfaye, A., Hansen, J., Kagabo, D., Birachi, E., Radeny, M., & Solomon, D. (2023). Modeling farmers' preference and willingness to pay for improved climate services in Rwanda.

Environment and Development Economics, *28*(4), 368-386. https://doi.org/10.1017/S1355770X22000286

Tesfaye, A., Hansen, J., Kassie, G. T., Radeny, M., & Solomon, D. (2019). Estimating the economic value of climate services for strengthening resilience of smallholder farmers to climate risks in Ethiopia : A choice experiment approach. *Ecological Economics*, *162*, 157-168. https://doi.org/10.1016/j.ecolecon.2019.04.019

Train, K. E. (2001). *Discrete Choice Methods with Simulation* (2e éd.). Cambridge University Press. https://doi.org/10.1017/CBO9780511805271

Trogrlić, R. (2020). *The role of local knowledge in community-based flood risk management in Malawi* [PhD Thesis].

Wang, Y., Wang, Z., Wang, Z., Li, X., Pang, X., & Wang, S. (2021). Application of Discrete Choice Experiment in Health Care : A Bibliometric Analysis. *Frontiers in Public Health*, *9*, 673698. https://doi.org/10.3389/fpubh.2021.673698

Yegbemey, R. N., Bensch, G., & Vance, C. (2023). Weather information and agricultural outcomes : Evidence from a pilot field experiment in Benin. *World Development*, *167*, 106178. https://doi.org/10.1016/j.worlddev.2022.106178

Zongo, B., Diarra, A., Barbier, B., Zorom, M., Yacouba, H., & Dogot, T. (2015). Farmers' Perception and Willingness to Pay for Climate Information in Burkina Faso. *Journal of Agricultural Science*, *8*(1), 175. https://doi.org/10.5539/jas.v8n1p175

Zuma-Netshiukhwi, G., Stigter, K., & Walker, S. (2013). Use of Traditional Weather/Climate Knowledge by Farmers in the South-Western Free State of South Africa : Agrometeorological Learning by Scientists. *Atmosphere*, *4*(4), 383-410. https://doi.org/10.3390/atmos4040383

Appendix 1.A – Comparison between MNL, MIXL et Latent classes models

Table 1.7 - Comparison between MNL, MIXL et Latent classes models

	MNL (1)	MIXL (2)		LC (3)	
Attributes		Mean	Std. Dev	LC1	LC2
ASC	2.64***	1.54***		3.92***	4.16***
	(0.24)	(0.11)		(0.38)	(0.45)
Seasonal forecasts	0.01	0.23***	0.67***	0.40***	0.28**
	(0.05)	(0.11)	(0.16)	(0.09)	(0.09)
LFK	−0.12*	0.02	0.03***	-0.00	−0.18*
	(0.05)	(0.10)	(0.17)	(0.09)	(0.08)
SMS	−0.11	−2.26**	6.72***	−3.51***	2.24***
	(0.06)	(0.33)	(0.53)	(0.24)	(0.12)
Mobile application	−1.03***	−1.91***	3.33***	−4.12***	0.75***
	(0.08)	(0.22)	(0.15)	(0.29)	(0.12)
Cooperative	0.83***	2.45***	8.47***	1.08***	0.54***
	(0.06)	(0.31)	(0.66)	(0.08)	(0.13)
Price	−0.58***	−4.75***	1.33***	−0.84***	0.97***
	(0.04)	(0.08)	(0.15)	(0.08)	(0.3)
Share of the sample				64.2%	35.8%
AIC	8946.48	5242.38		7226.58	
BIC	8991.45	5325.91		7322.96	
Log Likelihood	-4466.24	-2608.19		-3598.29	
Num. obs.	4560	4560		4560	

Notes: ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively. Standard errors are reported between parentheses.
The Alternative Specific Constant (ASC) is the preference for alternative 1 or 2 rather than alternative 3 i.e. the "Statu quo" option. MNL = Multinomial Logit, MIXL = Mixed Logit, LC = Latent Class Logit, LC1 = Latent class one, LC2 = Latent class two.

Appendix 1.B – Effect of education on means of dissemination preferences

Table 1.8 - Effect of education on means of dissemination preferences

Attributes	Mean	Std. Dev.	Dissemination Means Covariates
ASC	-1.53^{***}	–	
	(0.12)		
Seasonal forecasts	0.35^{***}	0.01^{***}	
	(0.10)	(0.15)	
LFK	0.09	0.32^{***}	
	(0.10)	(0.14)	
SMS	-5.24^{***}	8.12^{***}	
	(0.62)	(0.68)	
Education level			7.67^{***}
			(0.83)
Mobile application	-2.65^{***}	3.29^{***}	
	(0.24)	(0.28)	
Education level			2.21^{***}
			(0.27)
Cooperative	3.64^{***}	8.53^{***}	
	(0.35)	(0.57)	
Education level			-4.07^{***}
			(0.44)
Price	-4.91^{***}	1.20^{***}	
	(0.09)	(0.05)	
AIC		4813.41	
BIC		4915.29	
Log Likelihood		-2390.71	
Number of observations		4560	

Notes: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are shown in parentheses.
The Alternative Specific Constant (ASC) refers to the preference for alternatives 1 or 2 compared to the status quo (alternative 3).

Appendix 1.C – Full inventory of LFK

Table 1.9 – Short-term rainfall indicators

Indicators	*Caracteristics*	*Examples of quotes*	*Average Time Before Event*	*Occurrence of Indicator*	*Average Reliability*	*Reliability Trend*
Sky appearance	Ominous/dark in the east Blue Red clouds in the evening Clouds clustered to the east Clouds moving east	*"Lorsque le ciel devient sombre à l'est je sais qu'il va pleuvoir dans la journée"* *"Lorsque le ciel devient bleu je sais qu'il va pleuvoir"* *"Le soir si les nuages sont rouges"* *"Quand les nuages se regroupent dans le Ciel à l'est"*	0 to 1 day	30	2,8	1,4
Perceived temperatures	Intense	*"Lorsque qu'on constate que la chaleur est forte sur plusieurs jours."*	0 to 1 day	27	3,2	1,4
Wind	One way Eastbound Northbound Strong wind No wind	*"Le vent va dans un seul sens"* *"Lorsque le vent va vers l'est, je sais qu'il va pleuvoir"* *"Le retour du vent au nord"* *"Durant la saison des pluies lorsque les arbres ne sont pas bousculés par le vent, je sais qu'il va pleuvoir"*	0 to 2 days	25	3,2	1,5

Ants	Walking towards a single direction Aligned Carry their eggs in holes Black/Magnan	*"Quand tu vois un matin les fourmis sortir d'un trou pour se diriger ensemble dans une direction"* *"Les fourmis magnans marchent en ligne vers l'est"* *"Lorsque les fourmis transportent leurs œufs pour entrer dans les trous"*	0 to 1 day	23	3,0	1,4
Earthworms	Presence in the open air	*"Quand tu vois en plein soleil les vers de terres"*	0 to 1 day	17	3,4	1,5
Frogs	Singing/shouting	*"Lorsque les crapauds chantent toute la nuit, ce, durant deux ou trois jours"*	0 to 2 days	16	2,6	1,1
Birds	Presence Singing/shouting Flight direction (Est/Nord)	*"Il y a un oiseau qui a son cou rouge, gnamatoutou, quand il crie"* *"Lorsque les oiseaux blancs volent vers le nord"* *"Lorsque que les oiseaux vont vers l'est en groupe"*	0 to 1 day	12	2,4	1,3
Caterpillars	Presence	*"L'apparition des chenilles, en sénoufo on l'appelle Dori"*	0 to 1 day	5	3,0	1,6
Solar Radiations	Intense Split shadow	*"Quand le soleil est trop fort"* *"Quand on voit son ombre deux fois en pleine journée"*	0 to 1 day	4	3,7	1,7
Stars	Numerous around the moon No stars	*"Les étoiles n'apparaissent pas la nuit"*	0 to 3 days	2	3,5	1,0
Evaporation	fog above the mountains	*"Quand on voit des fumées au-dessus des collines"*	1 to 3 days	2	4,0	1,0
Crocodiles	Shouting	*"Lorsque le caïman crie dans l'eau"*	0 day	1	1,0	1,0

Notes: Indicator occurrence corresponds to the number of citations of this indicator, average reliability is rated on a scale of 1 (low) to 5 (high), and indicator reliability trend is rated as 1 for decreasing, 2 for stable and 3 for increasing.

Table 1.10 - Indicators relative to the characteristics of the upcoming rainy season

Indicators	Caracteristics	*Indications pour la saison des pluies à venir*	*Examples of quotes*	*Occurrence of the Indicator*	*Average Reliability*	*Reliability Trend*
Wind	Towards east	Abundant amount of rain	*"Quand le vent va vers l'est, cela montrait qu'on aura beaucoup de pluie dans la saison de pluie"*	1	4,0	1
Sky appearance	Cloudy/dark skies in April	Abundant amount of rain	*"Lorsque je vois des nuages durant le mois d'avril je sais que cette saison sera une saison où il va beaucoup pleuvoir"*	2	4,0	2
	Clouds moving eastwards	Short rainy season	*"Lorsque les nuages noirs vont vers l'est, cela dit que la saison des pluies ne va pas trop durer"*	1	2,0	1
		Rainy season coming to the end			2,0	
	Few clouds	Small amount of rain	*"Lorsque le ciel ne présente pas trop de présence nuageuse, il va pleuvoir peu pendant la saison des pluies à venir"*	1	1,0	1
	Clear sky	Short rainy season	*"Lorsque que le ciel est beaucoup dégagé, la saison des pluies ne va pas durer"*	1	1,0	2
				1	2,0	2
		Rainy season coming to the end		1	1,0	1

Stars	Visibility of some stars and new moon	Abundant amount of rain	*"Avant lorsqu'on apercevait plusieurs étoiles autour de la nouvelle lune, cela annonçait que les pluies allaient être abondantes."*	1	4,0	1
	New moon	Rainy season coming to the end	*"C'est la lune que je comptais"*	1	2,0	1
	Star positions / constellations	Start of the rainy season	*"Quand l'étoile mère poule et enfant'' apparait à l'ouest, ça annonce le début de la saison des pluie"*	4	3,0	2
Frogs	Shouting	Abundant amount of rain	*"Les cris des crapauds lorsqu'ils sont récurrents, il va beaucoup pleuvoir la saison à venir"*	1	3,0	1
Birds	Nesting lower than usual	Abundant amount of rain	*"Les oiseaux font leurs nids en bas les branches des arbres, il va pleuvoir beaucoup pendant la saison prochaine"*	1	1,0	2
	Singing	Start of the rainy season	*"Il y a un oiseau, tjiloto en sénoufo, lorsqu'il chante cela veut dire que la saison des pluies commence"*	1	3,0	1
Ants	Number of ants in the field	Abundant amount of rain	*"Quand les fourmis magnans sont*	1	4,0	1

			beaucoup au champ, on sait qu'il va beaucoup pleuvoir pendant la saison des pluies"			
	Ants going out of their holes	Rainy season coming to the end	*"Lorsque les fourmis commencent à ressortir de leur cachette, la saison des pluies ne va pas durer"*	1	2,0	1
	Number of red ants in the field	Small amount of rain	*"Quand tu vois les fourmis rouges sortir dans les champs, ça montre que cette saison des pluies ne sera pas abondante"*	1	4,0	1
Earthworms	Frequency/number of earthworms in the open air	Abundant amounts of rain	*"Lorsque les vers de terre sortent beaucoup, il va pleuvoir beaucoup pendant la saison des pluies"*	1	2,0	1
Caterpillars	Presence	Start of the rainy season	*"La présence des chenilles annonce le début de la saison des pluies"*	1	3,0	2
Spiders	Web	Rainy season coming to the end	*"Les morceaux de toile d'araignée qui tombent du ciel"*	1	4,0	2
Perceived temperatures	Persistent heat	Abundant amount of rain	*"Quand il pleut et on a toujours de la chaleur, ça montre que les pluies seront*	1	4,0	1

			abondantes cette année"			
	Cool in the shallows	Small amount of rain	*"Quand il pleut et il y a beaucoup de fraicheur en bas, ça montre que les pluies ne seront pas beaucoup cette année"*	1	4,0	1
Phenological stage of plants	Leaf growth (Baobab, Como)	Start of the rainy season	*"Quand des feuilles, en sénoufo on l'appelle Cobo, commencent à pousser du sol"*	1	2,0	2
				1	3,0	2
	Flowering (trees, plants)	Start of the rainy season	*"Il y avait des arbres qui sont très difficiles à voir maintenant qui permettaient de savoir que la saison des pluies va commencer lorsqu'ils commençaient à fleurir"*	1	3,0	1,0
				1	4,0	2,0
		Abundant amount of rain	*"Quand les arbres commencent à fleurir vite, ça montre qu'il va beaucoup pleuvoir cette saison"*	1	4,0	2
		Small amount of rain	*"Quand les plantes ne fleurissent pas vite, ça montre que la pluie ne va pas bien venir cette saison"*	1	4,0	2
		Short rainy season				
	Fructification (mangoes, others...)	Start of the rainy season	*"Il y a des arbres lorsqu'ils se mettent à produire, je sais que la*	4	3,0	2

			saison des pluies va commencer"			
	Number of fruits	Start of the rainy season	*"Si les arbres de Néré ont bien produit, la saison prochaine il y aura beaucoup de pluie"*	1	4,0	2

Notes: Indicator occurrence corresponds to the number of citations of this indicator, average reliability is rated on a scale of 1 (low) to 5 (high), and indicator reliability trend is rated as 1 for decreasing, 2 for stable and 3 for increasing.

Table 1.11 - Indicators of an upcoming period without rain

Indicators	**Caracteristics**	***Time without rain***	***Examples of quotes***	***Occurrence of the Indicator***	***Average Reliability***	***Reliability Trend***
Wind	Towards west	On the same day	*"Quand le vent souffle vers l'ouest avec les nuages"*	1	3,0	1
Sky appearance	Cloudy	On the same day	*"Quand le ciel est nuageux, il ne va pas pleuvoir"*	2	3,0	1
	Fog in the morning	1 week to 1 month	*"Lorsque le matin il y a le brouillard, je sais que nous allons faire une période sans pluie"*	2	3,0	2
	No clouds	1 to 2 weeks	*"Lorsque le ciel est très propre sans risque nuageux pendant toute une journée"*	2	2,5	1
	Red sky	5 to 7 days	*"Quand on voit qu'une partie du ciel commence à être rouge"*	2	3,5	2
Animals	Noises	2 to 3 weeks	*"Les animaux font beaucoup de bruit"*	1	2,0	2
Ants	Number of red ants in the field	On the same day	*"Quand on voit les fourmis rouges en nombre élevé dans les champs"*	1	4,0	1
Caterpillars	Hairy	1 to 2 weeks	*"Lorsque les chenilles à poil sortent, je sais qu'il aura un moment où il ne va pas pleuvoir"*	4	3,5	2
Perceived temperature	Cold	1 month	*"Lorsqu'il fait trop froid"*	1	3,0	1
Flora	Flowering of particular trees	1 to 2 weeks	*"Il y a un arbre du nom de katjon lorsque ce arbre fleurie je sais qu'il aura une période de sécheresse durant la saison de pluie"*	5	3,0	2,0
	Germination (Finant)	N/a	*"Il y a une plante (Finant en Koyaka) lorsqu'elle pousse une période sans pluie va commencer"*	1	3,0	2
	Bleeding	N/a	*"Il y a un arbre qui commence à saigner lorsqu'il aura une période sans pluie."*	1	3,0	2

Past rains	Intensity	1 week	*"Lorsque qu'une forte pluie arrive durant la saison des pluies, il peut se passer plus d'une semaine sans une autre pluie"*	1	3	2

Notes: Indicator occurrence corresponds to the number of citations of this indicator, average reliability is rated on a scale of 1 (low) to 5 (high), and indicator reliability trend is rated as 1 for decreasing, 2 for stable and 3 for increasing.

Chapter 2: Forecasts in the field: Could a dry spell probability shift farmers' sowing behaviour?

2.1. Introduction

Climate change is altering rainfall patterns across West Africa and causing a higher likelihood of dry spells in the western Sahel during future rainy seasons (Basse et al., 2024; Gaetani et al., 2020). Given that agriculture in this region is predominantly rain-fed, this trend represents a significant threat to farmers by heightening the risk of crop losses and food insecurity (Roudier et al., 2011; Sultan et al., 2019; Sultan & Gaetani, 2016). In this context, climate services (CS) play a crucial role in enabling farmers to anticipate weather-related hazards. Delivered through various channels—including radio, television, and mobile applications—climate services provide decision-makers with weather and climate information across multiple time horizons: from short-term forecasts (1 to 15 days) to seasonal forecasts (up to 3 months), and climate projections (Nkiaka, 2019; Vaughan & Dessai, 2014). Among the various agricultural decisions influenced by climate services, the choice of sowing date is particularly important (Born et al., 2021). This paper adopts an experimental approach to analyze the role of weather information in shaping farmers' maize sowing decisions.

Our lab-in-the-field experiment was conducted in ten villages in the Bagoué region of northern Côte d'Ivoire, involving 314 farmers. In this region, instability in the onset of the rainy season disrupts traditional cultivation calendars, with rainfall interruptions damaging maize at sowing time (Adesina & Ouattara, 2000; Boko-Koiadia Adjoua et al., 2016; Dekoula et al., 2018, 2019). Moreover, these localities generally have low literacy rates, limited access to climate services and often rely on local knowledge to predict the weather. In practice, the concept of probability underlying forecasts is also often poorly understood by populations with low literacy levels, and a wide range of contextual barriers can influence whether farmers adopt or disregard climate and weather information (Antwi-Agyei et al., 2021; Carr & Onzere, 2018; Kumar et al., 2021; Lemos et al., 2012).

The mechanisms underlying farmers' decision-making in response to forecasts have become an area of growing multidisciplinary research (Müller-Mahn et al., 2020 ; Guido et al., 2020; Kusunose & Mahmood, 2016; Nyamekye et al., 2021, Roudier et al., 2014). This multidisciplinary research provides deep qualitative insights into farmers decision-making, but relatively little quantitative evidence on the mechanisms behind these choices as it was mostly participatory research workshops. Out of agriculture, to our knowledge, there is only one experiment on hydraulic dam management based on seasonal forecasts providing quantitative scientific insights into decision-making based on meteorological information (Crochemore et al., 2021). Experimental approaches offer a structured means of modelling real-world decision-making over extended time horizons (e.g., months, seasons, or years), while maintaining simplicity and clarity (Crochemore et al., 2021; Leblois et al., 2020). In parallel, behavioural economics has increasingly sought to contextualize standard individual risk preference elicitation frameworks—such as multiple price lists (MPL) (Brick et al., 2012; Holt & Laury, 2002)—by embedding them in real-world agricultural decision-making settings. In most cases, this involves presenting MPL choices as crop variety selections for the upcoming season, with payoffs contingent on seasonal rainfall variability (Julia Ihli et al., 2022; Kemeze et al., 2020; Schrieks et al., 2024). This chapter contributes to this emerging body of experimental literature by providing new empirical evidence on farmer decision-making in response to meteorological information.

In doing so, it places particular emphasis on the behavioural dimension of these decisions, recognizing that the interpretation of forecasts is also shaped by individual characteristics, which in turn influence how farmers respond to the information. As with any form of probabilistic information, the same dry spell probability can be perceived and interpreted differently from one individual to another (Tversky & Kahneman, 1992). The literature on climate shocks indicates that personal experience of past losses can lead to higher subjective loss probabilities (Brown et al., 2018; Menapace et al., 2016). Experiencing a low-probability disaster can cause individuals to overestimate the likelihood of similar events occurring in the future (Li et al., 2011; Tversky & Kahneman, 1974, 1992). To account for these effects, we included in our analysis of decision-making mechanisms, variables related to the appraisal of dry spell risks such as the severity of past maize losses due to this weather event and their perceived frequency. In addition, psychological traits such as locus of control and self-efficacy have been shown to influence risk perception (Schrieks et al., 2024) but also decision-making in agriculture (Carter, 2016; Wuepper et al., 2023), technology adoption (Abay et al., 2017) and, climate change adaptation (Kreft et al., 2021; van Valkengoed et al., 2023). To our knowledge, their role in the context of climate services remains largely unexplored, we then introduced these factors too into our study.

Building on these insights, we developed an experimental protocol tailored to the agricultural context, with the aim of analysing how farmers respond to dry spell probabilities at sowing time and identifying the factors that shape their decision-making. We employed an experimental protocol inspired by the investment game developed by Gneezy & Potters, (1997). However, our objective was not to measure individual risk aversion, but to assess whether farmers adjust their maize sowing decisions in response to a dry spell probability and to explore the factors influencing their decision-making processes. During the experiment, each farmer was asked to allocate maize sowing between a “usual” period—associated with a specified dry spell probability —and a “late” sowing period, which guaranteed lower but certain yields. If a dry spell occurred, all maize sown during the risky period was entirely lost.

The probabilities were randomly varied across five seasons and compared with a scenario without information. In this experiment, we therefore developed visual tools to overcome the conceptual barrier associated with probability, allowing us to focus our analysis on decision-making mechanisms once the information is properly understood. Each farmer repeated this sequence of decisions twice, allowing us to assess whether prior exposure to a given probability influenced their subsequent choices.

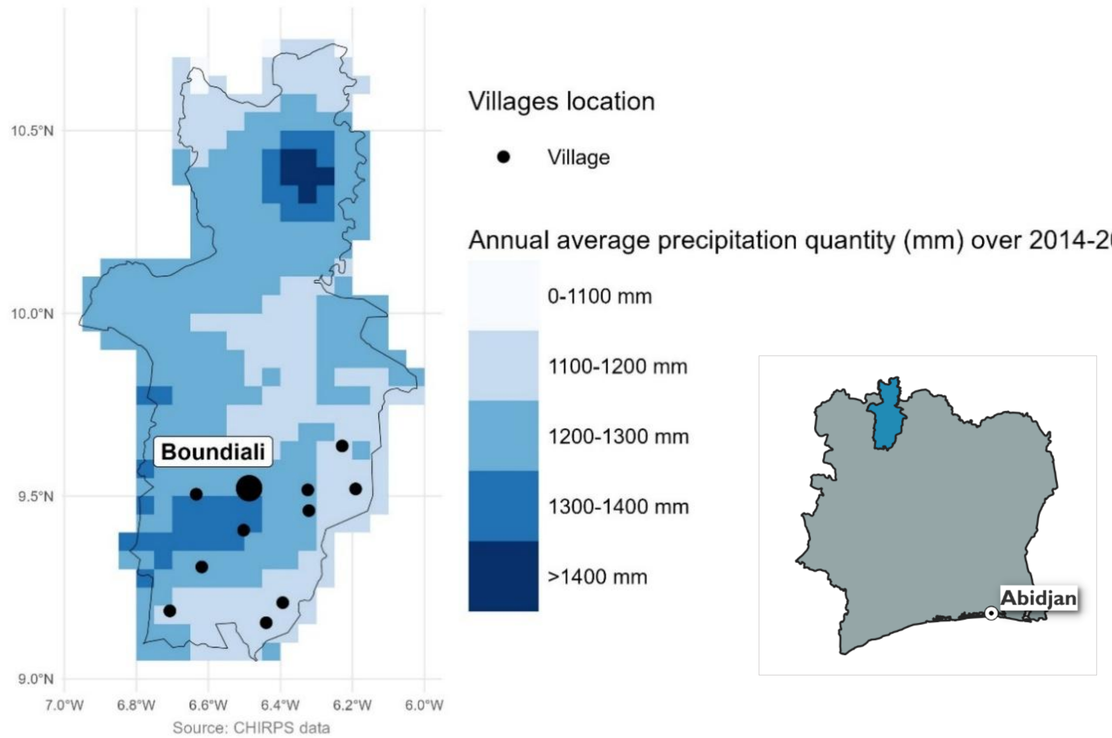
Our findings demonstrate that farmers adjust their sowing strategies to dry spell probabilities. However, even under very low probabilities of dry spells, many farmers remain cautious and do not fully allocate their seeds to the risky option. Despite forecasts being the primary factor influencing sowing decisions in this experiment, responses to forecasts are also mediated by a combination of psychological and experiential factors.

This paper pursues several objectives: i) to measure the individual impact of dry spell forecasts on potential maize yields; ii) to analyze the determinants of farmers' sowing decisions; and iii) the effect of the information on the maize seed allocation. The chapter is organized as follows: Section 2 presents the context of the experiment; Section 3 describes the experimental methodology; Section 4 provides a sample analysis; Section 5 presents the results, which are discussed in Section 6; and Section 7 concludes.

2.2. Context

The experiment took place in ten villages in the Bagoué department in northern Côte d'Ivoire (see *Figure 2.1*). Agriculture is almost entirely rainfed in this area, making farms highly dependent on rainfall conditions (Dekoula et al., 2018). The climate in the study area is classified as transitional tropical (Sudano-Guinean) and is characterized by a monomodal rainfall pattern, with a dry season from November to April and a rainy season from May to October. Average annual rainfall ranges between 1,000 mm and 1,500 mm (Dekoula et al., 2018).

Figure 2.1 - Annual average precipitation quantity in the Bagoué region

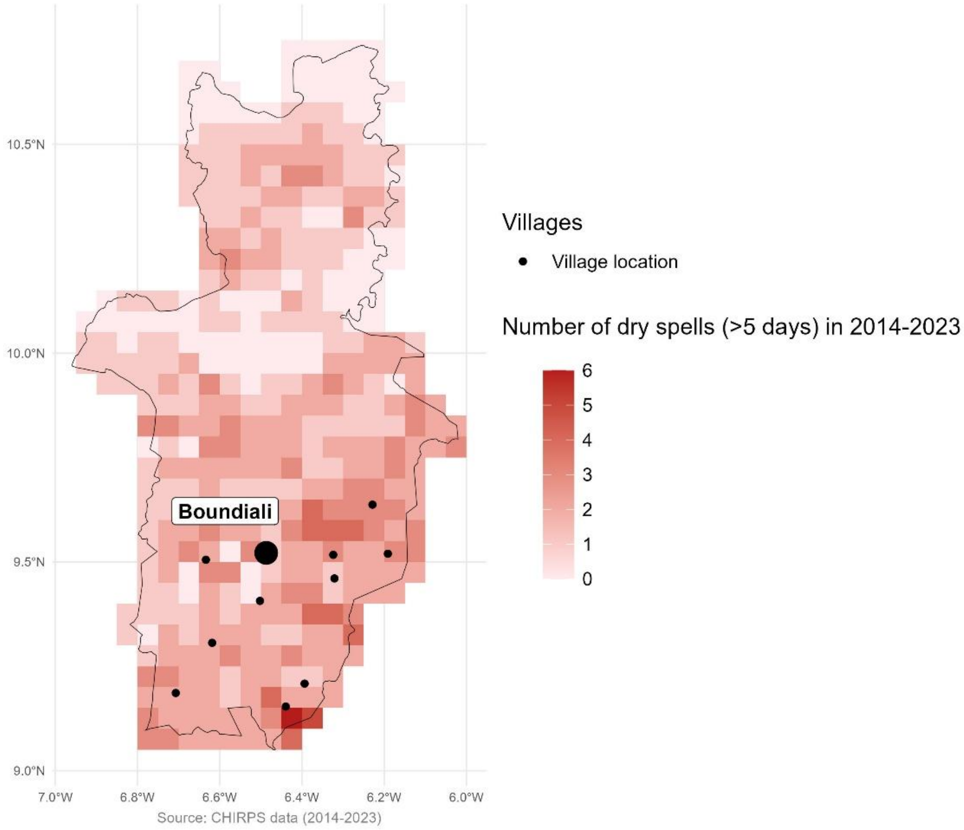


Notes: The map above, based on CHIRPS data (Funk et al., 2015), displays the annual average precipitation between 2014 and 2023 in the Bagoué region, using a spatial resolution of 0.05 × 0.05 degrees.

Dry days in the study area—defined as days with less than 1 mm of rainfall (Stern et al., 2006)—average between 3 and 8 days during the months of June, July, August, and September (Dekoula et al., 2019). In northern Côte d'Ivoire, the perceived frequency and duration of dry spells during the rainy season have been increasing, particularly in June and July (Boko-Koiadia Adjoua et al., 2016). Maize is known to be particularly sensitive to dry spells, especially during the stages of seedling emergence and flowering, and households in the region consume a large share of their harvest (Adesina & Ouattara, 2000; Ducroquet et al., 2017; interviews with the National Agency for Rural Development Support – ANADER).

The spatial variability of dry spells longer than five days across the studied localities is considerable, ranging from 0 to 6 episodes over the last ten years. In *Figure 2.2*, we apply the Sivakumar criterion to determine the onset of the rainy season (Sivakumar, 1988), with the end of the season fixed at the end of September. This criterion accounts for “false starts”, defined as dry spells occurring shortly after the rainy season onset, which are the focus of our analysis.

Figure 2.2- Number of dry spells (> 5days) in the Bagoué region in 2014-2023



Notes: The map above, based on CHIRPS data (Funk et al., 2015), displays the total number of dry spells lasting more than five days during rainy seasons in the region between 2014 and 2023, using a spatial resolution of 0.05 × 0.05 degrees.

2.3. Methodology

2.3.1. Experimental design

We are interested in how a dry spell probability influences maize sowing decisions, compared to decisions made under ambiguity, in the sense of Ellsberg (1961). In ambiguous situations, individuals can enumerate possible states of nature—such as continuous rainfalls and rainfall interruptions harmful to seedlings (i.e. "dry spells")—but cannot assign objective probabilities to these outcomes. We will refer to this ambiguous situation in the chapter as the *No-Forecast* situation.

In practice, farmers in the Bagoué region make decisions under uncertainty in the sense of Knight (1921), rather than ambiguity. Indeed, it is also difficult for them to identify and enumerate all weather-related states of nature. In our experiment, we simplify this uncertainty by reducing the state space to two possible events: i) uninterrupted rainfall; and ii) a harmful dry spell. The introduction of a probability thus shifts the decision context from one of ambiguity to one of risk, in the sense of Knight (1921) and Keynes (1921), as the farmer is now informed about the likelihood of each state of nature and the corresponding outcomes.

We chose an experimental protocol derived from the investment game developed by Gneezy & Potters, (1997). This approach is widely recognized for its ease of understanding in developing countries, particularly among rural and less-educated populations (Charness & Viceisza, 2016). It allows participants considerable flexibility in allocating their initial endowment, making it particularly well suited to representing farmers' sowing decisions. Our protocol is also closely related to that used by Hill & Viceisza (2012) to study decisions related to fertilizer purchase and agricultural insurance investment. In line with this literature, our objective is to foster design simplicity to minimize decision inconsistencies (Dave et al., 2010).

In the experiment, each farmer is asked to decide how to allocate maize sowing under two types of scenarios: i) a baseline scenario with no information on dry spell probability—referred to the *No-Forecast* situation; and ii) several scenarios that provide a dry spell probability.

For each scenario, the producer faces a risk/return trade-off:

1. Sowing at the usual planting time, during a risky period t^{risky} offers the possibility of a high yield but carries the risk of losing seedlings if a dry spell occurs.
2. Sowing later, during a safe period t^{safe} ensures a lower but certain yield.

This decision is not binary in this experiment: the farmer may allocate his entire seed endowment across the two periods but may also choose to sow all seeds in a single period with different allocations.

Let :

- $\hat{X} = 10$ denote the initial seed endowment for farmer$j$, representing the full stock of seeds he owns and must sow during the ongoing season
- $x_j^{risky} \in \{0,1,2, \dots ,10\}$ the quantity sown in the risky period t^{risky}
- $\left(1 + i^{risky}\right)$ the yield associated with sowing in t^{risky}, with $i^{risky} = 4$ if no dry spells occurs or $i^{risky} = -1$, if a dry spell occurs.
- $(1 + i^{safe})$, the yield associated with the safe period, with $i^{safe} = 1$.

This setup corresponds to a standard portfolio allocation problem, in which the farmer invests in a combination of a risky asset with contingent return $i^{risky} \in \{4, -1\}$ and a safe asset with return $i^{safe} = 1$. The value V of a portfolio at the end of the period depends on the occurrence of a dry spell:

If a dry spell occurs, then:

$$V = \left(\hat{X} - x_j^{risky}\right)(1 + i^{safe}) \tag{1}$$

If a dry spell does not occur, then:

$$V = x_j^{risky}\left(1 + i^{risky}\right) + \left(\hat{X} - x_j^{risky}\right)\left(1 + i^{safe}\right) \quad (2)$$

With i^{risky}= 4

Let P_s be the probability of a dry spell occurring, with $P_s \in \{0.1, 0.3, 0.5, 0.7, 0.9\}$.

The expected payoff for choosing a portfolio g is therefore as follows:

$$E(g) = P_s\left(\left(\hat{X} - x_j^{risky}\right)\left(1 + i^{safe}\right)\right) + (1 - P_s)\left(x_j^{risky}\left(1 + i^{risky}\right) + \left(\hat{X} - x_j^{risky}\right)\left(1 + i^{safe}\right)\right) \quad (3)$$

With i^{risky}= 4, $i^{safe} = 2$

In the *No-Forecast* situation, P_s is unknown and reflects the farmer's subjective belief. In all other scenarios, the probability P_s is known and provided to the farmer.

The experiment was conducted over two rounds, each one consisting of five rainy seasons. In each round, the five dry spell probabilities were presented in a randomized order to farmers.

The initial endowment $\hat{X}$ is renewed at the beginning of each season k, representing a new cultivation cycle. This design reflects the idea, supported by the literature, that farmers conceptualize each season as a new and independent opportunity to cultivate and harvest (Boko, 1992).

Our model is based on several assumptions:

- The period t^{risky} is defined in the instructions as *"the period when the farmer is used to sow maize".*
- Farmers face no constraints related to labor, inputs, or equipment availability.
- All agroclimatic conditions observed by the farmer before receiving a dry spell probability, appear favorable for sowing at period t^{risky} , as they would be in a typical season.
- Maize yields are fixed for each season and depend solely on the sowing decision and the occurrence or absence of a dry spell.
- All psychological preferences are assumed to be constant throughout the experiment.

2.3.2. Data collection & experimental settings

A total of 314 farmers participated in the experiment, conducted across ten villages in the Bagoué region of northern Côte d'Ivoire. A pilot survey was first carried out in the village of Ndara with fifteen producers. Villages were selected based on several criteria: low security risks, sufficient geographical separation to limit communication between villages, and adequate road access, as the entire team of nine interviewers needed to travel together to each site. The sampling strategy was developed in partnership with Ivoire Coton, a cotton company operating in the region. While farmers were informed of our presence in advance, they were not made aware of the exact purpose of the study. In each village, we interviewed nearly all the farmers listed in the cotton company's records.

The experiment offered no financial incentives linked to gains in the game, but rather a fixed compensation intended to cover the opportunity cost of participation. The value of the compensation was set at 2,000 FCFA, corresponding to the estimated daily wage of an agricultural worker in the region (Interview with the Interprofession of Cotton Professionals in Côte d'Ivoire – InterCoton). The survey period was also carefully selected to coincide with the middle to end of the dry season, a time when agricultural workload is relatively low[2].

This decision to exclude financial incentives was based on important concerns related to the implementation of the experiment, as documented by Brañas-Garza et al. (2021, 2023). It is also a frequent choice among researchers working in rural Africa (Schrieks et al., 2024a). In low-income contexts such as ours, the main concerns are: i) the perceived unfairness that may arise from unequal payoffs among participants, ii) the security risks for researchers carrying and distributing money in areas with high poverty rates, and iii) the reputational risk for the Agence Française de Développement (AFD), which financed the data collection, of being associated with direct cash payments. Moreover, Brañas-Garza et al. (2021, 2023), using a Holt and Laury-type lottery, find that the presence or absence of performance-based incentives does not significantly affect participants' behaviour.

During the pilot phase of our lab-in-the-field experiment, we observed that farmers were intrinsically motivated to participate, primarily due to their interest in discussing the challenges posed by climate change and rainfall variability. Nevertheless, to enhance the validity of the data collected, we introduced a system in which interviewers rated each respondent's level of personal engagement at the end of the experimental session. Only 11 farmers were rated by interviewers as *"The respondent was only minimally engaged and did not take the game seriously*". As this rating is subjective, we decided to keep the entire sample for the data analysis but proceeded with robustness checks excluding the concerned farmers in *Appendix 2.E*. Participants were also informed that they would receive compensation only after completing both the experiment and the accompanying survey questionnaire, in order to preserve their initial motivation and avoid any distortion of behaviour due to early payment.

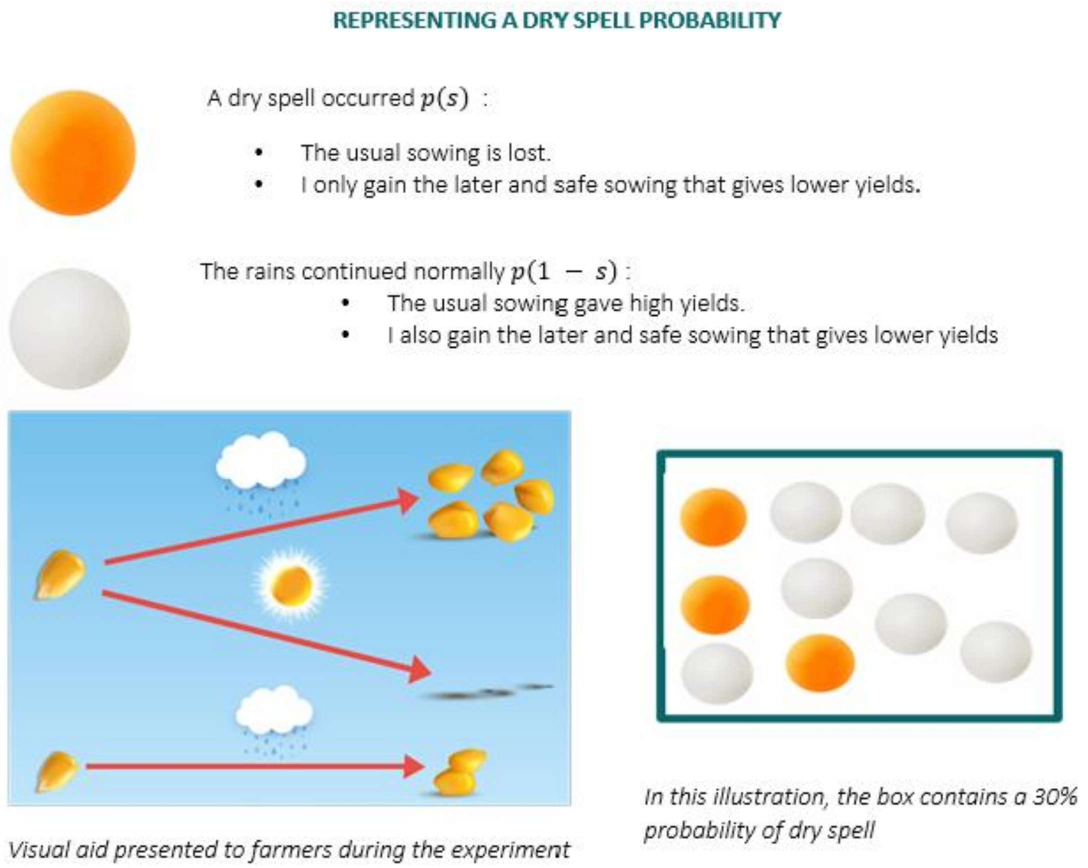
The calibration of the game's numerical parameters was conducted in consultation with agricultural advisors from ANADER and InterCoton and was subsequently validated during the pilot survey through qualitative post-game interviews with farmers. The initial endowment was set at 10 seeds, representing the total number of seedlings each farmer planned to sow during the rainy season. For each seed sown in the risky period (i.e., at the usual sowing time), the return i^{risky} was defined as4 if no dry spell occurred, and-1 if a dry spell occurred. For

[2] The experiment took place at the end of February 2024

seeds sown later, the return was fixed at $i^{safe} = 1$, as the risk of a dry spell is assumed to be negligible but shortens the growing period, and so, assumes to result in low maize yields.

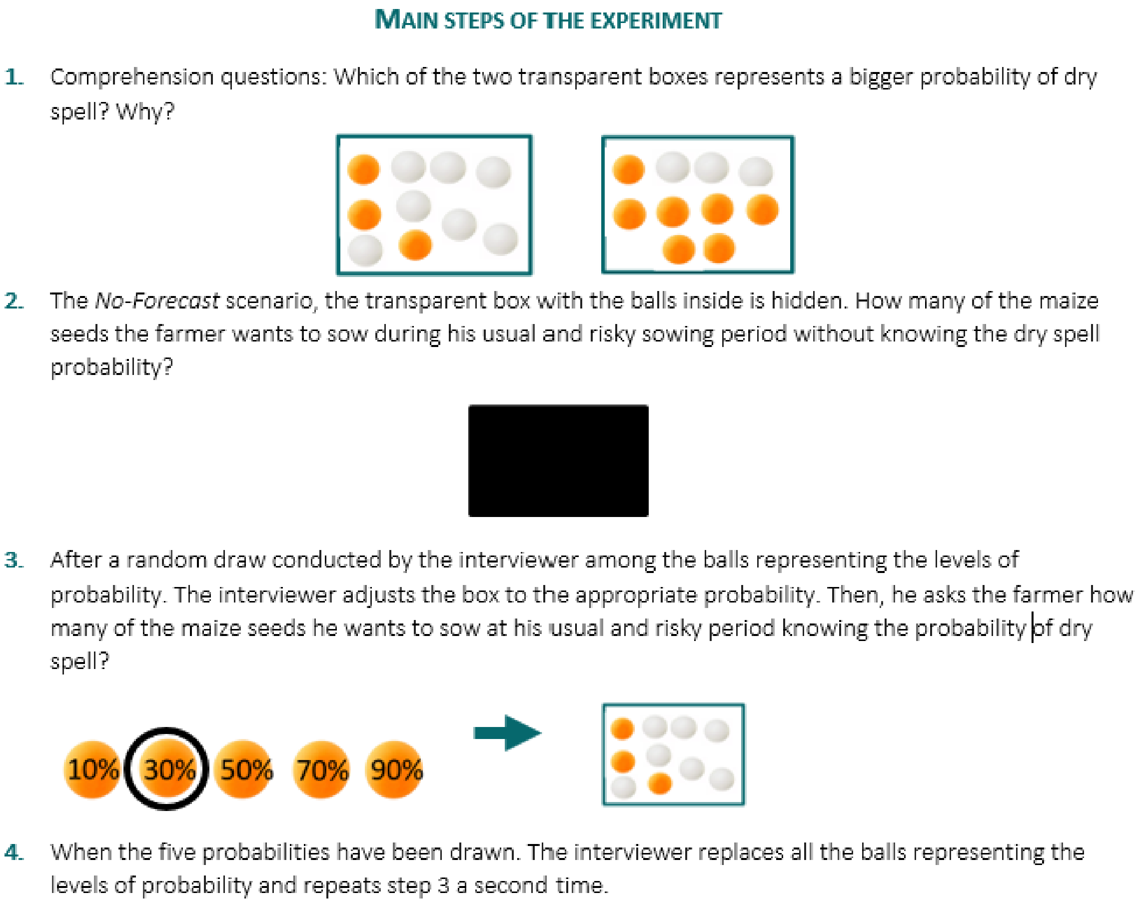
A total of nine interviewers were mobilized. After receiving training, each interviewer was able to independently administer the game and was provided with a script detailing the experimental protocol, as well as all necessary materials (see *Appendix 2.G*). The script was printed and readily accessible throughout the interviews. Visual aids were systematically used to enhance participant comprehension. Ensuring the clarity of explanations is essential to reduce inconsistencies and misunderstandings during the task (Bauermeister & Musshoff, 2016; Estepa-Mohedano & Espinosa, 2023; Ihli et al., 2013). Interviews were conducted individually in quiet settings, with sufficient spacing between participants to prevent overhearing of responses.

Figure 2.3 - Visual representation of dry spell probabilities during the experiment



Interviews were conducted in French or in one of the two local languages, Djoula and Sénoufo, depending on the participant's preference. All participants were informed that their data would be anonymized and treated confidentially. Prior to the start of the experiment, each respondent was asked a series of comprehension questions to ensure that they had understood the instructions, thereby supporting the validity of the responses collected during the experiment. Following the protocol described by Freudenreich & Musshoff (2022), participants in the *No-Forecast* situation were informed that the urn contained both yellow and white balls, but they were not told the total number or the proportion of each color—thereby creating a condition of ambiguity consistent with Ellsberg-type setups.

Figure 2.4 - Representation of the main steps of the experiment



The average dry spell rate experienced by individuals during the experiment was 47%. Overall, the protocol was well understood: 97% of participants successfully passed the comprehension test administered before the start of the game. The remaining 3% received a second explanation, after which they proceeded with the experiment. No inconsistencies were observed in the responses of participants who initially failed the comprehension test. The average duration of the experimental game was approximately 30 minutes, followed by a 30-minute questionnaire. This post-experiment questionnaire collected information on psychological traits, climate perceptions, and a range of socio-economic and demographic characteristics relating to the farmer, the farm, and the household.

2.4. Sample description

2.4.1. Demographic and farming statistics

Cotton cultivation in northern Côte d'Ivoire is almost only cultivated by men due to ethnic and gender norms (Bassett, 2002) even though we were interested in the maize culture, our sample relied on producer lists provided by Ivoire Coton, and therefore did not include any women in the villages studied. The average age of participants was 43.2 years, the majority of whom identified as Sénoufo (85.9%) or Malinké (10.2%). All participants declared a religious affiliation. The sample included a large proportion of animists (43.6%), Muslims (48.9%), and Christians (7.5%). The level of formal education was generally low among the sample: 71.2% had never attended school, and only 10 farmers had reached secondary education. In terms of household structure, 84.0% of participants were heads of household, and 70% reported land ownership (either traditional or legal). Households were generally intergenerational, with an average household size of 13.9 people (including the respondent), and an average of five individuals available for farm labor. The average farm size was 22.8 hectares, predominantly non-irrigated (only 9 respondents used irrigation), and farmers cultivated approximately five different crops on average. In addition to crop production, 55.3% of farmers also engaged in breeding.

In 2023, farmers devoted an average of 4 hectares to maize, with an average yield of 0.98 tonne per hectare. The vast majority (96.7%) cultivated a composite maize variety (classic) with a short cycle (approximately 90 days, 93.8%). On average, 44.7% of maize production was used for household consumption. Only five farmers reported not having cultivated maize in 2023; however, as all had prior experience growing it, they were retained in the sample.

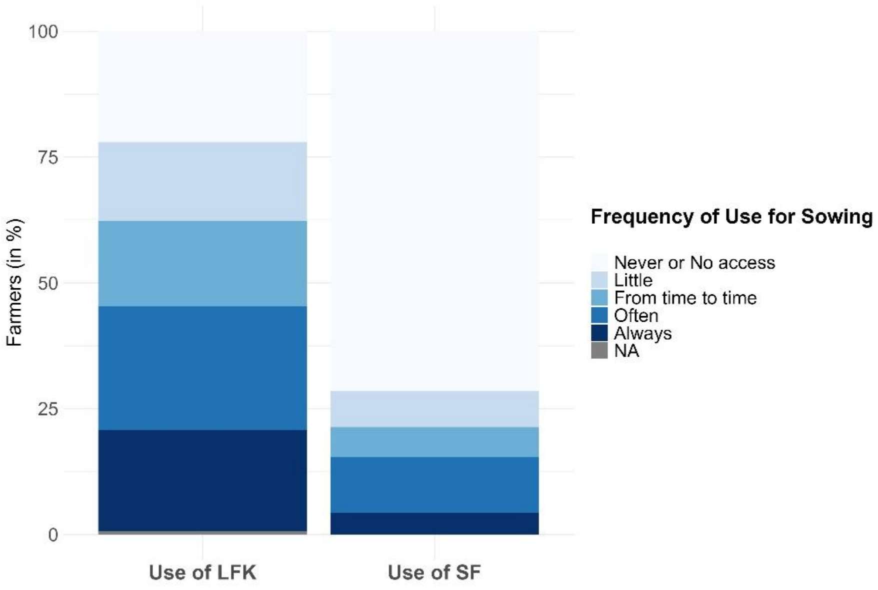
According to the Food Insecurity Experience Scale (FIES), the average food insecurity score was 1.81 out of 8, indicating a moderate level of food insecurity overall. However, 14.70% of respondents reported that they or a household member had skipped a meal in the past 12 months due to insufficient financial resources or food availability. (T.J. Ballard et al., 2013)

2.4.2. Use of forecasts

51.8% of farmers reported having access to scientific forecasts (SF), almost exclusively through television (82.7%) and radio (19.1%). These forecasts typically consist of general national-level weather forecast for the current and upcoming days—such as rainfall, thunderstorms, cloud cover, sunshine, and temperature. However, the data indicates that 70.6% of farmers use scientific forecasts in their decision-making process with substantial disparity between villages (see *Figure 2.6*). For example, in Ouazomon, more than 61.5% of farmers reported using SF for their sowing decisions, with 15.4% stating that they always use it. By contrast, in Ponondougou, only 12.0% of farmers reported using SF, most of whom indicated minimal or occasional use.

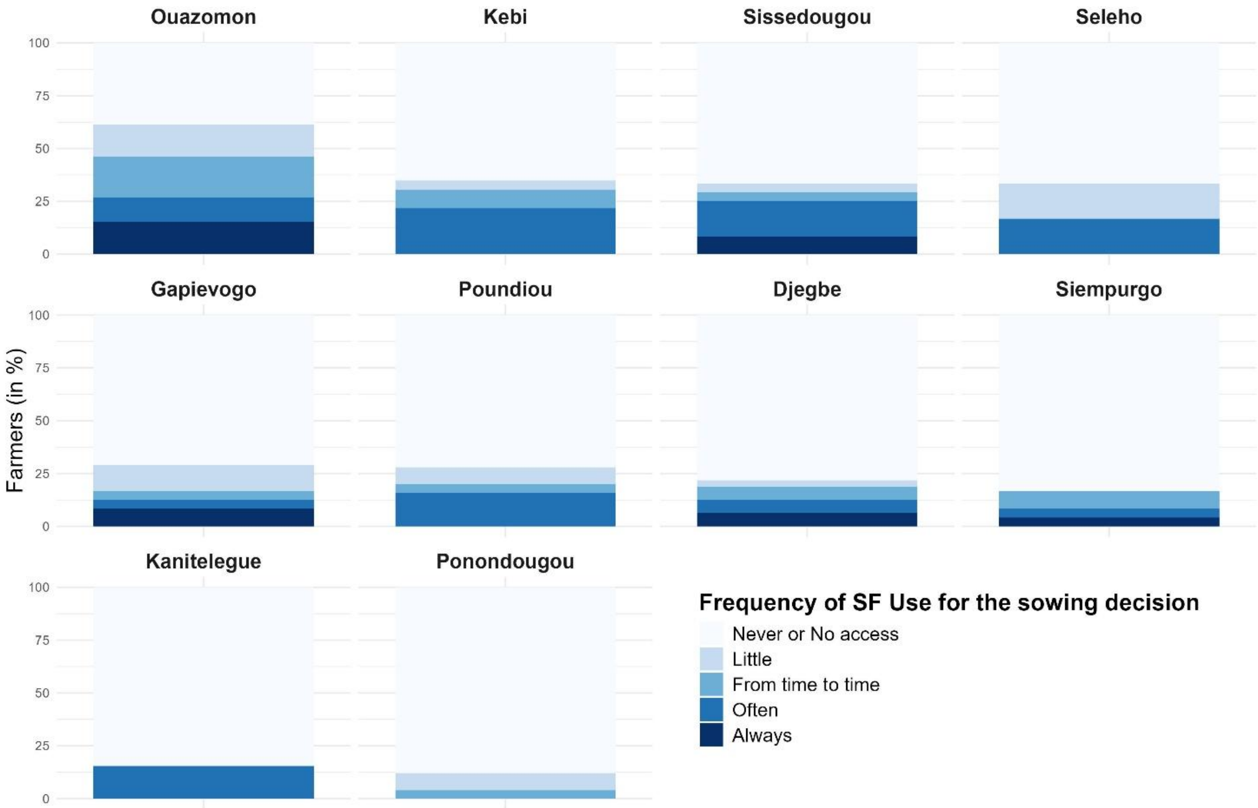
By contrast, more than half of respondents (44.7%) report often or always relying on local forecasting knowledge (LFK), based either on their own knowledge or on information provided by others, to determine when to sow.

Figure 2.5 - Frequency of SF and LFK use for sowing decisions



Notes: *Figure 2.5* presents the percentage of farmers using Local Forecasting Knowledge (LFK) and Scientific Forecasts (SF) in their sowing decisions, broken down by frequency of use. The category *"NA"* refers to respondents who answered, *"I don't want to answer."*

Figure 2.6 - Frequency of SF use for sowing decisions



Notes: *Figure 2.6* ranks villages according to the percentage of farmers using Scientific Forecasts (SF) in their sowing decisions, from highest usage (top left) to lowest (bottom right).

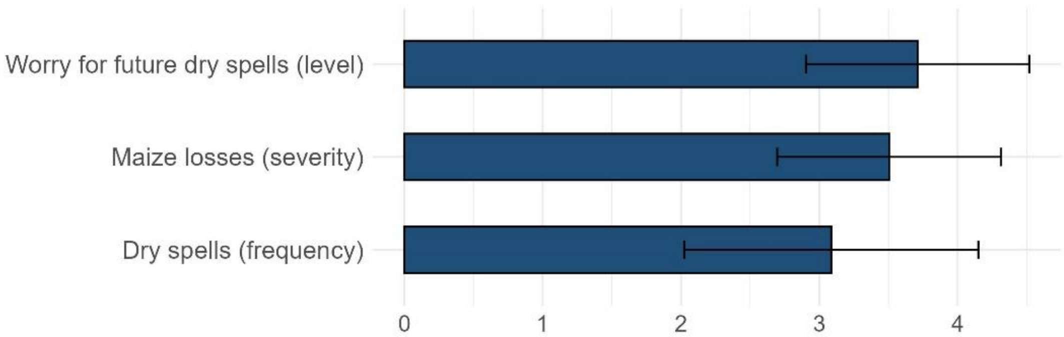
2.4.3. Dry spells perceptions

According to Grothmann & Patt, (2005) individuals' willingness to adapt to climate risks depends in part on their risk appraisal, which includes: i) the perception of the likelihood of being exposed to a negative event[3], and ii) the perception of the potential severity of the resulting damage.

In the study region, dry spells causing agricultural losses are perceived as moderately frequent (see *Figure 2.7*), with relatively homogeneous perceptions across the sample. Almost all farmers reported having previously experienced maize losses due to dry spells, and such events are generally perceived as severe when they occur. Most respondents stated that the last damaging dry spell occurred two years ago, although reported dates ranged from the current year to thirteen years ago, reflecting notable variability in individual recall or perception.

Overall, the level of concern regarding the impact of dry spells on household income is very high, with limited variations across the sample.

Figure 2.7- Average perception of dry spells indicators



Notes: *Figure 2.7* displays average scores (on a 0–5 scale, where 0 = very low and 5 = very high, with standard deviations in parentheses) for the following three variables: 1) Farmers' level of concern about the future impact of dry spells on household income, 2) Perceived severity of maize losses due to past dry spells, 3) Perceived frequency of dry spells.

2.4.4. Psychology and adaptation to climate change

Behavioural economics is increasingly applied in agricultural economics (see Wuepper et al., 2023, for a detailed review) to explain farmers' individual choices in climate change adaptation and technology adoption—often incorporating concepts such as locus of control and self-efficacy (Abay et al., 2017; Kreft et al., 2021; Streletskaya et al., 2020; van Valkengoed

[3] After the first two villages, it became clear that the question of the frequency of past dry spells was not easily understood by the respondents ("every X years it happens"). We therefore developed a qualitative frequency scale from 1 - rare to 5 - extremely frequent. The results of the first two villages surveyed were converted to the new scale.

et al., 2023). Psychological variables are also known to influence risk perceptions and individuals' risk preferences (Maltby et al., 2021; Schrieks et al., 2024). Therefore, we assume that, within our experimental framework, psychological variables may also shape the perception of dry spell probabilities and decide to include them in our analysis of the mechanisms underlying sowing decisions.

Individuals with an internal locus of control believe that they can influence the outcomes of life events through their own actions, whereas those with an external locus of control attribute outcomes primarily to external forces beyond their control (Rotter, 1966). The locus of control measure used in this study was adapted from the survey instrument developed by Abay et al. (2017). On average, respondents in our sample exhibit a moderately internal locus of control, with a mean score of 3.5 out of 6. This suggests that farmers generally feel they can influence most events in their lives through their own efforts, although they still acknowledge the importance of external factors.

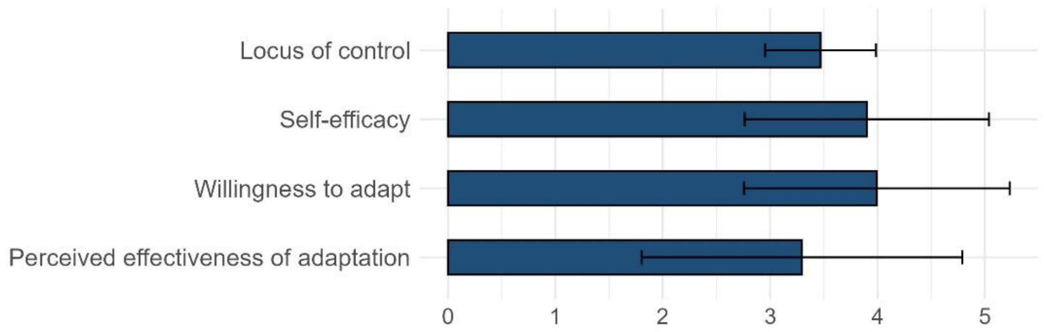
Self-efficacy refers to an individual’s belief in their ability to succeed in a specific domain (Bandura, 1977). In this study, following Grothmann & Patt (2005) we focus on self-efficacy in the context of climate change adaptation. Specifically, we measure perceived adaptive self-efficacy, defined here as farmers’ belief in their ability in real life to adjust their agricultural practices in response to a forecast, without relying on external support from professionals or the state.

In addition to this measure, we include two complementary variables:

1. an intention variable, capturing farmers’ stated willingness to adapt their practices upon receiving a real-life forecast (Burnham & Ma, 2017);
2. a variable reflecting their perceived effectiveness of adaptive practices, i.e. the extent to which they believe that modifying their farming practices can mitigate the impacts of dry spells.

Farmers generally appear to believe that, if provided with weather information sufficiently in advance, they are capable of adjusting their agricultural practices or livelihoods to avoid losses caused by dry spells—without relying on support from agricultural professionals or government services. However, while they express a strong willingness to adapt their practices, they seem less confident in the effectiveness of these changes in mitigating the adverse impacts of dry spells.

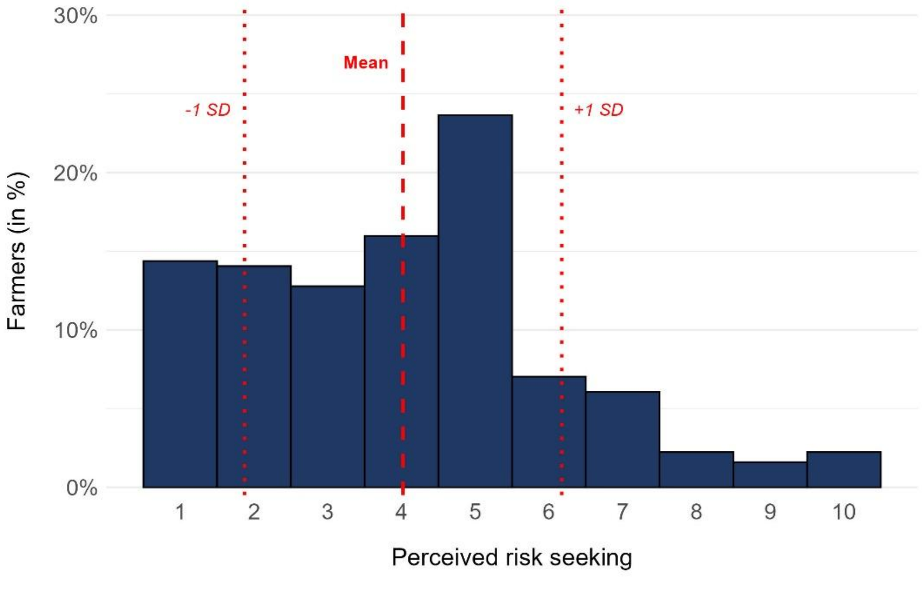
Figure 2.8 - Average levels of psychological indicators



Notes: *Figure 2.8* presents average scores (on a 0–6 scale, where 0 = very low and 6 = very high, with standard deviations in parentheses) for the following psychological variables: 1) Locus of control; 2) Self-efficacy; 3) Willingness to adapt; 4) Perceived effectiveness of adaptation.

We measured general risk preferences using a self-assessment scale ranging from 1 (extremely risk-averse) to 10 (risk-seeking), based on the method proposed by (Dohmen et al., 2011). Respondents were asked to rate their general willingness to take risks. On average, farmers considered themselves to be moderately inclined to take risks (see *Figure 2.9*).

Figure 2.9 - Farmer perceived risk seeking on a 10 units' scale



Notes: *Figure 2.9* shows the distribution (in %) of general risk-seeking preferences among the total farmer population. Risk preferences were assessed using a self-perception scale ranging from 1 (extremely risk-averse) to 10 (risk-seeking). The red bars indicate the sample mean and the standard deviations.

2.5. Results

2.5.1. Impact of a dry spell probability on potential harvests

The potential impact of a dry spell probability on maize harvests can be assessed by comparing outcomes from sowing under the *No-Forecast* scenario *(NF)*—in which farmer *j* has no information about the probability of a dry spell during the risky period—with outcomes under the *Forecast* scenarios *(F)*, where the farmer is informed about the probability of a dry spell (10%, 30%, 50%, 70% or 90%).

Denote:

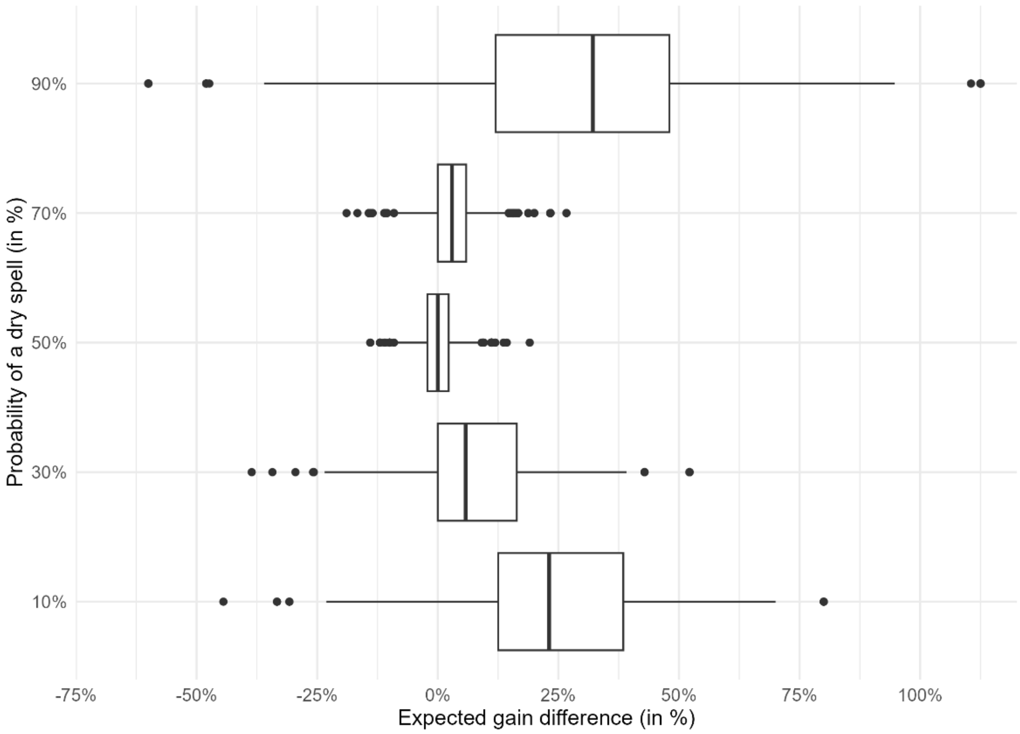
- $E_{NF}\ (x_j^{risky}|P_s)$ denote the expected gain from the risky sowing quantity x_j^{risky} as a function of the dry spell probability P_s under the *No-Forecast* scenario *(NF)*;
- $E_F(x_j^{risky}|P_s)$ denote the expected gain from the same risky sowing quantity x_j^{risky} as a function of P_s under the *Forecast* scenario *(F)*, where the probability of a dry spell is provided.

The difference in expected gain attributable is expressed as follows:

$$\Delta E(x_j^{risky}|P_s) \ = E_F(x_j^{risky}|P_s) \ - E_{NF}(x_j^{risky}|P_s) \tag{4}$$

The graph below illustrates the results in terms of variation in expected gain across different levels of dry spell probability. Results hold when replicating the same analysis excluding farmers with low engagement scores and those who failed the comprehension questions (see *Appendix 2.E*).

Figure 2.10 - Expected gain difference between risky sowing with a dry spell probability and without this probability



Notes: *Figure 2.10* shows the expected difference in yield (in %), by probability, between risky sowings made with access to a dry spell probability and those made without such information. The box plot shows the interquartile range (IQR), with the midline indicating the mean. For clarity, outliers greater than 125% of the absolute difference have been excluded.

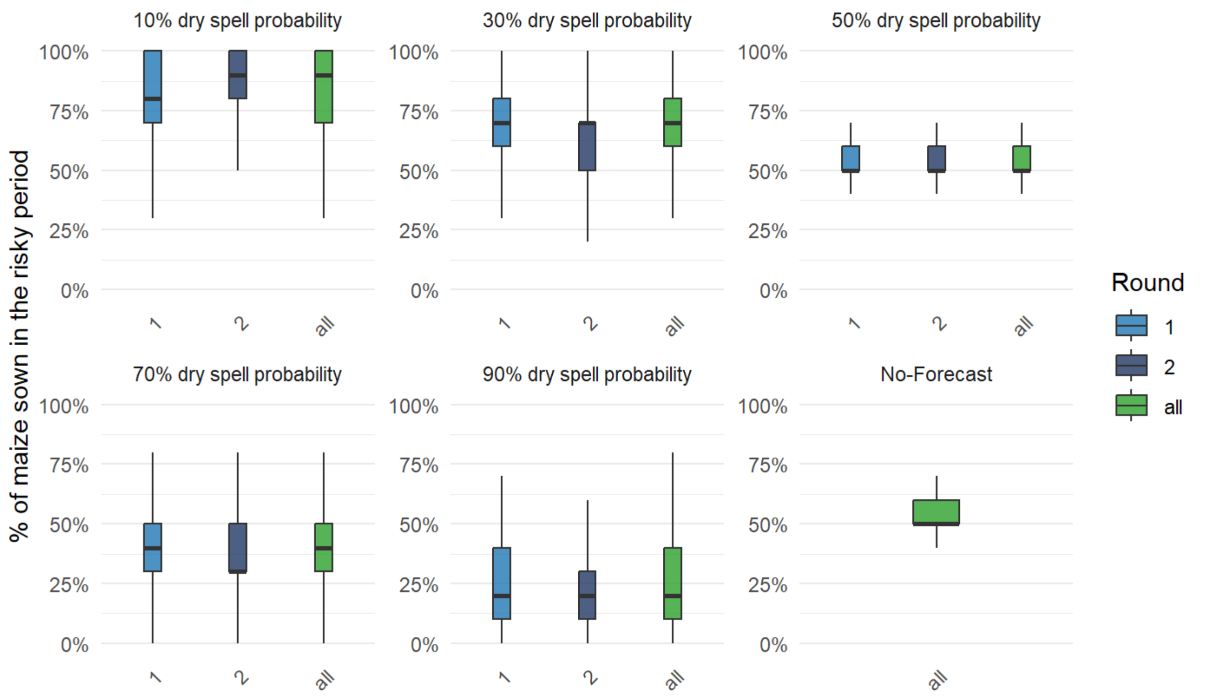
For all dry spell probabilities, the results indicate that from the first quartile onward, the expected gain with a provided probability exceeds that observed in the *No-Forecast* scenario. On average, the variation in expected gain is positive, and particularly pronounced for the 10% and 90% levels of probability. Although outlier values are not shown in *Figure 2.10*, they show that at a 90% dry spell probability, some farmers could achieve up to +300% yield improvements by adjusting their sowing strategy. In contrast, moderate probabilities (30%, 50% and 70%) are associated with more limited increases in expected returns. At 50% probability, changes in sowing behaviour compared to the *No-Forecast* scenario are minimal, resulting in a negligible difference in expected outcomes.

Overall, providing information on the probability of a dry spell leads to an average increase of +13.9% in expected harvests. These gains are positive for approximately three-quarters of the farmers, with individual variations in expected gain ranging from +300% to -60% compared to the *No-Forecast* scenario.

2.5.2. Determinants of the risky sowing

Figure 2.11 plots the distribution of risky sowings as a function of the dry spell probability. The figure highlights heterogeneity in sowing decisions both within individuals and across different probability levels, as well as variation in behaviour between rounds of the experiment (i.e. between the first and second time each individual is exposed to a given probability).

Figure 2.11 - Percentage of maize sown in the risky period as a function of the level of dry spell risk



Notes: *Figure 2.11* shows the distribution of the percentage of maize sown during the risky period for each level of dry spell probability, expressed as a share of the total seed endowment. The box represents the interquartile range (IQR), and the mid-line indicates the mean. The first round of the experiment corresponds to rainy seasons 1 to 5, during which farmers encountered each of the five probability levels in a random order. The second round corresponds to rainy seasons 6 to 10, again with the five probabilities presented in a random order. The "All" round represents the average response across the two rounds for each probability level, excepting for the *No-Forecast* scenario, which was presented only once, during season 0 for all farmers.

The volume of risky sowings changes according to the dry spell probability provided. Risky sowing levels differ from those observed in the *No-Forecast* scenario, with the exception of the 50% dry spell probability, where sowing behaviour appears to be similar. However, a key distinction emerges: in the *No-Forecast* scenario, the minimum risky sowing never dropped to zero, whereas at 50% dry spell probability, some farmers completely withdrew from risky sowing. We also observe differences in the distribution of risky sowings between rounds 1 and 2 of the experiment, indicating that some farmers did not sow in the same way when faced with the same dry spell probability for a second time.

Given the apparent heterogeneity in farmers' sowing decisions observed in the graph, we incorporate individual characteristics into the analysis to better understand the mechanisms underlying farmers' responses to dry spell probabilities. As a first step, we estimate a fixed-effects model to isolate within-individual variations by controlling. individual-level unobservable characteristics. Since the focus of this section is on the variation in dry spell probabilities, the *No-Forecast* scenario is excluded from the estimations. Results including the *No-Forecast* scenario are provided in *Appendix 2.C*.

In addition to individual fixed effects, we include round fixed effects to account for the experience accumulated over the experiment, as well as for any repetition effects between the first and second exposure to a given dry spell probability (i.e. across rounds 1 and 2 of the experiment). Finally, the dry spell probability is treated as a categorical variable rather than a continuous one, to identify potential non-linear effects. As a robustness check, all subsequent estimations were replicated using a restricted sample, excluding farmers with low engagement ratings and those who failed the comprehension test (see *Appendix 2.E*). These checks reveal no significant differences, confirming the robustness of the following results.

The following equation can be interpreted as the average causal effect of the dry spell probability on the risky sowing decision:

$$x_{jk}^{risky} = \beta_0 + \sum_{s \in S'} \beta_s D_{jk}(P_s) + \alpha_j + \gamma_k + \varepsilon_{jk} \quad (5)$$

With

x_{jk}^{risky}: Number of seeds sown in the risky period by farmer *j* at season k

$D_{jk}(P_s)$:Indicator variable equal to 1 if farmer $j$received probability $P_s$at season k, and 0 otherwise.

$P_s \in \{0.1,0.3,0.5,0.7,0.9\}$: Probability categories used in the model (with $P_s = 0.1$ as the reference group)

α_j: Individual fixed effects for farmer *j*

γ_k : Time fixed effects for season k

ε_{jk}: Idiosyncratic error term

We then extended the model to an autoregressive specification to account for time-dependent correlations in the regression errors, a common feature in panel data. We initially considered estimating a dynamic panel model using the Blundell–Bond (1998) system GMM estimator to account for the endogeneity of the lagged dependent variable. However, after several specifications, attempts to reduce instrument count using collapsed instruments and limited lags still proved unstable. Consequently, we rely on fixed effects estimation with cluster-robust standard errors. System GMM model can still be found in *Appendix 2.A*.

While this approach may be subject to dynamic panel bias, such as the Nickell bias, it offers a more stable and interpretable alternative in our context and allows us to capture temporal dynamics that are not addressed in *Equation 4*. Furthermore, we have sufficiently large number of observations per individual that any resulting Nickell Bias is small. Therefore, we include lagged sowing decisions and cumulative exposure to dry spells directly in the specification.

The resulting autoregressive model is given by:

$$x_{jk}^{risky} = \beta_0 + \beta_1 x_{j,k-1}^{risky} + \beta_2 dry_{j,k-1} + \sum_{s \in S'} \beta_s D_{jk}(P_s) + \alpha_j + \gamma_k + \varepsilon_{jk} \quad (6)$$

Where

x_{jk}^{risky}: Number of seeds sown in the risky period by farmer *j* at season k

$x_{j,k-1}^{risky}$: Number of seeds sown in the risky period by farmer *j* at season $k-1$

$dry_{j,k-1}$: Binary variable indicating dry spell occurrence for farmer $j$at season $k-1$,

$D_{jk}(P_s)$:Indicator variable equal to 1 if farmer $j$received probability $P_s$at season k, and 0 otherwise.

$P_s \in \{0.1,0.3,0.5,0.7,0.9\}$: Probability categories used in the model (with $P_s = 0.1$ as the reference group)

α_j: Individual fixed effects for farmer j,

γ_k : Time fixed effects for season k,

ε_{jk}: Idiosyncratic error term

Results are presented in *Table 2.1*. The provision of a dry spell probability accounts for a substantial share of the variation in farmers' risky sowing decisions, with an $R^2$of 0.57 in the baseline specification. As expected, the higher the probability of a dry spell, the fewer seeds are allocated to the risky sowing period. This decrease is non-linear. However, on average, farmers sow approximately 1.3 fewer seeds for each step increase in dry spell probability, representing a 13-percentage point reduction in the proportion of seeds allocated to the risky period. These results are robust to the inclusion of lagged variables in column (2). The coefficient of the lagged risky sowing is already small and precisely estimated in the Fixed Effects Model, suggesting that the dynamic bias is small enough in magnitude not to compromise the interpretation or validity of the results. The coefficient suggests that farmers tend to maintain a consistent volume of risky sowing across seasons, regardless of the dry spell probability provided. In contrast, experiencing a dry spell shock in the previous season leads to a substantial reduction in risky sowing in the current one—on average, farmers sow 12.6% fewer seeds in the season following the shock regardless of the dry spell probability, reflecting greater caution.

Table 2.1 – Effects on the number of seeds sown in the risky period in the Fixed Effects Model and in the Autogressive Model

Number of seeds sown in the risky period *(dependent variable)*	**Fixed Effects Model** (1)	**Autoregressive Model** (2)
30% dry spell probability	−1.546***	−1.538***
	(0.086)	(0.086)
50% dry spell probability	−2.838***	−2.827***
	(0.093)	(0.092)
70% dry spell probability	−4.146***	−4.101***
	(0.125)	(0.124)
90% dry spell probability	−5.597***	−5.546***
	(0.138)	(0.138)
Past sowing		−0.069***
		(0.014)
Past dry spell		−0.126*
		(0.069)
R^2	0.614	0.646
Adj. R^2	0.574	0.605
Num. obs.	3443	3130

Notes: *** p < 0.01; ** p < 0.05; * p < 0.1 significance levels Standard errors clustered at the individual level are reported in parentheses (HC3 robust). Coefficients are interpreted relative to the reference category: a 10% dry spell probability.

In the light of this results, it is interesting to further analyze the detailed effects of these individual characteristics on the risky sowing decision. We, thus, include relevant variables that reflect farmers' psychological and socioeconomic characteristics. These include: i) Risk appraisal, captured through the perceived likelihood and perceived severity of dry spell impacts; ii) Locus of control, self-efficacy, and willingness to adapt, in line with behavioural economics literature iii) Education level, as a proxy for familiarity with probabilistic reasoning; and iv) Household food security, given the subsistence role of maize in the study area. The methods used to construct the aforementioned variables are detailed in the sample description section of this chapter *(section 2.4.).*

As the fixed-effects models cannot estimate time-invariant variables, we regress the individual fixed effects estimated from the second model on individual characteristics in order to assess their influence on sowing decisions.

$$\alpha_j = \beta_0 + \beta_1 Psy_j + \beta_2 Risk_{appraisal_j} + \beta_3 Edu + \beta_4 FIES_j + \varepsilon_j \quad (7)$$

with:

α_j: Individual fixed effects for farmer j from equation 6;

Psy_j: Vector of psychological variables, including Locus of control LoC_j, perceived self-efficacy $self_{efficacy_j}$ and Willingness to adapt agricultural practices to climate changes in real life $Intent_j$;

$Risk_{appraisal_j}$: Vector capturing perceived risk, including the perceived frequency of dry spells $freq_{dry_j}$, and the severity of maize losses due to dry spells $loss_{corn_j}$;

Edu_j: Formal education level;

$FIESj$: Food Insecurity Experience Scale (FIES) of the farmer's household over the past 12 months.

ε_j: Idiosyncratic error term.

Results are presented in *Table 2.2*. These individual characteristics explain only a limited share of the variation in the fixed effects obtained from the first model. The following findings hold regardless of the dry spell probability, reflecting general patterns in farmers' behaviour across all probabilities. Among the psychological and perceptual variables, willingness to adapt agricultural practices is associated with less cautious sowing behaviour, although the effect size is small and only weakly significant. In contrast, the perceived severity of maize losses due to dry spells is significantly associated with more cautious sowing decisions. Additionally, a higher level of formal education is negatively correlated with risky sowing, suggesting that more educated farmers are less likely to adopt riskier sowing strategies. Other variables do not show statistically significant effects.

Table 2.2 - Weights of individual characteristics in the fixed effects

Fixed effects *(dependent variable)*	Coefficient
Psychological factors	
Locus of Control	0.155
	(0.117)
Self-efficacy	−0.066
	(0.062)
Willingness to Adapt	0.105*
	(0.057)
Risk appraisal	
Maize Losses	−0.154**
	(0.074)
Dry Spell Frequency	0.051
	(0.057)
Socioeconomic characteristics	
Food Security	0.007
	(0.029)
Education (Years)	−0.221**
	(0.101)
R^2	0.042
Adjusted R^2	0.020
Number of observations	313

Notes: *** p<0.01; ** p<0.05; * p<0.1 significance levels.
Standard errors clustered in parenthesis

However, the literature suggests that some of these individual characteristics may also influence risk perception (Maltby et al., 2021) or risk preferences (Schrieks et al., 2024). We therefore explore their indirect effects by examining interactions between these characteristics and the dry spell probabilities presented during the experiment.

$$x_{jk}^{risky} = \beta_0 + \beta_1 x_{j,k-1}^{risky} + \beta_2 dry_{j,k-1} + \sum_{s\in S'}\big[\beta_s D_{jk}(P_s) + \delta_{1s}\big(D_{jk}(P_s)\cdot Psy_j\big) + \delta_{2s}\big(D_{jk}(P_s) + \cdot\, RiskAppraisal_j\big) + \delta_{3s}\big(D_{jk}(P_s)\cdot Edu_j\big) + \delta_{4s}\big(D_{jk}(P_s)\cdot FIES_j\big)\big] + \alpha_j + \gamma_k + \varepsilon_{jk} \qquad (8)$$

With

x_{jk}^{risky}: Number of seeds sown in the risky period by farmer *j* at season k;

$x_{j,k-1}^{risky}$: Number of seeds sown in the risky period by farmer *j* at season $k-1$;

$dry_{j,k-1}$: Binary variable indicating dry spell occurrence for farmer $j$at season $k-1$;

$D_{jk}(P_s)$:Indicator variable equal to 1 if farmer $j$received probability $P_s$at season k, and 0 otherwise.

$P_s \in \{0.1,0.3,0.5,0.7,0.9\}$: Probability categories used in the model (with $P_s = 0.1$ as the reference group)

$\delta_{1s}\delta_{2s}\delta_{3s}\delta_{4s}$: Interaction coefficients between probability P_s and respectively:

Psy_j: Vector of psychological traits (e.g., locus of control, self-efficacy, and willingness to adapt);

$Risk_{appraisal_j}$: Vector representing risk appraisal (e.g., perceived frequency and severity of dry spells);

Edu_j: Farmer's level of formal education;

$FIESj$: Food Insecurity Experience Scale (FIES) of the farmer's household over the past 12 months.

α_j: Individual fixed effects for farmer j;

γ_k : Time fixed effects for season k;

ε_{jk}: Idiosyncratic error term.

To facilitate interpretation, we grouped dry spell probabilities into three categories: low probability (10%), medium probability (30% and 50%), and high probability (70% and 90%). The corresponding results are presented in *Table 2.3*. Results using disaggregated probabilities are available in *Appendix 2.B*. The following findings confirm the robust effect of dry spell probabilities on sowing decisions.

Consistent with findings in the literature, the locus of control appears to influence risk perception and behaviour. Specifically, a stronger internal locus of control—the belief that outcomes depend on one's own actions—reduces the precautionary response to medium and high dry spell probabilities. In other words, individuals with an internal locus of control are more likely to maintain risky sowing strategies under increasing levels of dry spell probabilities. Notably, this attenuation of the higher probability's cautionary effect is almost twice as pronounced for high probabilities compared to medium ones.

By contrast, a stronger willingness to adapt amplifies the precautionary response to medium and high probabilities: farmers who believe in their ability to adjust their practices are more responsive to the information and tend to reduce risky sowing volumes more significantly. Similarly, as expected, farmers who have previously experienced maize losses due to dry spells are also more sensitive to medium and high probabilities. Interestingly, the magnitude of their sowing reduction is comparable for both medium and high probabilities. Finally, higher levels of formal education are associated with greater responsiveness to medium and high probabilities. The remaining variables do not show statistically significant effects.

Table 2.3 - Interaction effects between dry spell probabilities and individual characteristics

Number of seeds sown in the risky period *(dependent variable)*	**Multiplicative Model** Coefficient
Main effects	
Medium dry spell probability [30%–50%]	−1.773**
	(0.719)
High dry spell probability [70%–90%]	−4.917***
	(1.104)
Past sowing	−0.069***
	(0.015)
Past dry spell	−0.096
	(0.074)
Interactions with a Medium dry spell probability	
Locus of Control	0.424***
	(0.160)
Self-efficacy	−0.103
	(0.077)
Willingness to adapt	−0.144**
	(0.073)
Maize losses	−0.352***
	(0.093)
Dry spell frequency	0.105
	(0.075)
Food security	0.045
	(0.036)
Education	−0.208*
	(0.118)
Interactions with a High dry spell probability	
Locus of Control	0.763***
	(0.259)
Self-efficacy	−0.141
	(0.125)
Willingness to adapt	−0.241**
	(0.111)
Maize losses	−0.387**
	(0.157)
Dry spell frequency	0.096
	(0.117)
Food security	0.092
	(0.058)
Education	−0.406**
	(0.198)
R^2	0.592
Adjusted R^2	0.542
Number of observations	3130

Notes**:** Significance levels: *** p<0.01; ** p<0.05; * p<0.1. Standard errors clustered at the individual level (HC3 robust) are reported in parentheses. Coefficients are interpreted relative to the reference category: a 10% dry spell probability.

2.5.3. Seed allocation

Under the expected gain maximization criterion, the theoretical optimal strategies in the experiment correspond to corner solutions, where all 10 seeds are allocated either to the risky or the safe period depending on the probability (see *Appendix 2.D*).

Let:

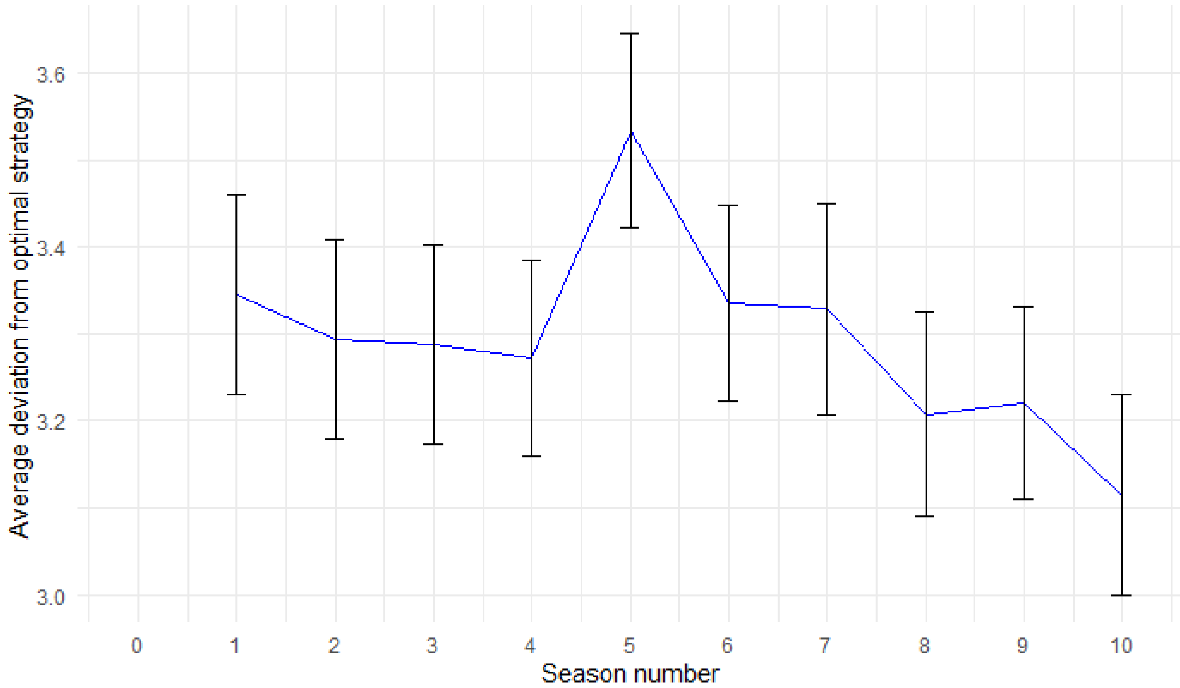
- $x_j^{risky*\vee P_s}$: the optimal risky sowing amount for farmer$j$, i.e., the allocation that maximizes expected gain at dry spell probability P_s;
- $x_j^{risky} \vee P_s$: the actual risky sowing amount chosen by farmer j for probability P_s.

The gap between the actual sowing decision and the optimal strategy is expressed as:

$$\theta_j = \qquad (9)$$

Figure 2.12 presents the average deviation from the optimal strategy across the sample for each dry spell probability. Additionally, we estimate the average number of additional seasons required for farmers to converge toward the optimal strategy—defined as the point at which the gap θ_j reaches zero or a value close to zero. Details of this convergence analysis are provided in *Appendix 2.D*.

Figure 2.12 - Evolution of the average deviation between farmers' sowing strategy and the optimal strategy



Notes: *Figure 2.12* illustrates the average deviation between farmers' actual sowing strategies and the optimal strategy, measured in terms of seeds allocated to the risky period. Season 0 corresponds to the *No-Forecast* scenario.

The gap between farmers' sowing strategies and the optimal sowing strategy ranges between 3.1 and 3.6 seeds which means that there is no major change in their allocation strategy. We do not observe any convergence in round 1 (Seasons 1 to 5). However, in round 2 (Seasons 6 to 10), the average gap tends to decrease over the seasons meaning that they seem to get closer to the optimal strategy.

To examine differences across dry spell probability levels, we estimate a simple fixed-effects regression that accounts for individual heterogeneity and time effects. As a robustness check, we replicate the analysis—both the graphical representation and the estimations presented in this section—using a restricted sample that excludes farmers with low engagement scores and those who failed the comprehension test (see *Appendix 2.E*). These checks confirm that the main results are robust to the exclusion of these respondents, with no substantive change in the quality of the estimates.

The following estimates can be interpreted as the average causal effect of dry spell probabilities on the gap between farmers' actual sowing decisions and the theoretical optimum, as defined by Equation (9):

$$\theta_{jk} = \beta_0 + \sum_{s \in S} \beta_s D_{jk}(P_s) + \alpha_j + \gamma_k + \varepsilon_{jk} \quad (10)$$

Where:

θ_{jk}: Deviation from the optimal strategy for farmer j at season$k$;

$D_{jk}(P_s)$:Indicator variable equal to 1 if farmer $j$received probability $P_s$at season k, and 0 otherwise.

$P_s \in \{0.1, 0.3, 0.5, 0.7, 0.9\}$: Probability categories used in the model (with $P_s = 0.1$ as the reference group)

α_j: Individual fixed effects

γ_k : Time fixed effects

ε_{jk}: Idiosyncratic error term

As with the previous analysis of sowing mechanisms, we also estimate an autoregressive specification to account for potential serial correlation in the error terms and to better capture temporal dynamics between consecutive seasons. System GMM specifications encountered the same problem as with the previous section (see *Appendix 2.A)*

This model incorporates both the lagged gap and the occurrence of a dry spell in the previous season as explanatory variables:

$$\theta_{jk} = \beta_0 + \beta_1 \theta_{j,k-1} + \beta_2 dry_{j,k-1} + \sum_{s \in S} \beta_s D_{jk}(P_s) + \alpha_j + \gamma_k + \varepsilon_{jk} \quad (11)$$

Where:

- $\theta_{j,k-1}$: Gap between actual and optimal sowing in season $k-1$;
- $dry_{j,k-1}$: Binary variable indicating whether a dry spell occurred for farmer j in season $k-1$.

Results are presented in *Table 2.4* below.

Table 2.4 - Determinants of the seed allocation under varying dry spell probability

Deviation from optimal strategy *(dependent variable)*	**Fixed Effects Model** (1)	**Autoregressive Model** (2)
30% dry spell probability	1.544***	1.559***
	(0.086)	(0.088)
50% dry spell probability	2.842***	2.810***
	(0.093)	(0.095)
70% dry spell probability	2.224***	2.134***
	(0.121)	(0.121)
90% dry spell probability	0.771***	0.711***
	(0.115)	(0.116)
Past sowing gap		−0.130***
		(0.021)
Past dry spell		−0.011
		(0.062)
R^2	0.288	0.321
Adjusted R^2	0.205	0.232
Number of observations	3130	2817

Notes: *** p<0.01; ** p<0.05; * p<0.1 significance levels. Standard errors clustered at the individual level are reported in parentheses. Coefficients are interpreted relative to the reference category: a 10% dry spell probability.

The deviation from the optimal sowing strategy tends to be larger at medium probabilities than at high or low dry spell probabilities. These findings suggest that under medium dry spell probabilities (30%, 50%, 70%), farmers are less likely to adopt corner solutions, preferring instead to allocate maize seeds between the risky and safe periods. In contrast, at the extremes of the probability distribution—namely 10% and 90%—farmers are more inclined to sow all seeds-or-no seeds. Interestingly, the gap is larger at the 10% probability than at 90%, indicating that even under conditions of low perceived risk, farmers remain somewhat cautious and do not fully allocate their seeds to the risky period. On the other hand, when the probability of a dry spell reaches 90%, farmers appear more comfortable allocating zero seeds to the risky period. These results remain robust when lagged variables are introduced into the model.

Unlike graphical analysis, the significant coefficient on the lagged sowing gap suggests that farmers adjust their behaviour over time, gradually aligning their choices more closely with the optimal strategy. The occurrence of a dry spell in the previous season does not have a statistically significant effect on the gap with the optimal strategy.

As with the analysis of risky sowing mechanisms, we also examine how individual characteristics contribute to variation in fixed effects of the autoregressive model, using the following specification:

$$\alpha_j = \beta_0 + \beta_1 Psy_j + \beta_2 Risk_{appraisal_j} + \beta_3 Edu + \beta_4 FIES_j + \varepsilon_j \quad (12)$$

Where:

α_j: Individual fixed effects for farmer j;

Psy_j: Vector of psychological traits (including locus of control, self-efficacy, and willingness to adapt);

$Risk_{appraisal_j}$: Vector capturing perceived frequency and severity of dry spells;

Edu_j: Farmer's level of formal education;

$FIESj$: Food Insecurity Experience Scale (FIES) for the household over the 12 last months;

ε_j: Idiosyncratic error term.

Results are presented in *Table 2.5*. Overall, individual characteristics explain only a small proportion of the variation in fixed effects. Nevertheless, farmers who report a strong willingness to adapt their practices are more likely to behave in line with the optimal strategy. In contrast, a stronger internal locus of control is associated with greater deviation from optimal behaviour, as these farmers tend to allocate their sowing across periods. A similar, though weaker, tendency is observed among farmers from food-insecure households. The other variables do not exhibit statistically significant effects.

Table 2.5 - Weights of individual characteristics in explaining the fixed effects

Fixed effects *(dependent variable)*	Coefficient
Psychological factors	
Locus of Control	0.233**
	(0.098)
Self-efficacy	−0.030
	(0.052)
Willingness to Adapt	−0.110**
	(0.048)
Risk appraisal	
Maize Losses	−0.040
	(0.062)
Dry Spell Frequency	0.006
	(0.048)
Socioeconomic characteristics	
Food Security	0.042*
	(0.025)
Education (Years)	−0.093
	(0.085)
R^2	0.065
Adjusted R^2	0.044
Number of observations	313

Notes: *** p<0.01; ** p<0.05; * p<0.1 significance levels. Standard errors in parentheses

2.6. Discussion

Despite the presence of some extreme negative values, access to dry spell probabilities consistently improves farmers' potential harvests compared to a situation without any information available. These expected gains are especially pronounced at the lowest and highest probability levels of dry spells (10% and 90%). This finding is consistent with the results of Roudier et al. (2016), who observed similar outcomes in their simulations of seasonal forecasts for millet in Niger.

In the experiment, farmers rely mainly on dry spells probabilities for their sowing decision making. The highest is the dry spell probability, the lowest is the risky sowing. The observed effects are non-linear, as a stronger effect is observed for extreme levels of probability (10% and 90%). These results remain robust with the inclusion of autoregressive terms and interaction variables. The risky sowing associated with the *No-Forecast* scenario closely mirrors that of the 50% dry spell probability, a finding consistent with Laplace's principle, which posits that in the absence of information, individuals tend to assign equal probabilities to all possible outcomes. Farmers sowed an average of 5.28 seeds in the *No-Forecast* scenario, versus 5.34 seeds under a 50% probability. These finding echoes those of Charness & Gneezy (2010), who argue that individuals do not necessarily reduce investment under ambiguity than under risk. However, a key distinction emerges in the *No-Forecast* scenario, since the minimum risky sowing never dropped to zero, whereas at 50% dry spell probability, some farmers completely withdrew from risky sowing. Observed levels of risky sowing at 50% probability also align with Charness and Viceisza (2016), whose field experiment with Senegalese farmers—though based on a single season with a 50% drought probability and monetary returns in CFA francs—yielded similar average sowing levels among men (5.72 seeds). Interestingly, in their study, women sowed significantly fewer risky seeds, averaging 4.18. This suggests that incorporating a female sample in future replications of our experiment could yield insightful gender-based comparisons.

Furthermore, the results reveal a hysteresis effect of previous sowing quantities on current sowing behaviour. Farmers appear to adjust their sowing decisions based on their prior risky sowing levels, even though the game clearly stipulates each season's settings are solely independent in the experiment. This behaviour deviates from a fully rational interpretation of the experimental rules and is consistent with findings by Holden et al. (2022), who argue that investment decisions in repeated Gneezy and Potters-type experiments can be influenced by previous risky investment levels and prior gains or losses. In a similar vein, our results show that risky sowing adjustments also respond to the experience of a dry spell in the previous season. Specifically, a dry spell shock tends to reduce the risky sowing in the following season, regardless of the probability of dry spell. Nevertheless, the primary explanatory factor of sowing behaviour in the experiment remains the information on dry spell probability, which alone accounts for 57% of the variation in risky sowing decisions ($R^2 = 0.57$). Yet, it is not the only determinant.

To better understand the role of individual heterogeneity, we analysed both the composition of fixed effects and the interactions between dry spell probabilities and individual characteristics—including psychological traits, risk appraisal, education, and food insecurity. The fixed effects capture the direct influence of these characteristics on risky sowing behaviour, while the interaction terms reveal their indirect effects—namely, whether they amplify or mitigate the behavioural response to the forecast. The results suggest that the response to dry spell probabilities may vary significantly depending on farmers' profiles.

Contrary to Schrieks et al. (2024)—who found, in a study with agro-pastoralists in Kenya using a MPL, that a high internal locus of control is associated with greater risk-taking, we do not observe such a general effect in our data. However, we find that this psychological trait moderates the influence of dry spell probabilities, by reducing the sowing response in medium and high-risk levels. The willingness to adapt agricultural practices shows a dual influence on sowing behaviour. On the one hand, farmers with strong adaptive intentions are more likely to engage in risky sowing regardless of the probability level presented. On the other hand, when confronted with medium or high dry spell risks, these same individuals reduce their risky sowing more significantly. Farmers who have previously experienced maize losses due to dry spells tend to be more cautious overall. Their responses to medium and high dry spell probabilities are also more pronounced, indicating that personal experience with weather shocks amplifies the effects of the information. This result supports the existing literature on the influence of past shocks on risk behaviour. For example, Freudenreich and Musshoff (2022) show that farmers in Mexico who have suffered maize losses became more risk averse. However, they also noted that these farmers tended to overweight low-probability events and underweight high-probability ones, a pattern that does not emerge in our findings. Lastly, the results related to formal education follow a similar trend to that of maize loss experience. Farmers with higher levels of formal education tend to reduce risky sowing according to probability levels, a finding that partially contradicts previous research—such as Zeweld et al., (2019) which often links higher education with increased willingness to take agricultural risks. These findings underline the importance of designing climate services that are more closely aligned with users' individual characteristics.

The variables tested in this study explain part of the decision-making process regarding sowing strategies. However, further research is needed to explore additional mechanisms, such as the role of *worry* (Schrieks et al., 2024) or, more broadly, *eco-anxiety*. Given the challenges of adapting existing eco-anxiety scales to developing country contexts (Hogg et al., 2021), two proxy variables were included in the data collection: concern for income and concern for household food security due to future dry spells. However, both indicators exhibited low response variability, limiting their analytical usefulness. A broader response scale may have improved their discriminative power.

Concerning sowing allocation strategies, farmers tend to not adopt corner solutions — sowing either all or none of their seeds in the risky period — even though it is supposed to be the rational behaviour with this experiment settings. They only do when faced with extreme probabilities (10% or 90%). At medium levels (30%, 50%, 70%), they are more likely to divide their seeds endowment between the risky and safe periods. Notably, the deviation from the corner solution is greater at 10% than at 90%, suggesting that even under low probability conditions, many farmers remain cautious and do not fully allocate their seeds to the risky option. This behaviour may reflect an endowment effect associated with the Gneezy and Potters investment game, as discussed by Holden & Tilahun, (2022) or a safety-first strategy aimed at minimizing potential losses. The latter explanation appears particularly plausible given that farmers in food-insecure households are less inclined to adopt an 'all-or-nothing' sowing strategy. These findings underline the relevance of complementary instruments—such as climate insurance—to enhance the uptake and effectiveness of climate services. Such mechanisms are especially important for populations that depend heavily on rainfed agriculture for their food security.

The study's main limitations arise from the necessary simplifications inherent to experimental modelling. These include the exclusion of constraints such as labour availability or input access, and the absence of social interactions such as imitation effects. Additionally, we assume that the psychological impacts of losing all or part of a maize harvest due to dry spells may be underestimated in this type of modelling, given the importance of these harvests for household food security in the region. Finally, the experiment assumes perfect information reliability, which is not the case in real-world settings with forecasts. Furthermore, including mid-experiment attention checks could have refined response patterns.

2.7. Conclusion

This article has modelled, through an experimental approach, the impact of dry spell probabilities on maize sowing decisions among farmers in northern Côte d'Ivoire. It contributes to the literature on the effects of climate services on agricultural decision-making by introducing an innovative intra-individual design. The experiment is both easily comprehensible and replicable among low-educated rural populations in developing countries.

The results demonstrate that farmers adjust their sowing strategies to probabilistic weather information, and it consistently improves farmers' expected harvests in comparison to a situation without information. However, even under very low probabilities of dry spells, many farmers remain cautious and do not fully allocate their seeds to the risky option.

Dry spell probabilities emerge as the primary factor influencing sowing decisions in this experiment. However, the findings indicate that behavioural responses to forecasts are mediated by a combination of psychological and experiential factors. Farmers with a strong internal locus of control appear less responsive to medium and high dry spell probabilities, indicating a tendency to rely more on their own agency than on external information. By contrast, individuals who have experienced significant maize losses in the past or who have higher levels of formal education are more likely to adjust the quantity of risky sowing in response to forecasts, reflecting greater sensitivity to probabilistic signals.

Behavioural patterns emerge also in seed allocation strategies. Farmers with a high willingness to adapt are more inclined to adopt an all-or-nothing approach, concentrating their sowing exclusively in either the risky or the safe period, depending on the forecast. In contrast, those with a strong internal locus of control or experiencing food insecurity are more likely to distribute their sowing across both periods, thereby maintaining a diversified strategy regardless of the probability. These findings suggest that adaptation is not solely driven by external information but is also strongly influenced by individual perceptions and psychological traits.

From an operational perspective, the findings underscore the potential of using probability formats to communicate weather information to low-literate farmers. This type of information could deliver considerable productivity gains, particularly if paired with compensatory mechanisms such as Index-Based insurance to bridge the gap between potential and realized outcomes. Lastly, given that individual characteristics shape how farmers perceive and act upon weather information, future climate services should be tailored to farmers' profiles to reach their full potential.

References of Chapter 2

Abay, K. A., Blalock, G., & Berhane, G. (2017). Locus of control and technology adoption in developing country agriculture: Evidence from Ethiopia. *Journal of Economic Behaviour & Organization*, *143*, 98-115. https://doi.org/10.1016/j.jebo.2017.09.012

Adesina, A. A., & Ouattara, A. D. (2000). Risk and agricultural systems in northern Côte d'Ivoire. *Agricultural Systems*, *66*(1), 17-32. https://doi.org/10.1016/S0308-521X(00)00033-0

Antwi-Agyei, P., Dougill, A. J., & Abaidoo, R. C. (2021). Opportunities and barriers for using climate information for building resilient agricultural systems in Sudan savannah agro-ecological zone of north-eastern Ghana. *Climate Services*, *22*, 100226. https://doi.org/10.1016/j.cliser.2021.100226

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioural change. *Psychological Review*, *84*(2), 191-215. https://doi.org/10.1037/0033-295X.84.2.191

Basse, J., Camara, M., Diba, I., & Diedhiou, A. (2024). Projected Changes in Dry and Wet Spells over West Africa during Monsoon Season Using Markov Chain Approach. *Climate*, *12*(12), Article 12. https://doi.org/10.3390/cli12120211

Bassett, T. J. (2002). Women's Cotton and the Spaces of Gender Politics in Northern Cote d'Ivoire. *Gender, Place & Culture*, *9*(4), 351-370. https://doi.org/10.1080/0966369022000024669

Bauermeister, G., & Musshoff, O. (Éds.). (2016). *Risk Aversion and Inconsistencies—Does the Choice of Risk Elicitation Method and Display Format Influence the Outcomes?* https://doi.org/10.22004/ag.econ.235348

Boko, M. (1992). Saisons et types de temps au Bénin : Analyse objective et perceptions populaires. *L'Espace géographique*, *21*(4), 321-332.

Boko-Koiadia Adjoua, N., Cissé, G., Koné, B., & Séri, D. (2016). Variabilité Climatique Et Changements Dans L'environnement À Korhogo En Côte D'ivoire : Mythes Ou Réalité ? *European Scientific Journal, ESJ*, *12*(5), 158. https://doi.org/10.19044/esj.2016.v12n5p158

Born, L., Prager, S., Ramirez-Villegas, J., & Imbach, P. (2021). A global meta-analysis of climate services and decision-making in agriculture. *Climate Services*, *22*, 100231. https://doi.org/10.1016/j.cliser.2021.100231

Brañas-Garza, P., Estepa-Mohedano, L., Jorrat, D., Orozco, V., & Rascón-Ramírez, E. (2021). To pay or not to pay: Measuring risk preferences in lab and field. *Judgment and Decision Making*, *16*(5), 1290-1313. https://doi.org/10.1017/S1930297500008433

Brañas-Garza, P., Jorrat, D., Espín, A. M., & Sánchez, A. (2023). Paid and hypothetical time preferences are the same: Lab, field and online evidence. *Experimental Economics*, *26*(2), 412-434. https://doi.org/10.1007/s10683-022-09776-5

Brick, K., Visser, M., & Burns, J. (2012). Risk Aversion: Experimental Evidence from South African Fishing Communities. *American Journal of Agricultural Economics*, *94*(1), 133-152. https://doi.org/10.1093/ajae/aar120

Brown, P., Daigneault, A. J., Tjernström, E., & Zou, W. (2018). Natural disasters, social protection, and risk perceptions. *World Development*, *104*, 310-325. https://doi.org/10.1016/j.worlddev.2017.12.002

Burnham, M., & Ma, Z. (2017). Climate change adaptation: Factors influencing Chinese smallholder farmers' perceived self-efficacy and adaptation intent. *Regional Environmental Change*, *17*. https://doi.org/10.1007/s10113-016-0975-6

Carr, E. R., & Onzere, S. N. (2018). Really effective (for 15% of the men) : Lessons in understanding and addressing user needs in climate services from Mali'. *Climate Risk Management*, *22*, 82-95. https://doi.org/10.1016/j.crm.2017.03.002.

Carter, M. R. (2016). What farmers want: The "gustibus multiplier" and other behavioural insights on agricultural development. *Agricultural Economics*, *47*(S1), 85-96. https://doi.org/10.1111/agec.12312

Charness, G., & Gneezy, U. (2010). PORTFOLIO CHOICE AND RISK ATTITUDES: AN EXPERIMENT. *Economic Inquiry*, *48*(1), 133-146. https://doi.org/10.1111/j.1465-7295.2009.00219.x

Charness, G., & Viceisza, A. (2016). Three Risk-elicitation Methods in the Field: Evidence from Rural Senegal. *Review of Behavioural Economics*, *3*(2), 145-171. https://doi.org/10.1561/105.00000046

Crochemore, L., Cantone, C., Pechlivanidis, I. G., & Photiadou, C. S. (2021). How Does Seasonal Forecast Performance Influence Decision-Making? Insights from a Serious Game. *Bulletin of the American Meteorological Society*, *102*(9), E1682-E1699. https://doi.org/10.1175/BAMS-D-20-0169.1

Dave, C., Eckel, C. C., Johnson, C. A., & Rojas, C. (2010). Eliciting risk preferences: When is simple better? *Journal of Risk and Uncertainty*, *41*(3), 219-243. https://doi.org/10.1007/s11166-010-9103-z

Dekoula, C. S., Kouame, B., N'goran, E. K., Yao, F. G., Ehounou, J.-N., & Soro, N. (2018). Impact De La Variabilité Pluviométrique Sur La Saison Culturale Dans La Zone De Production Cotonnière En Côte d'Ivoire. *European Scientific Journal, ESJ*, *14*(12), 143. https://doi.org/10.19044/esj.2018.v14n12p143

Dekoula, C. S., Kouame, B., N'Goran, K. E., Ehounou, J.-N., Yao, G. F., Kassin, K. E., Kouakou, J. B., N'Guessan, A. E. B., & Soro, N. (2019). Variabilité des descripteurs pluviométriques intrasaisonniers à impact agricole dans le bassin cotonnier de Côte d'Ivoire : Cas des zones de

Boundiali, Korhogo et Ouangolodougou. *Journal of Applied Biosciences*, *130*(1), 13199. https://doi.org/10.4314/jab.v130i1.7

Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., & Wagner, G. G. (2011). Individual Risk Attitudes: Measurement, Determinants, and Behavioural Consequences. *Journal of the European Economic Association*, *9*(3), 522-550. https://doi.org/10.1111/j.1542-4774.2011.01015.x

Ducroquet, H., Tillie, P., Louhichi, K. et G.-Y.-P., & S. (2017). L'agriculture de la Côte d'Ivoire à la loupe : Etats des lieux des filières de production végétales et animales et revue des politiques agricoles'. In *EUR 28754 FR*. Publications Office of the European Union. https://doi.org/10.2760/126254

Ellsberg, D. (1961). Risk, Ambiguity, and the Savage Axioms*. *The Quarterly Journal of Economics*, *75*(4), 643-669. https://doi.org/10.2307/1884324

Estepa-Mohedano, L., & Espinosa, M. P. (2023). Comparing risk elicitation in lotteries with visual or contextual aids. *Journal of Behavioural and Experimental Economics*, *103*, 101974. https://doi.org/10.1016/j.socec.2022.101974

Freudenreich, H., & Musshoff, O. (2022). Experience of losses and aversion to uncertainty—Experimental evidence from farmers in Mexico. *Ecological Economics*, *195*, 107379. https://doi.org/10.1016/j.ecolecon.2022.107379

Gaetani, M., Janicot, S., Vrac, M., Famien, A. M., & Sultan, B. (2020). Robust assessment of the time of emergence of precipitation change in West Africa. *Scientific Reports*, *10*(1), 7670. https://doi.org/10.1038/s41598-020-63782-2

Gneezy, U., & Potters, J. (1997). An Experiment on Risk Taking and Evaluation Periods*. *The Quarterly Journal of Economics*, *112*(2), 631-645. https://doi.org/10.1162/003355397555217

Grothmann, T., & Patt, A. (2005). Adaptive capacity and human cognition: The process of individual adaptation to climate change. *Global Environmental Change*, *15*(3), 199-213. https://doi.org/10.1016/j.gloenvcha.2005.01.002

Guido, Z., Zimmer, A., Lopus, S., Hannah, C., Gower, D., Waldman, K., ... & Evans, T. (2020). Farmer forecasts: Impacts of seasonal rainfall expectations on agricultural decision-making in Sub-Saharan Africa. *Climate Risk Management*, *30*, 100247.

Hill, R. V., & Viceisza, A. (2012). A field experiment on the impact of weather shocks and insurance on risky investment. *Experimental Economics*, *15*(2), 341-371. https://doi.org/10.1007/s10683-011-9303-7

Hogg, T. L., Stanley, S. K., O'Brien, L. V., Wilson, M. S., & Watsford, C. R. (2021). The Hogg Eco-Anxiety Scale: Development and validation of a multidimensional scale. *Global Environmental Change*, *71*, 102391. https://doi.org/10.1016/j.gloenvcha.2021.102391

Holden, S. T., & Tilahun, M. (2022). Endowment effects in the risky investment game? *Theory and Decision*, *92*(1), 259-274. https://doi.org/10.1007/s11238-021-09821-4

Holt, C. A., & Laury, S. K. (2002). *Risk Aversion and Incentive Effects*.

Ihli, H. J., Chiputwa, B., & Musshoff, O. (Éds.). (2013). *Do Changing Probabilities or Payoffs in Lottery-Choice Experiments Matter? Evidence from Rural Uganda*. https://doi.org/10.22004/ag.econ.158146

Julia Ihli, H., Chiputwa, B., Winter, E., & Gassner, A. (2022). Risk and time preferences for participating in forest landscape restoration: The case of coffee farmers in Uganda. *World Development*, *150*, 105713. https://doi.org/10.1016/j.worlddev.2021.105713

Kemeze, F. H., Miranda, M. J., Kuwornu, J. K. M., & Anim-Somuah, H. (2020). Smallholder Farmer Risk Preferences in Northern Ghana:Evidence from a Controlled Field Experiment. *The Journal of Development Studies*, *56*(10), 1894-1908. https://doi.org/10.1080/00220388.2020.1715945

Kreft, C., Huber, R., Wuepper, D., & Finger, R. (2021). The role of non-cognitive skills in farmers' adoption of climate change mitigation measures. *Ecological Economics*, *189*, 107169. https://doi.org/10.1016/j.ecolecon.2021.107169

Kumar, U., Werners, S., Paparrizos, S., Datta, D., & Ludwig, F. (2021). Co-producing Climate Information Services with Smallholder Farmers in the Lower Bengal Delta: How forecast visualization and communication support farmers' decision-making. *Climate Risk Management*, *33*, 100346. https://doi.org/10.1016/j.crm.2021.100346

Leblois, A., Le Cotty, T., & Maître d'Hôtel, E. (2020). How Might Climate Change Influence Farmers' Demand for Index-Based Insurance? *Ecological Economics*, *176*, 106716. https://doi.org/10.1016/j.ecolecon.2020.106716

Lemos, M. C., Kirchhoff, C. J., & Ramprasad, V. (2012). Narrowing the climate information usability gap. *Nature Climate Change*, *2*(11), 789-794. https://doi.org/10.1038/nclimate1614

Li, J.-Z., Li, S., Wang, W.-Z., Rao, L.-L., & Liu, H. (2011). Are people always more risk averse after disasters? Surveys after a heavy snow-hit and a major earthquake in China in 2008. *Applied Cognitive Psychology*, *25*(1), 104-111. https://doi.org/10.1002/acp.1648

Maltby, K. M., Simpson, S. D., & Turner, R. A. (2021). Scepticism and perceived self-efficacy influence fishers' low risk perceptions of climate change. *Climate Risk Management*, *31*, 100267. https://doi.org/10.1016/j.crm.2020.100267

Menapace, L., Colson, G., & Raffaelli, R. (2016). A comparison of hypothetical risk attitude elicitation instruments for explaining farmer crop insurance purchases. *European Review of Agricultural Economics*, *43*(1), 113-135. https://doi.org/10.1093/erae/jbv013

Müller-Mahn, D., Moure, M., & Gebreyes, M. (2020). Climate change, the politics of anticipation and future riskscapes in Africa. *Cambridge Journal of Regions, Economy and Society*, *13*(2), 343-362. https://doi.org/10.1093/cjres/rsaa013

Nkiaka, E. (2019). Identifying user needs for weather and climate services to enhance resilience to climate shocks in sub-Saharan Africa'. *Environmental Research Letters*, *14*(12), 123003. https://doi.org/10.1088/1748-9326/ab4dfe.

Nyamekye, A. B., Nyadzi, E., Dewulf, A., Werners, S., Van Slobbe, E., Biesbroek, R. G., ... & Ludwig, F. (2021). Forecast probability, lead time and farmer decision-making in rice farming systems in Northern Ghana. Climate Risk Management, 31, 100258.

Rotter, J. B. (1966). *Rotter's Internal-External Control Scale*.

Roudier, P., Alhassane, A., Baron, C., Louvet, S., & Sultan, B. (2016). Assessing the benefits of weather and seasonal forecasts to millet growers in Niger. *Agricultural and Forest Meteorology*, *223*, 168-180. https://doi.org/10.1016/j.agrformet.2016.04.010

Roudier, P., Muller, B., d'Aquino, P., Roncoli, C., Soumare, M., Batté, L., & Sultan, B. (2014). The role of climate forecasts in smallholder agriculture: Lessons from participatory research in two communities in Senegal. *Climate Risk Management*, *2*, 42-55. https://doi.org/10.1016/j.crm.2014.02.001

Roudier, P., Sultan, B., Quirion, P., & Berg, A. (2011). The impact of future climate change on West African crop yields: What does the recent literature say? *Global Environmental Change*, *21*(3), 1073-1083. https://doi.org/10.1016/j.gloenvcha.2011.04.007

Schrieks, T., Botzen, W. J. W., Haer, T., & Aerts, J. C. J. H. (2024). Drought risk attitudes in pastoral and agro-pastoral communities in Kenya. *Journal of Behavioural and Experimental Economics*, *108*, 102143. https://doi.org/10.1016/j.socec.2023.102143

Sivakumar, M. V. K. (1988). Predicting rainy season potential from the onset of rains in Southern Sahelian and Sudanian climatic zones of West Africa. *Agricultural and Forest Meteorology*, *42*(4), 295-305. https://doi.org/10.1016/0168-1923(88)90039-1

Stern, R., Rijks, D., Dale, I., & Knock, J. (2006). *Instat Climatic Guide.* (UK: University of Reading.).

Streletskaya, N. A., Bell, S. D., Kecinski, M., Li, T., Banerjee, S., Palm-Forster, L. H., & Pannell, D. (2020). Agricultural Adoption and Behavioural Economics: Bridging the Gap. *Applied Economic Perspectives and Policy*, *42*(1), 54-66. https://doi.org/10.1002/aepp.13006

Sultan, B., Defrance, D., & Iizumi, T. (2019). Evidence of crop production losses in West Africa due to historical global warming in two crop models. *Scientific Reports*, *9*(1), 12834. https://doi.org/10.1038/s41598-019-49167-0

Sultan, B., & Gaetani, M. (2016). Agriculture in West Africa in the Twenty-First Century: Climate Change and Impacts Scenarios, and Potential for Adaptation. *Frontiers in Plant Science*, *7*. https://doi.org/10.3389/fpls.2016.01262

T.J. Ballard, A.W. Kepple, & C. Cafiero. (2013). *The food insecurity experience scale: Developing a global standard for monitoring hunger worldwide*. FAO. https://www.fao.org/3/X0490E/x0490e0r.htm#fao%20technical%20papers

Tversky, A., & Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases. *Science*, *185*(4157), 1124-1131.

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, *5*(4), 297-323. https://doi.org/10.1007/BF00122574

van Valkengoed, A. M., Perlaviciute, G., & Steg, L. (2023). From believing in climate change to adapting to climate change: The role of risk perception and efficacy beliefs. *Risk Analysis*, *n/a*(n/a). https://doi.org/10.1111/risa.14193

Vaughan, C., & Dessai, S. (2014). Climate services for society: Origins, institutional arrangements, and design elements for an evaluation framework: Climate services for society. *Wiley Interdisciplinary Reviews: Climate Change*, *5*(5), 587-603. https://doi.org/10.1002/wcc.290

Wuepper, D., Bukchin-Peles, S., Just, D., & Zilberman, D. (s. d.). Behavioural agricultural economics. *Applied Economic Perspectives and Policy*, *n/a*(n/a). https://doi.org/10.1002/aepp.13343

Zeweld, W., Van Huylenbroeck, G., Tesfay, G., & Speelman, S. (2019). Impacts of socio-psychological factors on smallholder farmers' risk attitudes: Empirical evidence and implications. *Agrekon*, *58*(2), 253-279. https://doi.org/10.1080/03031853.2019.1570284

Appendix 2.A – Generalized Method of Moments (GMM) specifications

2.A.1. Sowing decision mechanisms

To account for the potential endogeneity of past sowing behaviour and time-dependent correlation in the error term, we also estimated a dynamic panel model using the one-step System GMM estimator (Blundell and Bond, 1998). The model is specified as follows:

$$x_{jk}^{risky} = \beta_0 + \beta_1 x_{j,k-1}^{risky} + \beta_2 dry_{j,k-1} + \sum_{s \in S} \beta_s D_{jk}(P_s) + \varepsilon_{jk} \quad (1)$$

Where

x_{jk}^{risky}: Number of seeds sown in the risky period by farmer *j* at season k

$x_{j,k-1}^{risky}$: Number of seeds sown in the risky period by farmer *j* at season $k-1$

$dry_{j,k-1}$: Binary variable indicating dry spell occurrence for farmer $j$at season $k-1$,

$D_{jk}(P_s)$:Indicator variable equal to 1 if farmer $j$received probability $P_s$at season k, and 0 otherwise.

$P_s \in \{0.1, 0.3, 0.5, 0.7, 0.9\}$: Probability categories used in the model (with $P_s = 0.1$ as the reference group)

ε_{jk}: Idiosyncratic error term

System GMM with one step is supposed to be more efficient on short panels like ours. The model used lagged sowing behaviour as an instrument, with instruments collapsing to avoid instrument proliferation.

Results show a clear reduction in risky sowing with increasing levels of dry spell probability. Coefficients on the risk dummies are large and highly significant, supporting the hypothesis that farmers adapt their risky sowing to the provided probabilities. In this system GMM model, the past dry spell and past risky sowing are unsignificant. Second-order autocorrelation is absent (p = 0.34).

However, the Sargan test rejects the overidentifying restrictions (p = 0.004) suggesting potential issues with instrument validity and therefore instability despite the use of instruments collapsed and only one lag.

Table 2.6 - Results of the System GMM (One-Step) Model to explain the determinants of the sowing decision

Number of seeds sown in the risky period *(dependent variable)*	**System GMM (One-Step)** Coefficient
Main predictors	
Lagged sowing decision ($x_{1,t-1}$)	-0.025
	(0.021)
Previous dry spell (dry_{t-1})	-0.102
	(0.085)
30% dry spell probability	-1.608^{***}
	(0.092)
50% dry spell probability	-2.885^{***}
	(0.096)
70% dry spell probability	-4.173^{***}
	(0.127)
90% dry spell probability	-5.657^{***}
	(0.140)
Model diagnostics	
Number of individuals (n)	313
Time periods (T)	10
Total observations	3130
Observations used in GMM	5321
Sargan test statistic	18.825
Degrees of freedom (Sargan)	6
p-value (Sargan test)	0.004
Wald test (coefficients): χ^2	1696.806
Degrees of freedom (Wald coefficients)	6
p-value (Wald coefficients)	< 0.001
Wald test (time dummies): χ^2	6.983
Degrees of freedom (Wald time dummies)	8
p-value (Wald time dummies)	0.538

Notes: *** p < 0.01; ** p < 0.05; * p < 0.1 significance levels. Standard errors reported are asymptotic and robust to heteroskedasticity, but not explicitly clustered by group (e.g., by id).

2.A.2. Seed allocation

The model explaining the seed allocation with GMM estimates is specified as follows:

$$\theta_{jk} = \beta_0 + \beta_1\theta_{j,k-1} + \beta_2 dry_{j,k-1} + \sum_{s\in S} \beta_s D_{jk}(P_s) + \varepsilon_{jk}$$

Where:

θ_{jk}: Deviation from the optimal strategy for farmer j at season$k$;

$\theta_{j,k-1}$: Gap between actual and optimal sowing in season $k-1$;

$dry_{j,k-1}$: Binary variable indicating whether a dry spell occurred for farmer j in season $k-1$.

$D_{jk}(P_s)$:Indicator variable equal to 1 if farmer $j$received probability $P_s$at season k, and 0 otherwise.

$P_s \in \{0.1,0.3,0.5,0.7,0.9\}$: Probability categories used in the model (with $P_s = 0.1$ as the reference group)

ε_{jk}: Idiosyncratic error term

The following results confirm the robustness of the previous findings in section 2.5.3. Coefficients on the dry spell probability dummies are large and highly significant, supporting the hypothesis that farmers adapt their seed allocation to the provided probabilities. In this system GMM model, the past dry spell and past risky sowing are unsignificant. Second-order autocorrelation is absent (p = 0.26). The standard errors reported are asymptotic and robust to heteroskedasticity, but not explicitly clustered by group (e.g., by id).

However, the Sargan test rejects the overidentifying restrictions (p = 0.001) suggesting potential issues with instrument validity and instability despite the use of instruments collapsing and only one lag.

Table 2.7 - Results of the System GMM (One-Step) Model

Deviation from optimal strategy *(dependent variable)*	**System GMM (One-Step)** Coefficient
Main effects	
Past sowing gap	-0.007
	(0.014)
Past dry spell	-0.021
	(0.079)
30% dry spell probability	1.617***
	(0.098)
50% dry spell probability	2.860***
	(0.103)
70% dry spell probability	-5.810***
	(0.141)
90% dry spell probability	-4.333***
	(0.152)
Model diagnostics	
Number of individuals (n)	313
Number of time periods (T)	10
Number of observations (N)	3130
Number of observations used	5321
Sargan test statistic (df = 6)	23.328
Sargan test p-value	0.001
Wald test (coefficients) χ^2 (df = 6)	10318.628
Wald test p-value	< 0.001
Wald test (time dummies) χ^2 (df = 8)	5.609
Wald test p-value	0.691

Notes: *** p < 0.01; ** p < 0.05; * p < 0.1 significance levels. Standard errors reported are asymptotic and robust to heteroskedasticity, but not explicitly clustered by group (e.g., by id).

Appendix 2.B- Multiplicative Model with every dry spell probability

Table 2.8 - Interaction effects between dry spell probabilities and individual characteristics

Number of seeds sown in the risky period *(dependent variable)*	**Coefficient (SE)**
Main effects	
30% dry spell probability	−1.217 (0.784)
50% dry spell probability	−2.331*** (0.850)
70% dry spell probability	−3.738*** (1.171)
90% dry spell probability	−6.130*** (1.182)
Past sowing	−0.063*** (0.014)
Past dry spell	−0.118* (0.068)
Interactions with 30% dry spell probability	
Locus of Control	0.344* (0.181)
Self-efficacy	−0.043 (0.081)
Willingness to adapt	−0.094 (0.077)
Maize losses	−0.420*** (0.100)
Dry spell frequency	0.140 (0.086)
Food security	0.043 (0.040)
Education	−0.041 (0.132)
Interactions with 50% dry spell probability	
Locus of Control	0.498*** (0.177)
Self-efficacy	−0.157* (0.092)
Willingness to adapt	−0.196** (0.088)
Maize losses	−0.282** (0.118)
Dry spell frequency	0.071 (0.083)
Food security	0.042 (0.043)
Education	−0.388*** (0.136)
Interactions with 70% dry spell probability	
Locus of Control	0.526** (0.264)
Self-efficacy	−0.088 (0.134)
Willingness to adapt	−0.180 (0.119)
Maize losses	−0.378** (0.163)
Dry spell frequency	0.076 (0.120)
Food security	0.059 (0.060)
Education	−0.425** (0.200)
Interactions with 90% dry spell probability	
Locus of Control	1.000*** (0.283)
Self-efficacy	−0.191 (0.130)
Willingness to adapt	−0.303** (0.119)
Maize losses	−0.393** (0.169)
Dry spell frequency	0.118 (0.128)
Food security	0.123* (0.064)
Education	−0.407* (0.220)
R^2	0.660
Adjusted R^2	0.616
Number of observations	3130

Notes: *** p<0.01; ** p<0.05; * p<0.1 significance levels. Standard errors (SE) clustered at the individual level in parentheses (HC3 Robust). The coefficients here are compared with a 10% dry spell probability.

Appendix 2.C – The No Forecast specifications

For the *No Forecast* model specifications, we include a variable to control for season order effects, as time fixed effects cannot be used in this case—the *No Forecast* scenario was systematically presented in season 0 for all farmers.

The following specification can be interpreted as estimating the average causal effect of the dry spell probability on the risky sowing decision:

$$x_{jk}^{risky} = \beta_0 + \sum_{s \in S} \beta_s D_{jk}^{(P_s)} + \alpha_j + season_k + \varepsilon_{jk} \tag{4}$$

With

x_{jk}^{risky} : Number of seeds sown in the risky period by farmer j at season k

$D_{jk}^{(P_s)}$: Indicator variable equal to 1 if farmer j received probability P_s at season k, and 0 otherwise.

$P_s \in \{0.1, 0.3, 0.5, 0.7, 0.9\}$: Set of probability categories.

α_j : Individual fixed effects for farmer j

$season_k$: Control for the order of the season

ε_{jk} : Idiosyncratic error term

The coefficient associated with the *No Forecast* scenario is similar to that observed under the 50% dry spell probability, suggesting that farmers' subjective priors tend to align with this intermediate level of probability.

Table 2.9 - Results of the No Forecast model

Number of seeds sown in the risky period *(dependent variable)*	Coefficient
30% probability	-1.546^{***}
	(0.087)
50% probability	-2.838^{***}
	(0.088)
70% probability	-4.146^{***}
	(0.088)
90% probability	-5.597^{***}
	(0.088)
No Forecast	-2.787^{***}
	(0.133)
R^2	0.617
Adjusted R^2	0.576
Number of observations	3443

Notes: *** p < 0.01; ** p < 0.05; * p < 0.1 significance levels Standard errors clustered at the individual level are reported in parentheses (HC3 robust).

Coefficients are interpreted relative to the reference category: a 10% dry spell probability.

Appendix 2.D – Optimal strategies in the experimental framework

The following table displays the optimal seed allocation strategies in the experiment (shaded in gray) based on dry spell probabilities. For 10%, 30%, and 50% dry spell probabilities, the optimal strategy, according to the expected gain maximization criterion, is to sow all seeds in the risky period. Conversely, for 70% and 90% dry spell probabilities, it is preferable to sow all seeds in the safe period.

Table 2.10 - Optimal seed allocation strategies based on the expectation gain criterion

x_{risky}	$x_{safe} = \overline{X}$-x_{risky}	10%	30%	50%	70%	90%
0	**10**	20	20	20	20	20
1	**9**	22,5	21,5	20,5	19,5	18,5
2	**8**	25	23	21	19	17
3	**7**	27,5	24,5	21,5	18,5	15,5
4	**6**	30	26	22	18	14
5	**5**	32,5	27,5	22,5	17,5	12,5
6	**4**	35	29	23	17	11
7	**3**	37,5	30,5	23,5	16,5	9,5
8	**2**	40	32	24	16	8
9	**1**	42,5	33,5	24,5	15,5	6,5
10	**0**	45	35	25	15	5

We can estimate the average number of additional seasons required for a farmer to converge toward the optimal strategy (i.e., for the gap to reach zero or a value close to zero) depending on each dry spell probability. Convergence toward the optimal strategy is measured by the reduction of $\Delta\theta$ over successive encounters with each probability.

To measure the learning effect L for the farmer$j$ over rounds z, we observe the trend of this gap decreasing, which represents the speed of convergence of the individual toward the optimal strategy. The average convergence rate for an individual in z rounds is thus defined as:

$$\overline{L} = \sum_{z=1}^{2} \frac{\Delta\theta_{jz-1} - \Delta\theta_{jz}}{\Delta\theta_{jz-1}} \tag{11}$$

From which the global average convergence rate across Nindividuals is given by:

$$\acute{L} = \frac{1}{N} \sum_{j=1}^{N} \left(\sum_{z=1}^{2} \frac{\Delta\theta_{jz-1} - \Delta\theta_{jz}}{\Delta\theta_{jz-1}} \right) \tag{12}$$

We aim to calculate the number of additional encounters n required for the gap $\Delta\bar{\theta}_z$ to reach zero. The base equation is therefore:

$$n = \frac{\Delta\bar{\theta}_z}{\acute{L}} \tag{13}$$

Table 2.11 – Average number of seasons necessary for a farmer to reach the optimal strategy

Probabilities	Round 1	Round 2	Convergence rate	Average number of seasons required to reach the optimal strategy
10%	1.95	1.70	-0.25	7
30%	3.25	3.49	0.24	*Does not converge*
50%	4.68	4.63	-0.05	97
70%	4.17	3.91	-0.26	15
90%	2.69	2.48	-0.20	12

The 10%, 70%, and 90% probabilities show convergence toward the optimal strategy, with the number of seasons required to reach the optimal strategy ranging between 7 and 15 seasons. The 50% probability also converges, but at a very slow rate. The 30% probability diverges, meaning that strategies move away from the optimal strategy instead of approaching it. However, these results are based on only two sessions and should therefore be interpreted with caution.

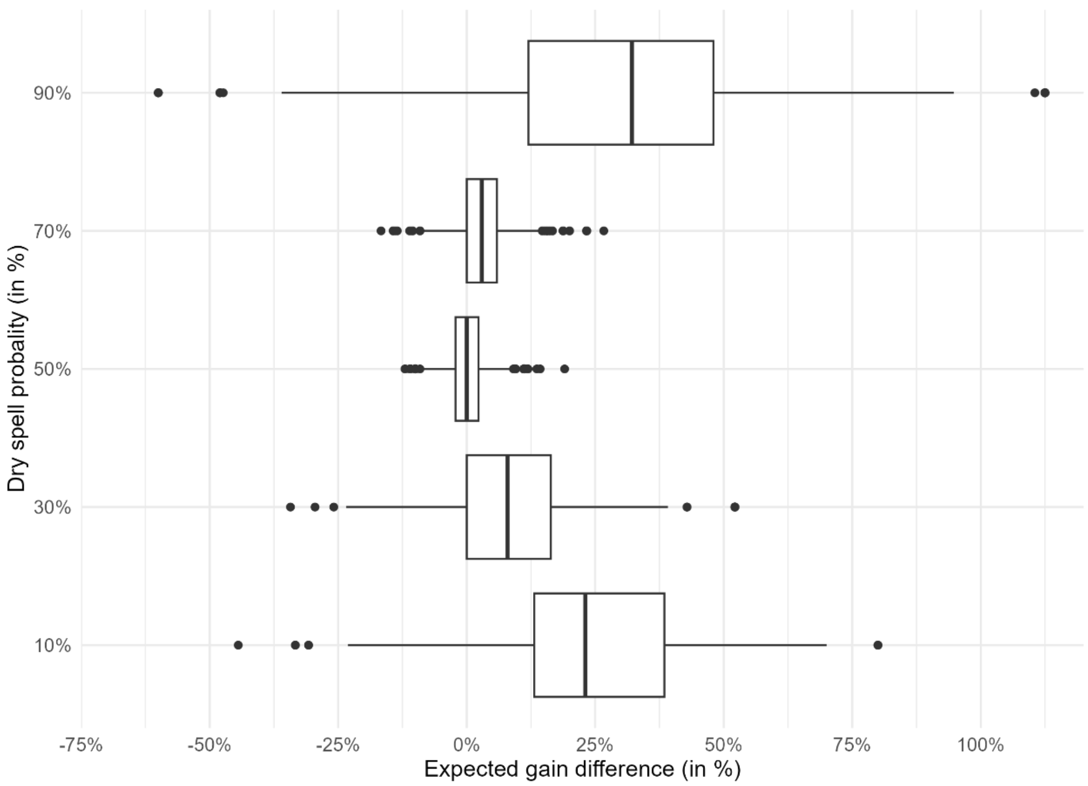
Appendix 2.E – Robustness checks

To assess the robustness of the results, we repeated the same analyses using a reduced sample. Farmers who did not pass the comprehension test at the beginning of the experiment, as well as those rated as having low engagement by the interviewers, were excluded from the sample—resulting in 280 selected individuals instead of 313.

2.E.1. Impact of forecasts on potential harvests

The results in this section are consistent with those obtained using the full sample. No major differences are observed.

Figure 2.13 - Expected gain difference between risky sowing with a probability of dry spell and without this probability



<u>Notes:</u> *Figure 2.13* shows the expected difference in yield (in %), by probability, between risky sowings made with access to a dry spell probability and those made without such information. The box plot shows the interquartile range (IQR), with the midline indicating the mean. For clarity, outliers greater than 125% of the absolute difference have been excluded.

2.E.2. Determinants of the risky sowing

The following table presents results similar to those obtained with the full sample. The influence of a dry spell in the previous season becomes statistically more significant.

Table 2.12 - Effects on the number of seeds sown in the risky period in the Fixed Effects Model and in the Autoregressive Model

Number of seeds sown in the risky period *(dependent variable)*	**Fixed Effects Model** (1)	**Autoregressive Model** (2)
30% dry spell probability	−1.525***	−1.517***
	(0.092)	(0.091)
50% dry spell probability	−2.877***	−2.865***
	(0.099)	(0.098)
70% dry spell probability	−4.227***	−4.182***
	(0.132)	(0.131)
90% dry spell probability	−5.644***	−5.595***
	(0.146)	(0.145)
Past sowing		−0.076***
		(0.015)
Past dry spell		−0.195***
		(0.073)
R^2	0.622	0.652
Adj. R^2	0.582	0.611
Number of observations	3080	2800

Notes: *** p<0.01; ** p<0.05; * p<0.1 significance levels. Standard errors clustered at the individual level in parentheses (HC3 Robust). The coefficients here are compared with a 10% dry spell probability.

Results for the weight of the individual characteristics in the fixed effects are similar to those obtained with the full sample.

Table 2.13 - Weights of individual characteristics in the fixed effects

Fixed Effects *(dependent variable)*	Coefficient
Psychological factors	
Locus of Control	0.138
	(0.127)
Self-efficacy	−0.054
	(0.065)
Willingness to Adapt	0.080
	(0.060)
Risk appraisal	
Maize Losses	−0.155**
	(0.078)
Dry Spell Frequency	0.039
	(0.060)
Socioeconomic characteristics	
Food Security	0.004
	(0.031)
Education (Years)	−0.256**
	(0.108)
R^2	0.043
Adjusted R^2	0.018
Number of observations	280

Notes: *** p<0.01; ** p<0.05; * p<0.1 significance levels. Standard errors in parentheses

Results for the multiplicative model are similar to those obtained with the full sample. The interaction between a high dry spell probability provided and having experienced maize losses in real life is slightly more significant.

Table 2.14 - Interaction effects between dry spell probabilities and individual characteristics

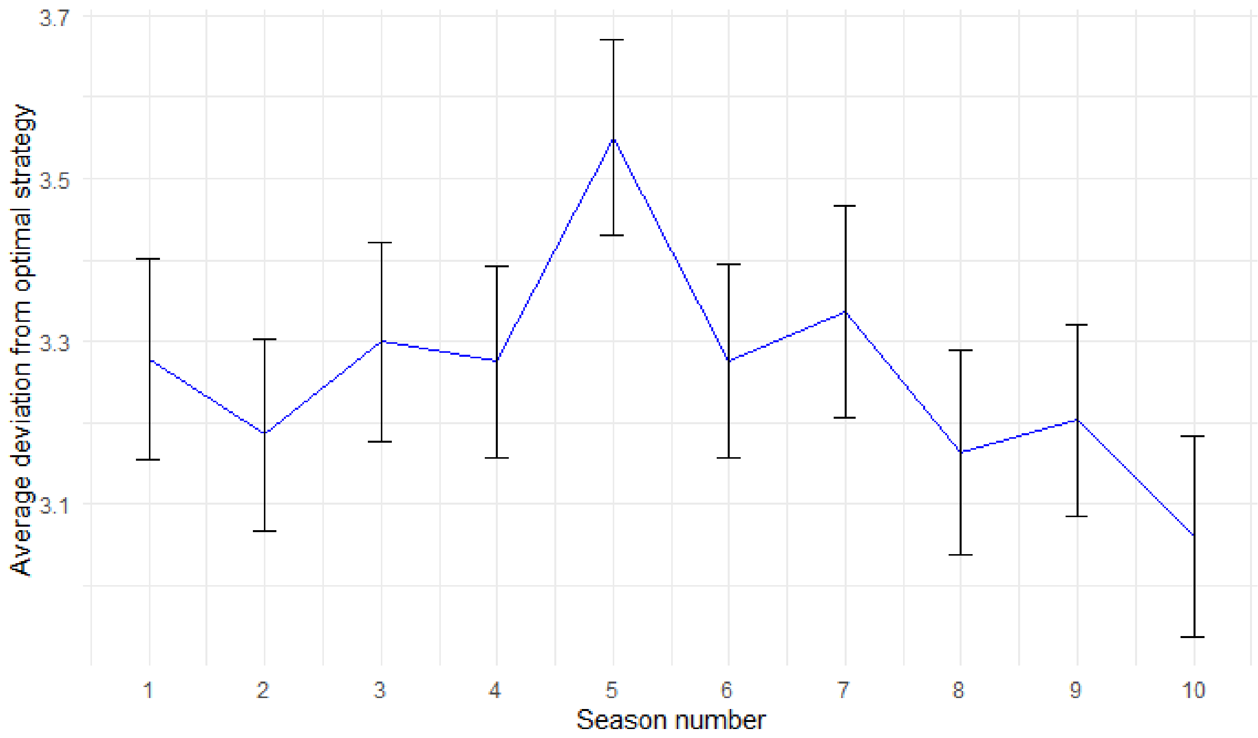
Number of seeds sown in the risky period *(dependent variable)*	**Multiplicative Model** Coefficient
Main effects	
Medium dry spell probability [30%–50%]	−1.584**
	(0.769)
High dry spell probability [70%–90%]	−4.405***
	(1.163)
Past sowing	−0.076***
	(0.016)
Past dry spell	−0.157**
	(0.076)
Interactions with a Medium dry spell probability	
Locus of Control	0.404**
	(0.174)
Self-efficacy	−0.085
	(0.080)
Willingness to Adapt	−0.150*
	(0.078)
Maize Losses	−0.370***
	(0.098)
Dry Spell Frequency	0.080
	(0.080)
Food Security	0.034
	(0.038)
Education	−0.207*
	(0.124)
Interactions with a High dry spell probability	
Locus of Control	0.653**
	(0.277)
Self-efficacy	−0.118
	(0.130)
Willingness to Adapt	−0.241**
	(0.117)
Maize Losses	−0.440***
	(0.167)
Dry Spell Frequency	0.062
	(0.123)
Food Security	0.085
	(0.062)
Education	−0.298
	(0.208)
R^2	0.598
Adjusted R^2	0.548
Number of observations	2800

Notes: *** p<0.01; ** p<0.05; * p<0.1 significance levels. Standard errors clustered at the individual level in parentheses (HC3 Robust). The coefficients here are compared with a 10% dry spell probability.

2.E.3. Seed allocation

As with the full sample, the results do not graphically show any convergence toward the 'all-or-nothing' optimal strategy.

Figure 2.14 - Evolution of the average deviation between farmers' sowing strategy and the optimal strategy



Notes: The graph represents the average deviation of farmers' seeding strategy from the optimal strategy calculated in risky seeds difference. Season 0 represents the *No-Forecast* scenario.

The regression results on the deviation from the optimal strategy by probability also do not differ.

Table 2.15- Determinants of the seed allocation under varying dry spell probability

Deviation from optimal strategy *(dependent variable)*	**Fixed Effects Model** (1)	**Autoregressive Model** (2)
30% dry spell probability	1.523***	1.541***
	(0.092)	(0.093)
50% dry spell probability	2.873***	2.841***
	(0.100)	(0.102)
70% dry spell probability	2.231***	2.137***
	(0.129)	(0.128)
90% dry spell probability	0.816***	0.770***
	(0.120)	(0.121)
Past sowing gap		−0.128***
		(0.021)
Past dry spell		−0.027
		(0.065)
R^2	0.288	0.322
Adjusted R^2	0.205	0.232
Number of observations	2800	2520

Notes: *** p<0.01; ** p<0.05; * p<0.1 significance levels. Standard errors clustered at the individual level in parentheses (HC3 Robust). The coefficients here are compared with a 10% dry spell probability.

In contrast, the results concerning the influence of individual characteristics on fixed effects indicate that food insecurity is no longer a significant determinant in seed allocation decisions. This may be due to the loss of statistical power.

Table 2.16 - Weights of individual characteristics in the fixed effects

Fixed Effects *(dependent variable)*	Coefficient
Psychological factors	
Locus of Control	0.181*
	(0.106)
Self-efficacy	−0.029
	(0.054)
Willingness to Adapt	−0.102**
	(0.050)
Risk appraisal	
Maize Losses	−0.059
	(0.065)
Dry Spell Frequency	−0.001
	(0.051)
Socioeconomic characteristics	
Food Security	0.041
	(0.026)
Education (Years)	−0.022
	(0.090)
R^2	0.052
Adjusted R^2	0.028
Number of observations	280

Notes: *** p<0.01; ** p<0.05; * p<0.1 significance levels. Standard errors in parentheses

Appendix 2.F – Farming statistics

Table 2.17 – Farming statistics

Caractéristiques de l'exploitation agricole	Unité	%	Moyenne	Médiane	Min	Max
Nombre de cultures pratiquées en 2023	-		4,69	5	2	9
Anacarde	% de la population totale	73,2	-	-	-	-
Arachide	% de la population totale	70,6	-	-	-	-
Riz	% de la population totale	99,4	-	-	-	-
Sorgho	% de la population totale	1,6	-	-	-	-
Igname	% de la population totale	15,6	-	-	-	-
Haricot	% de la population totale	3,5	-	-	-	-
Maïs	% de la population totale	98,4	-	-	-	-
Variété à cycle court	% de maïs	93,8	-	-	-	-
Variété à cycle long	% de maïs	6,2	-	-	-	-
Taille des exploitations	ha	-	22,8	19	2	90
Surface de maïs cultivée en 2023	ha	-	4	3	0,5	16
Production de maïs en 2023	t/ha	-	3,8	3	0,01	25
Rendement de maïs en 2023	t/ha	-	0,98	0,83	0,02	5
Maïs produit et destiné à l'autoconsommation en 2023	% du maïs produit	-	44,7	33,3	0	100
Main d'œuvre familiale	Nombre de membres du ménage aidant à l'exploitation	-	5,4	4	0	40
Irrigation	% de la population totale	3	-	-	-	-
Pratique l'élevage	% de la population totale	55,3	-	-	-	-

Appendix 2.G – Experimental Procedure Script for Interviewers

1. *Présentation du déroulement du jeu*

Nous allons maintenant essayer de comprendre ***quel est l'apport d'une information météo sur votre gestion du risque d'interruption des pluies lors des semis de maïs.***

Nous aimerions comprendre si votre comportement change ***si vous êtes informé d'un risque, si le risque est plus ou moins grand et si celui-ci s'est réalisé.*** *Il est long et coûteux d'observer cela sur plusieurs années, à notre niveau nous pouvons seulement essayer de modéliser la réalité sous forme de jeu afin de représenter plusieurs saisons.*

Nous allons procéder en plusieurs étapes :

1. *Le premier représente une situation où vous devez semer le maïs sans prévisions scientifiques sur les pluies pendant les semaines qui suivent.*
2. *Le deuxième représente une situation où vous devez semer le maïs et où une prévision est disponible. Elle indique le risque d'arrêt des pluies dans les semaines à suivre.*

Les résultats de ces jeux permettront d'aider les météorologues à mieux construire des prévisions météo adaptées. C'est pourquoi, il n'y a pas de mauvaises réponses, il s'agit de réfléchir au plus proche de ce que vous feriez si la situation était réelle. Vous pourrez à tout moment demander que l'on vous réexplique. Si quelque chose n'est pas clair, n'hésitez pas à le dire.

Nous aimerions que vous preniez ces décisions au sérieux, comme vous le faites pour toute autre décision dans la vraie vie. Vous êtes venu ici aujourd'hui et vous passez votre temps avec nous. C'est pourquoi nous vous donnerons à tous un petit cadeau à la fin du jeu pour vous remercier.

Rappel enquêteur : Pour chaque jeu et pour chaque tour du jeu le résultat doit être indiqué au producteur

<u>Jeu n°1</u> - Incertitude

Les enquêteurs doivent contrôler la mise en place du matériel nécessaire pour chaque jeu.

<u>Matériel nécessaire pour chaque enquêteur :</u>

- 2 urnes /enquêteur
- 10 Balles de ping pong orange / 10 blanches

- 1 visuel récap
- 1 Cache noir
- Graines de maïs

<u>Explications:</u>

Nous supposons qu'il s'agit de la période habituelle à laquelle vous semez le maïs. Nous supposons également que vous n'avez pas de contraintes liées à la disponibilité des travailleurs ou du matériel agricole. En bref, les conditions idéales sont réunies pour semer.

Si vous semez maintenant, les rendements seront à priori très bons. Pour une graine plantée vous récoltez 5 graines. Toutefois, il existe un risque d'arrêt des pluies qui pourrait vous faire perdre tous ces semis. C'est un risque donc ce n'est pas sûr que la pluie s'arrête.

Vous n'êtes pas obligé de tout semer maintenant, vous pouvez aussi mettre des graines de côté pour les semer plus tard. Cependant, les rendements seront moins bons. Pour une graine semée vous récoltez 2 graines. Vous n'êtes pas non plus obligé de répartir vous pouvez tout semer maintenant ou tout mettre de côté.

Par exemple : J'ai dix graines, je décide d'en semer 5 maintenant et j'en mets 5 de côté. (L'enquêteur fait la démonstration avec les graines et les balles en direct)

- *La pluie s'est arrêtée, j'ai perdu mes premiers semis : il me reste donc les 5 que j'ai mis de côté. 5x2 = 10, donc mon gain est de 10.*
- *Il n'y pas eu d'arrêt prolongé des pluies, j'ai gagné mes premiers semis 5x5 = 25 + les semis que j'ai mis de côté 5x2 = 10. Au total, mes rendements sont de 35.*

Pour savoir s'il a plu ou non, nous allons piocher une balle dans cette urne noire.

- *Si la balle est jaune alors c'est interruption des pluies, la pluie a cessé. Les premiers semis sont perdus.*
- *Si la balle sort blanche alors tout va bien, le risque ne s'est pas réalisé.*

Comme nous n'avons pas de prévision météo, nous ne pouvons pas voir combien il y a de balles jaunes ou blanches dans l'urne. Nous pouvons simplement nous fier à ce que nous pensons sur le fait que la pluie s'arrête.

Ne vous inquiétez pas si vous n'avez pas tout retenu. Pour vous aider, nous avons créé des aides mémoires visuels, n'hésitez pas à les consulter.

Combien de graines voulez-vous semer maintenant ?

Jeu n°2

Les enquêteurs doivent contrôler la mise en place du matériel nécessaire pour chaque jeu.

Matériel nécessaire par enquêteur :

- 2 urnes /enquêteur
- 10 Balles de ping pong orange / 10 blanches
- 1 visuel récap
- 1 Cache noir
- Graines de maïs

Explications:

Nous supposons toujours qu'il s'agit de la période habituelle à laquelle vous semez. Nous supposons également que vous n'avez pas de contraintes liées à la disponibilité des travailleurs ou du matériel agricole. En bref, les conditions sont réunies pour semer.

Contrairement au jeu précédent, la météo nous donne une prévision sur le risque d'arrêt des pluies. Si le risque est faible, il y a peu de balle jaune dans l'urne, plus il est élevé et plus il y a de balles jaunes dans l'urne.

Test de compréhension

1. *S'il n'y a que des balles blanches dans l'urne (c'est-à-dire que la météo annonce un risque nul d'arrêt des pluies), combien de graines voulez-vous semer maintenant ?*
2. *S'il n'y a que des balles jaunes dans l'urne (c'est-à-dire que la météo annonce un risque 100% d'arrêt des pluies), combien de graines voulez-vous semer maintenant ?*
3. *Présentez deux configurations d'urne : une avec 3 balles jaunes et 7 balles blanches, une avec 7 balles jaunes et 3 balles blanches. Quelle urne indique le risque d'arrêt des pluies le plus élevé ?*

Jeu avec les seuils 10% / 30% / 50% / 70% / 90%

Les seuils sont tirés au sort avec des balles de ping pong, une fois qu'on a fini la série de 5 seuils, on recommence une nouvelle fois.

Figure 2.15 - The interviewer kit

Chapter 3: Quantifying ex-post impacts of climate services for farmers: a methodological review

3.1. Introduction

As part of the international development agenda (Paris Agreement - article 7, ODD - target 13.7), climate services (CS) are essential decision-making tools for farmers in the context of climate change. They generate positive consequences for the farm (Roudier et al., 2016), though, quantifying these impacts is not simple. Firstly, the impact of a CS only exists when information delivered leads to farming decisions -*outcomes* (e.g. planting period, varieties, crops or lands used) that result in tangible benefits for the farmer (e.g. yields increases, decrease in the cost of inputs, etc.) -*impacts* (Bacci et al., 2023). However, access to and use of CS are influenced by specific farmer characteristics, such as ownership of a broadcasting device (radio, telephone, etc.), literacy, or the ability to make farming decisions based on the information received. These factors, if they are not carefully controlled, can significantly affect the uptake of CS, potentially leading to a high number of non-users and introducing selection biases within the treatment group. Secondly, it is difficult to quantify the relative contribution of CS among the many factors that influence farm household decisions and contribute to impacts (Vaughan et al., 2019). Last but not least, difficulty lies in establishing a distinct control group (i.e., a reference point) against which to measure the impacts of the CS. Indeed, it is difficult to control for climate variability (Tall et al., 2018) and spillover effects. Spillovers are of particular concern, since information can be reproduced and transmitted through informal networks (Simon et al., 2021a) which make it more difficult for the evaluator to identify which farmers are benefiting from the service and which are not.

That is why, the evaluation of CS most often took the form of contingent evaluations, that focus on the value of the information rather than the impacts, or the form of ex-ante modellings (Vaughan et al., 2019). Ex-ante modellings (i.e. computed simulations) allow evaluators to more easily isolate the impacts of CS by controlling for external factors. Ex-ante modellings mainly documented impacts of CS on agricultural yields (Vaughan et al., 2019). Ex-post evaluations on existing or experimental services are recent and emerged in the wake of the literature on information and communication technlogies' (ICT) impacts (Camacho & Conover, 2019). The question of metrics for ex-post impact assessments is then an increasingly significant issue for climate services, notably due to: i) the emergence of econometric ex-post impact analyses integrated within climate services projects, ii) the expansion of services co-

constructed with farmers, whose benefits are essentially assessed qualitatively but for which quantitative and mixed methodologies are emerging (Visman et al., 2022) and, finally, iii) the gradual integration of social and environmental dimensions into ex-post evaluation methods.

Recently, several systematic reviews and meta-analyses have focused on outcomes such as behavioural changes in decision-making (Born et al., 2021), climate risk management and adaptation strategies (Madhuri, 2023; Muller et al., 2024; Mwangi et al., 2021), as well as factors influencing the use of climate services (Gouroubera et al., 2024; Warner et al., 2022) or globally on the benefits and value of these services without focusing on a specific type of evaluation (Agyekum et al., 2022; Suckall & Soares, 2022). To our knowledge, no specific methodological review has been conducted on the ex-post evaluation of climate services impacts.

This methodological review, carried out on a global research spectrum without geographical distinction, analyzes the quantitative ex-post evaluation methodologies currently used to rigorously measure the impacts of climate services for farmers. Section 2 looks at the methodology of the systematic review conducted. Section 3 details the results of the articles selected in the review. Section 4 discusses the methodologies used to measure the impacts of climate services. Section 5 concludes.

3.2. Methodology

The search methodology consisted of a Web of Science paper search (conducted on the 5th of November 2024) using keywords within titles, abstracts and keywords of papers ("all") *(cf.figure 1, for the key research words)*. Both peer-reviewed and gray-literature studies were included. The Web of Science search was supplemented by additional searches in the main journals for climate services publications : Climate Services and Climate Risk Management with the following keywords respectively:

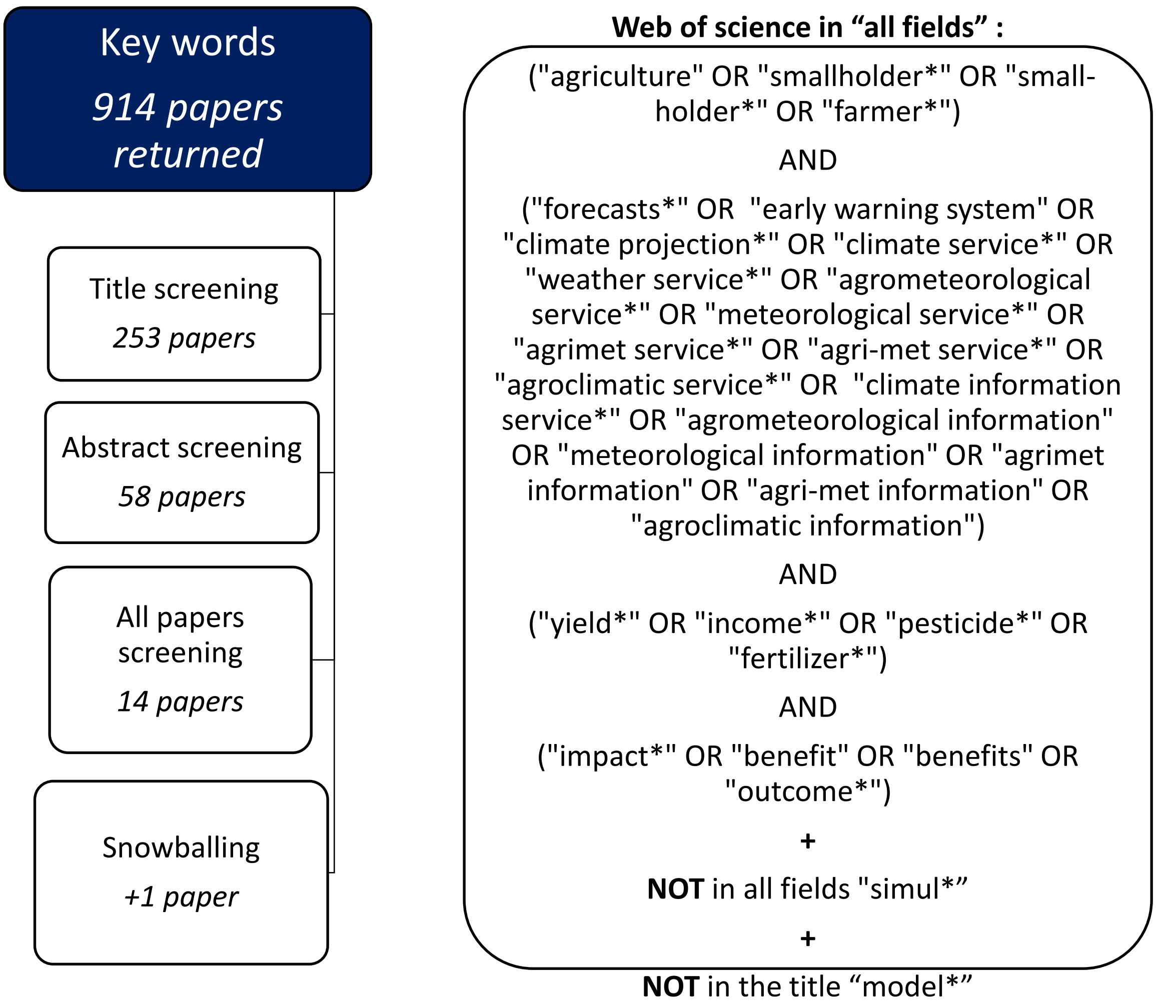
("agriculture" OR "farmer") AND ("impact" OR "outcome" OR effect) AND (yield OR income OR pesticide OR fertilizer)

("agriculture" OR "farmer") AND ("forecast" OR "climate service" OR "agrometeorological" OR "agrimet") AND ("impact" OR "outcome" OR "benefit")

Searches were downloaded in bibtex format and brought together in a single database for analysis in R using the revtools package (Westgate, 2019). The Web of Science search returned 497 papers where as the Climate Services search returned 241 papers and the Climate Risk Management search returned 201 papers, giving a total of 939 papers. 25 duplicates were eliminated leading to a total of 914 selected papers.

The papers were screened step by step : first by title, then by abstract and finally by manual analysis of the entire paper. Papers identified at the end of the three screening steps were complemented by snowballing, i.e. identifying the papers through their references and online citations. Only one article was added by snowballing. This search methodology is detailed in the diagram below (see *Figure 3.1*). All papers that did not provide sufficient detail to be eliminated during one of the selection phases were retained for the next phase.

Figure 2.1 - Selection Process for Papers



Screening by title and abstract was carried out solely on a relevance criterion, with papers having to meet the following criteria:

- *Be ex-post quantitative evaluations*
- *Measure impacts of climate services for farmers*

Papers reporting only perceived and qualitative impacts were eliminated.

In the next screening phase, the entire paper was used to judge whether to include the paper. In order to retain the most rigourous methodologies, the papers needed to meet the following criteria:

- Causality established between climate services and impacts (Yes/No). The article goes beyond descriptive statistics.

- Credible counterfactual (Yes/No): for rigorous quantification, it is crucial to compare what happened with what would have happened without CS, by establishing similar comparison groups.

Consequently, only the following methodologies were selected for the establishment of a coherent counterfactual *(15 papers):*

- Experimental or quasi-experimental methods
- Relevant econometric models: Use of instruments (IV) or econometric techniques such as Difference-in-Differences (DID) to reduce potential biases (such as selection bias or spillovers).

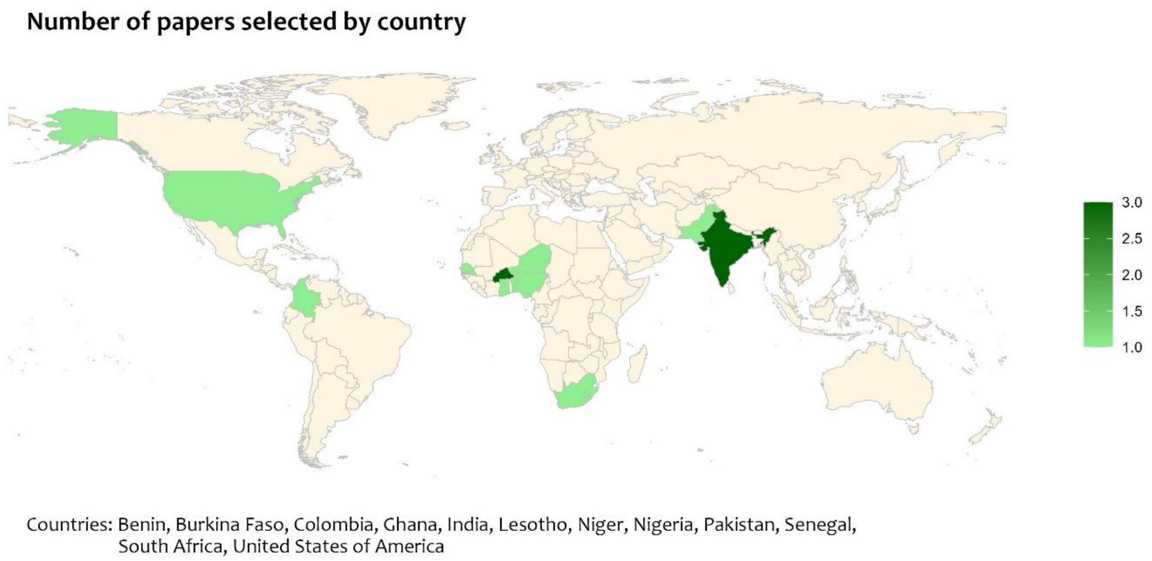
In the RCTs selected, randomization is accompanied by verification and control of the similarity of the observable characteristics in the control and treated samples. The geographical and sectoral distribution of the articles selected was noted, and the climate services evaluated were analyzed, along with their impact results and evaluation methods.

3.3. Results

3.3.1 Geographical and sectoral distribution

Most of the *15* selected ex-post evaluations come from developing countries (see *Figure 3.2*), with a greater concentration on India and West Africa. With one exception, all these articles were published after 2019.

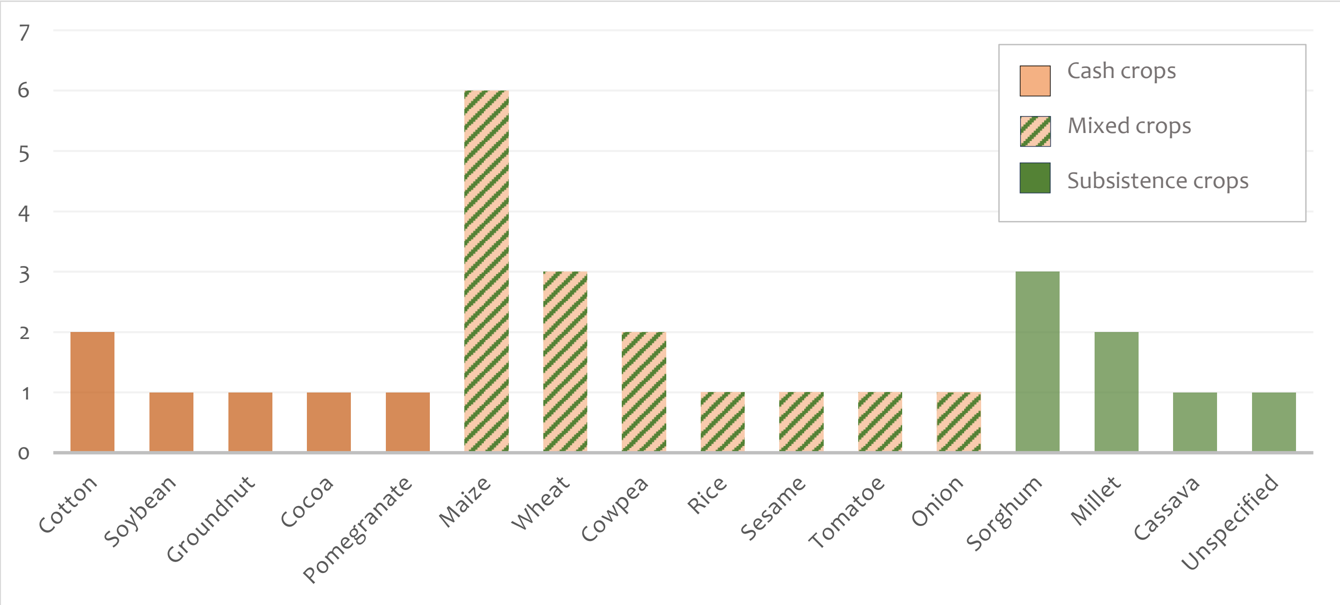
Figure 3.2. - Map showing the distribution of selected studies



This geographical distribution is partly explained by the concomitance of evaluations with the introduction of new climate services in a territory.

Almost all the papers selected focus on microeconomic evaluations of CS for farms (13 papers). Only one paper addresses livestock farming (Manjunath et al., 2024). Generally speaking, the papers evaluate the effect of climate services on several crops (2.4 crops studied by evaluation on average), At the macroeconomic scale the two articles focus on the maize sector, but also the Sorghum sector for Lesotho and South Africa (Coughlan de Perez et al., 2024; Miller et al., 2023). The occurrence of the various crops is described in the graph below (see *Figure 3.3*). Agriculture is predominantly rain-fed, with only 4 articles containing irrigated farms in their samples.

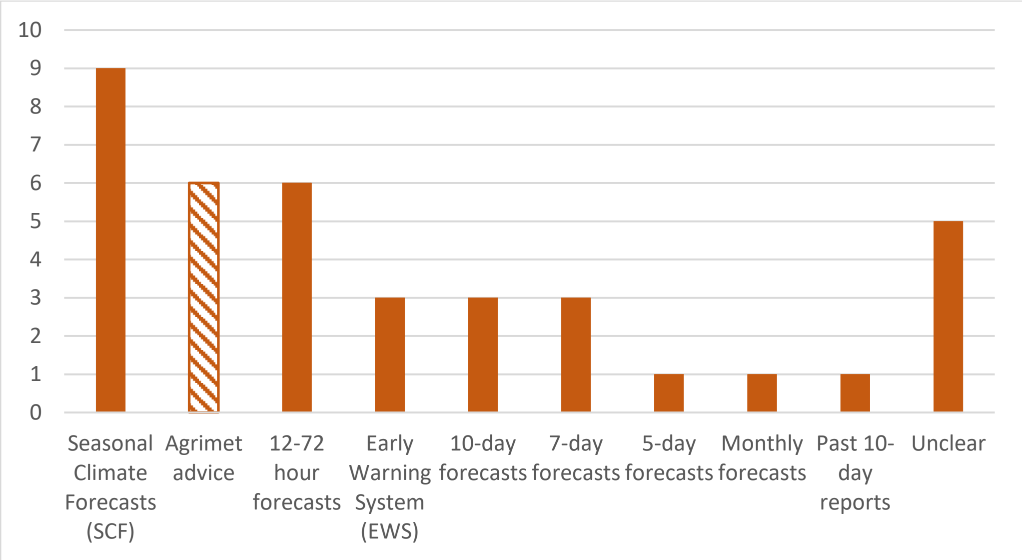
Figure 3.3. - Types of crops studied in the selected ex-post evaluations



3.3.2. Typology of climate services

Establishing a comparison across climate services' evaluations is complex because the services are compositions of diverse characteristics information, both in terms of forecasts (indicators, time horizons, etc.) and agricultural advice. They are generally contextualized to one particular territory and have their own intervention logic. They use multiple means of communication, digital or otherwise (Gouroubera et al., 2024; Yegbemey & Egah, 2021), and different time intervals to disseminate information. They are sometimes accompanied by training and are developed with different levels of co-construction with farmers. The level of geographical accuracy and reliability of these services also varies. The latter is evaluated in a third of the selected papers.

Figure 3.4 - Type of CS information by the number of papers



In this systematic review, the majority of papers evaluate the effect of a specific service disseminated by one or more means of communication, containing several types of forecasts and optionally accompanied by agricultural advice. Only a few papers choose a service associated with a single type of dissemination in the form of SMS or voice messages (Camacho & Conover, 2019; Sanfo et al., 2022; Sharma et al., 2021; Yegbemey et al., 2023). The majority of papers focus on climate services offering seasonal forecasts (9 papers). However, taken together, short-term forecasts (1 to 10 days) are the most numerous type of information in evaluations. For all papers from Africa, when the language used by the service is specified in the paper (6 papers), they state that the service is available in the local language. Two papers explicitly include agricultural advisors in addition to farmers as the targets of the CS (Bacci et al., 2023; Chiputwa et al., 2022). Sharma et al, (2021) are the only authors to offer a uniquely agrometeorological advice service, without explicitely showing the meteorological forecasts. Two papers include other information such as prices in the CS (Camacho & Conover, 2019; Fafchamps & Minten, 2012). The full table of climate services (types, weather and climate parameters, advice given, communication channels, frequency, language of dissemination, target, source of information and other information) per selected item is described in *Appendix 3.A*, together with the content of the trainings provided.

Only two papers evaluate the impact of using climate services at the microeconomic level without testing a particular service (Nepal et al., 2024; Onyeneke et al., 2023). This result is explained in particular by the collaboration of most authors with producers/distributors of climate services during the creation of new services facilitating the implementation of RCTs. Scientists from national meteorology or agronomy institutes are notably involved in the creation of services specially designed for evaluations (Manjunath et al., 2024; Yegbemey et al., 2023). This involvement reflects both a desire on the part of these organizations to better understand the uses and quantify the benefits of climate services for end-users, as well as the growing importance of multidisciplinary collaborations around the evaluation of climate services.

3.3.3. Typology of Impacts

Most of the papers selected focus on the access to, and/or the use of climate services, without sometimes making a distinction between the two. Other papers analyze the impact of service-related characteristics such as training provision or forecast accuracy (see *Table 3.1*).

Table 3.1 - Impacts Studied

Impacts of	References
Accessing climate services	*Manjunath et al. (2024), Camacho et al. (2019), Fafchamps et Minten (2012), Yegbemey et al. (2023), Sharma et al. (2021)*
Using climate services	*Tham-Agyekum et al. (2024), Nepal et al. (2024), Yegbemey et al. (2023), Onyeneke et al. (2023), Ouédraogo et al. (2023), Chiputwa et al. (2022), Sanfo et al. (2022)*
Trainings	*Bacci et al. (2023), Tarchiani et al. (2021)*
Accuracy of forecasts	*Coughlan de Perez et al. (2024), Miller et al. (2023)*

Since climate services are often considered as a package, it is difficult to isolate the effects of the individual components (i.e., the type of weather information) from the package. Except for Manjunath et al. (2024) that differentiate the impacts by the means of reception (SMS, WhatsApp and Mobile App), authors usually evaluate the total effect of the service. When the CS intervention being evaluated includes other information such as prices, authors generally make assumptions about the variables impacted by forecasts and those by prices (Camacho & Conover, 2019; Fafchamps & Minten, 2012). In the specific case of Sharma et al. (2021), where only agrometeorological advice is distributed, only farmers' compliance to the advice is assessed.

The list of impact types assessed in the selected papers is described in the following table:

Table 3.2 - Variables impacted by CS

Impacts on	N°	References

	Papers	
Crops		
Yields	11	*Bacci et al. (2023), Coughlan de Perez et al. (2024), Miller et al. (2023), Onyeneke et al. (2023), Ouédraogo et al. (2023), Tarchiani et al. (2021), Sanfo et al. (2022), Tham-Agyekum et al. (2024), Yegbemey et al. (2023), Sharma et al. (2021, Fafchamps et Minten (2012)*
Land productivity	1	*Sanfo et al. (2022)*
Crop Losses	2	*Camacho et al. (2019), Fafchamps et Minten (2012)*
Breeding		
Average daily milk yield, Lactation lengths	1	*Manjunath et al. (2024)*
Labor		
Labor costs	2	*Camacho et al. (2019), Yegbemey et al. (2023)*
Labor productivity	2	*Yegbemey et al. (2023), Sanfo et al. (2022)*
Farming inputs		
Chemicals, Irrigation	1	Nepal et al. (2024)
Fertilizer	2	Nepal et al. (2024), Tarchiani et al. (2021)
Farm efficiency		
Farming Costs, Benefits or Gross Value of crops production, Net income	6	*Nepal et al. (2024), Ouédraogo et al. (2023), Tarchiani et al. (2021), Fafchamps et Minten (2012), Manjunath et al. (2024), Chiputwa et al. (2022)*
Technical efficiency	1	*Ouédraogo et al. (2023)*
Household Welfare		
Household income, Household Food Insecurity Access Scale (HFIAS)	1	*Tham-Agyekum et al. (2024)*

11 papers measure the impact of climate services on yields (including milk) and/or land productivity (Sanfo et al., 2022). Camacho & Conover (2019) and Fafchamps & Minten, (2012) also measure avoided crop losses. 3 papers study the impact of CS on labor costs or productivity. Yegbemey et al. (2023) distinguish between paid and unpaid work. Only 2 papers examine the impact on inputs (fertilizers, chemicals or irrigation). However, Miller et al (2023) differentiate between the impact on yields of irrigated and non-irrigated farms.

6 papers assess the overall impact on farm results and management (farming costs, benefits, gross value of crops production or net income). Ouédraogo et al (2023) are also interested in the effect of CS on technical efficiency, which they define as "*the ratio between actual and potential production of a production unit*".

Among the selected papers, only (Tham-Agyekum et al., 2024) assesses the impact on household welfare indicators such as income and food security. The environmental and social dimension appears most often in the outcomes (i.e. decisions taken based on information) or in descriptive statistics. These results are listed in the following table:

Table 3.3 - List of CS Environmental and Social outcomes

Inputs outcomes	
Use	
Pesticide timing	*Bacci et al. (2023)*
Fertilizer timing	*Bacci et al. (2023), Sharma et al. (2024)*
Herbicide timing	*Sharma et al. (2024)*
Irrigation timing	*Sharma et al. (2024)*
Quantity	
Organic manure (kg/ha)	*Ouedraogo et al. (2023)*
Mineral fertilizer (kg/ha)	*Ouedraogo et al. (2023)*
Herbicide (L/ha)	*Ouedraogo et al. (2023)*
Insecticide (L/ha)	*Ouedraogo et al. (2023)*
Labor outcomes	
Working days	*Ouédraogo et al. (2023), Tarchiani et al. (2021)*
Number of farm workers	*Camacho & Conover (2019)*

3.3.4. Sampling and estimation processes

Potential selection biases play a decisive role in the choice of methodologies to evaluate the impacts of accessing or using climate services. Firstly, a selection bias may occur at the point of accessing the CS, particularly when access to the CS is determined by external factors and not by the evaluator. Indeed, farmers who have no means of communication such as telephone or radio, or who have access to a poor telephone network, are less likely to have access to information and thus less likely to be CS users. Secondly, another selection bias can occur at the point of using the CS. The farmer could access information but can be unable to use it because of observable characteristics (such as the level of education or not being a decision maker) or unobservable characteristics (such as knowledge of alternative strategies for a decision). At the country scale, the papers measure the impacts of forecasts accuracy on specific agricultural sectors. They do not need to address the questions of selection biases since the entire population is treated and the effect is observed throughout the time (Coughlan de Perez et al.,2024; Miller et al.,2023).

Reducing the selection bias on the access and the use of CS can be easier in RCTs, as authors can randomly allocate farmers into treatment and control groups. Furthermore, to increase covariate overlap between treatment and control, randomisation can be stratified by specific characteristics. Over the total of 9 RCTS, sampling characteristics selection include generally : i) *decision-making* (head of household and/or owner of farmlands (Bacci et al., 2023; Sanfo et al., 2022), ii) *ease of understanding* (being literate or having a literate relative (Bacci et al., 2023; Yegbemey et al., 2023)), and, iii) *access to the information* (possessing a cell phone (Camacho & Conover, 2019; Fafchamps & Minten, 2012)). It is important to note that because of gender inequalities and cultural characteristics, using these criteria could reduce the probability of having women in the sample. Indeed, only half of the selected papers detailed the gender repartition of their sample, and among them, only 3 papers with sampling criteria. Women, generally represent a third of the samples in the total reviewed papers that mentioned the gender repartition.

Before estimating, methods like inverse propensity score weighting (IPSW) (Ouedraogo et al., 2023; Sharma et al., 2021), Propensity score matching (Nepal et al., 2024) or Difference in Difference (Sharma et al.,2021 ; Manjunath et al., 2024; Fafchamps et Minten, 2012) could be used to ensure the validity of the counterfactual assuring balance of the characteristics in treated and control groups

Finally, spillover effects can arise in the control group, as information can be often easily transmitted. A third of the papers used instrumental variables to limit spillover effects in the non-treated sample (Camacho & Conover, 2019; Fafchamps & Minten, 2012; Yegbemey et al., 2023) using the random assignment to treatment as instrument. Chiputwa et al. (2022) used a combination of dummy variables to also control for CS use in the control group. For the impact of the CS trainings, the probabilities of spillovers is thinner since the sampling is based on the attendance list to the trainings and the comparison is made with other CS users.

As for papers evaluating the use of climate services without using experimental methods, they generally use a two-step process to estimate climate services impacts. They suppose that farmers endogenously self-select into use and non-use of CS. So, firstly, the authors analyze the determinants of access and use of CS to determine the probability of using CS and then, estimate impacts while controlling these determinants. Onyeneke et al. (2023) use a Heckman selection model, and then used a wide range of control variables to estimate the impacts. Tham-Agyekum et al. (2024) preferred an endogenous switching regression with two subgroups users and non-users. Nepal et al. (2024) tested different techniques to reduce selection biases, among them, they use the following instrumental variables to reduce selection bias: i) understanding of CS, ii) receiving inaccurate forecasts in the past and, iii) access to internet. These instruments are assumed to impact CS use, and to have no other effects on impacts (i.e. profits, income, costs and input use). However, the number of non-users for these papers is very small in the original sample (respectively 12% & 7.5% of an average sample of 400 farmers for Onyeneke et al. (2023) and Tham-Agyekum et al. (2024)). Therefore, the statistical power could make the conclusions of these papers limited.

Depending on the population targeted, authors used different estimates described in the following table. We note that for measures of CS training impacts (Bacci et al.,2023; Tarchiani et al.,2021), Intention to Treat (ITT) is equal to Average Treatment of the Treated (ATT) since the authors relied on training attendance lists.

Table 3.4 - Evaluating methods and targets of the impacts

Target of the evaluation	Estimates	Methods	Key references
All the population accessing the CS *"Has the program improved overall yields for farmers who have been offered access?"*	**Intention-To-Treat (ITT)**	OLS[4]	*Bacci et al. (2023), Fafchamps et Minten (2012), Sharma et al. (2021), Tarchiani et al. (2021), Yegbemey et al. (2023)*
		Random effects model	*Camacho et al. (2019),*
		Difference in Difference (DiD)	*Manjunath et al. (2024)*
		Matching	*Sanfo et al. (2022)*
		Generalized Estimating Equations (GEEs)	*Yegbemey et al. (2023)*
All the population *"What would be the average impact on the yields **if** every farmer were using CS?"*	**Average Treatment Effect (ATE)**	Inverse Propensity Score Weighting (IPSW)	*Ouédraogo et al. (2023)*
		Heckman probit model	*Onyeneke et al. (2023)*
CS users only *Ex: What is the average effect of using CS on the yields for farmers who actually use the service?*	**Average Treatment Effect on the Treated (ATT)**	DiD	*Sharma et al. (2021)*
		Matching	*Fafchamps et Minten (2012), Nepal et al. (2024)*
		Random effects model	*Chiputwa et al. (2022)*
		Parametric regression	*Bacci et al. (2023), Tarchiani et al., (2021)*
		Endogenous switching regression	*Tham-Agyekum et al. (2024)*
		Heckman probit model	*Onyeneke et al. (2023)*
		IPSW	*Ouédraogo et al. (2023), Sharma et al. (2021)*
A specific subgroup: « Compliers » using CS *"What is the average effect of using CS for farmers who decide to use the service only because they live close to a meteorological center (compliers)?"*	**Local Average Treatment Effect (LATE)**	Instrumental variables (IV)	*Camacho et al. (2019), Fafchamps et Minten (2012), Nepal et al. (2024), Yegbemey et al. (2023)*
All the population that doesn't use the CS *"What would the average impact on yields be **if** the untreated farmers were using the CS?"*	**Average Treatment Effect on the untreated (ATE0) or (ATU)**	Endogenous switching regression	*Tham-Agyekum et al. (2024)*
		IPSW	*Ouédraogo et al. (2023)*
		Heckman probit model	*Onyeneke et al. (2023)*

[4] This term includes OLS with covariates and fixed effects

3.3.5 Quantified impacts of CS

The following section details the quantitative results obtained by the selected articles. The impacts of using climate services on yields have been listed in the table below. Results in bold are the significant ones. Whenever possible, a combined coefficient constructed with a weighted average of the individual coefficients, where the weights are the inverse of the squares of the standard errors, has been calculated.

Table 3.5 – Impacts of using CS on yields

Crop	Unit	Coefficient *(s.e.)*	Estimation	References
Cassava	Kg/ha	+2928 *(51.52)*	*ATT*	*Onyeneke et al. (2023)*
Cocoa	Bag/ha	+4.525 *(67.42)*	ATE	Tham-Agyekum et al. (2024)
Cotton	Kg/ha	**+296.54**** *(130.04)*	*LATE*	*Yegbemey et al. (2023)*
Cowpea	Kg/ha	**+270.34*** *(151.900)*	*ATT*	*Ouédraogo et al. (2023)*
Maize	Kg/ha	+704,06 *(433.40)*	*LATE, ATT*[5]	*Yegbemey et al. (2023), Onyeneke et al. (2023)*
Rice	Kg/ha	**+1541***** *(11.05)*	*ATT*	*Onyeneke et al. (2023)*
Sesame	Kg/ha	+53.55 (100.64)	*ATT*	*Ouédraogo et al. (2023)*
Wheat	%	+0.33 *(0.42)*	*ITT*	*Sharma et al. (2021)*

****p<0.01; **p<0.05; *p<0.10% significance levels. Standard errors in parentheses.*

Concerning livestock, Manjunath et al. (2024) found a positive impact on the average daily milk yield of Murrah buffalos in summer (+0.5 kg/animal/day by mobile app and +0.44 by whatsapp). There was no effect on winter yield and lactation duration. They also analyze results related to farmers' choices regarding feed and fodder, and management practices with positive effects on feed and deworming. As for other variables related to agricultural production: land productivity increased by 200% for CS users (Sanfo et al., 2022). CS use had no impact on crop losses (Camacho et al., 2019; Fafchamps and Minten, 2012).

Among the CS users, trainings also make a positive difference in yields compared to the yields of non-trained farmers as in the following table:

[5] In these particular examples the ATT and the LATE are closely related since the instrument used is the randomized access to treatment.

Table 3.6 - Impacts of CS trainings on yields

Crop	Unit	Coefficient *(s.e.)*	Estimation	References
Millet	Kg/ha	**+116.70*** *(66.195)*	*ATT*	*Bacci et al. (2023)*
Sorghum	Kg/ha	**+408.07***** *(7.860)*	*ATT*	*Tarchiani et al. (2021)²*

****p<0.01; **p<0.05; *p<0.10% significance levels. Standard errors in parentheses*

However, forecasts accuracy has no effect on maize yields in South Africa (Coughlan de Perez et al., 2024) and very slight positive impacts for irrigated farms in the USA (Miller et al., 2023).

In terms of impacts on farm efficiency indicators, a positive impact CS use on gross margin was found with + 195 USD/ha for cowpea (Ouédraogo et al., 2023). No impact was found for sesame (Ouédraogo et al., 2023) and for the global farm gross margin (Fafchamps and Minten, 2012). A positive impact was found on crop value with +10.6% on total crop value for CS users compared to non-users (Chiputwa et al., 2022). As for yields, CS trainings seems to amplify these positive effects on farm management with + 220.1 USD[6]/ha for sorghum gross margin and + 128.3 USD/ha for sorghum income for trained farmers compared to CS users that were not trained to the use of CS (Tarchiani et al, 2021).

In terms of inputs, labor costs are considerably reduced by the use of CS (Camacho et al., 2019). Yegbemey et al. (2023) found a specific labor reduction of -51.6 USD/ha for maize labor costs and -80.7 USD/ha for cotton labor costs, leading to an increase in labor productivity of 53.11 kg/USD and 6.76 kg/USD respectively. Positive results on input use choices (timing and quantity of products used) are mainly measured by statistical differences for CS use. Nepal et al. (2024), found no impacts for chemical inputs and a slight increase in wheat irrigation comparing CS users to non-users. However, a causal relationship was found between CS users that were trained and untrained users leading to a -54.606 kg/ha of fertilizer used for CS farmers that were trained Tarchiani et al. (2021).

Finally, positive impacts of CS use on household welfare were also found, with an average treatment effect of -10.735 for food security (HFIAS) and +257.5 USD for household income (Tham-Agyekum et al., 2024.).

3.4. Discussion

It is important to note that the results of this methodological review as any review are subject to publication bias. It is therefore possible that other impacts and methods have been

[6] All amounts were translated from FCFA or GHS to USD based on 15/01/25 exchange rate

experimented already but are unpublished. In addition, we have not yet found any pre-registration plans for the articles selected in this review.

3.4.1. Environmental and social impacts are yet to be explored

Most of the papers selected quantify economic impacts and focus on yields and farm management variables (cost/benefit). The literature is recent, but CS do have significant quantified positive impacts on yields (between on average +116 kg/ha for millet to +1540 kg/ha for rice). Maize is the crop most frequently represented in the papers. However, there is less research on cash crops and only a single article describes the impact on livestock farming (Manjunath et al., 2024).

There are still very few papers evaluating social and environmental impacts, but promising results arise. The main results concerned irrigation, chemical inputs for farming, food security or household incomes (Nepal et al., 2024; Tarchiani et al., 2021; Tham-Agyekum et al., 2024). Tarchiani et al. (2021) found a decrease of fertilization quantity used when farmers are trained to CS use. Impact on irrigation is still uncertain, only a slight increase in wheat irrigation was found (Nepal et al., 2024) but irrigated farms are more likely to benefit from CS accuracy for increasing maize yields (Miller et al., 2023). There is no significant impact on other chemical inputs. Positive impacts of CS on food security and household income were found (Tham-Agyekum et al., 2024).

In addition to the previous variables, several other possible environmental and social impacts have been mentioned by the literature selected but are still unexplored such as the impact of CS on farmers' networks (Camacho & Conover, 2019) and soil fertility (i.e. carbon content) (Chiputwa et al., 2022). Since unpaid work is often household members work, the differentiation of paid and unpaid work (Yegbemey et al., 2023) is also an interesting opportunity to go further and to start exploring CS use in relation with household member activities like schooling and off-farm employment. Last but not least, as many new CS are co-built with farmers (Chiputwa et al., 2022), there is a recent growing literature on metrics for this specific type of CS (Visman et al., 2022). Qualitative benefits from co-built climate services highlight gender empowerment, a variable that is yet to be quantified (Paparrizos et al., 2023).

Moreover, differentiated impacts such as gender or education are more difficult to estimate rigorously since they require bigger samples but have begun to be explored by the literature (Diouf et al, 2020; Barrett et al., 2021). Due to cultural norms, women are also less likely to be farming decision-makers in some territories (Carr & Onzere, 2018) which make it more difficult to evaluate gender impacts. In the wake of these previous differentiated impacts, there is, in this review, only paper that compares impacts of the same information through different dissemination chains (Manjunath et al., 2024). Further research is needed to isolate impacts of the dissemination means.

Another grey area is the link between forecast accuracy and impacts that lead to little evidence for now (Miller et al., 2023) whereas it is a component often described as important for CS uptake (Vogel et al., 2017).

3.4.2. The challenges of spillovers

Except for trainings evaluations which are based on farmers' attendance list (Bacci et al., 2023; Tarchiani et al., 2021), spillovers effects are quite common with CS impacts. Indeed, as farmers' networks are very dense with the rise of new communication technologies, it is more and more easy for them to share weather and climate information (Simon et al., 2021a). Nevertheless, some papers chose to assume implicitly or explicitly that there are no spillovers (Manjunath et al., 2024) or that every farmer could access and use the information (Coughlan de Perez et al., 2024; Miller et al., 2023).

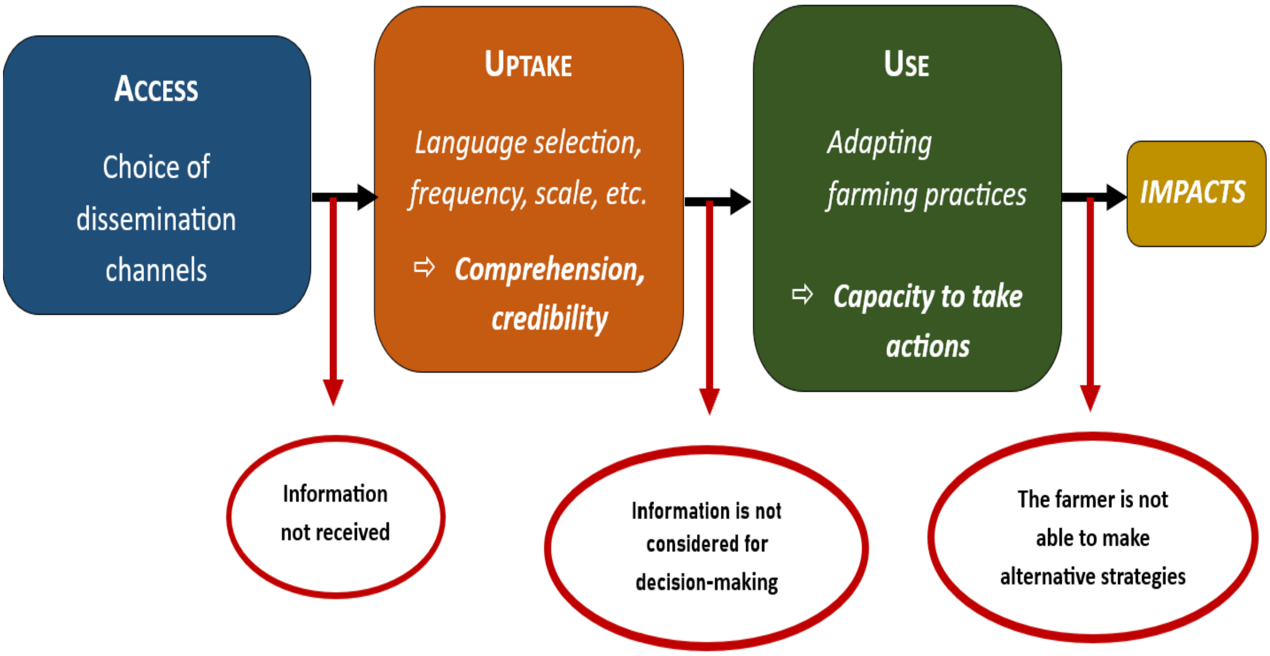
The spillover challenge for the evaluator can be divided into two types of issues: i) distinguishing the treated population from the counterfactual (who doesn't access/use CS), ii) measuring the spillover effects, as they could be regarded as a positive externality for a CS public investment. As an example, Chiputwa et al. (2022) specifically considered spillovers as a second level of CS impacts. For the later challenge, no method has yet been identified in our literature review.

On the contrary, several strategies have been used to control CS' spillovers. A first step, is to control ex-ante for the distance between treated and controlled farmers, randomizing at village level. For example, Yegbemey et al. (2023), used a minimum of a five-kilometer buffer. However, the distance between sample units cannot be too big otherwise the meteorological conditions can change too much between the treated and the control group. A second step, ex-post, could be to identify control-group farmers who gained access to the information. For example, Chiputwa et al. (2022) defined dummies variables allowing for combination: i) is exposed to a particular CS and ii) uses this particular CS. Then, the treatment became the cumulation of these two characteristics. Another method commonly used is to instrument the users of the CS from the all population (treated/controlled) with the random assignment to treatment (Camacho & Conover, 2019; Fafchamps & Minten, 2012; Yegbemey et al., 2023). However, this method, as with the previous method, can still be subject to self-reporting bias. An exploratory field could be the integration of farmer kin/friendship networks in the analysis of spillovers (Simon et al., 2021b). Calculating a social distance from each untreated farmer to the nearest treated farmer could be a perspective for doing it.

3.4.3. Improving uptake to reduce the non-compliance rate

Compliance in the use of climate services is not easy to reach for the treated group and demand the will and the ability for farmers to complete the different steps from accessing to using the service. Non-compliance rate or non-user rate is not always detailed in the papers, but Fafchamps et Minten (2012) had until 44.3% of their treated sample declaring not using the information sent. In that case ATT could be very different from ITT. Indeed, if one of the following steps *(access, uptake* and *use*) is not completed across the climate service implementation chain, there could be no impact or a smaller impact to measure. Receiving or accessing a CS can be considered as a necessary condition to use the information, but it is not a guarantee of information usage. Indeed, if access to CS could be mainly constrained by farmer awareness, price, access to the relevant distribution channels (via phones, radio or television) or farmer's ability to operate the service (literacy, languages command, etc.) (Vogel, 2017), using CS information is theoretically a farmer's choice. Nonetheless, it is a choice if, and only if: i) the farmer is a decision-maker and, ii) has the knowledge and the means of making alternative strategies based on the CS.

Figure 3.5 – Implementation process of a CS –adapted from Vogel et al.(2017)



In experimental methods, samples (treated and untreated) often account for specific characteristics in common relevant to the CS delivery channels and to the farmers' ability to make decisions. For example, Yegbemey et al. (2022), selected only farmers that can read SMS on their mobile phone or have a permanent household member that can do so whereas Fafchamps et Minten (2012) selected only heads of household, and Sanfo et al. (2022), landowners. For all papers from Africa, where the language used by the service is specified in the paper, they state that the service is available in the local language which also favor the uptake (Carr et al., 2020a). However, even as head of households or field owner, some social, gender and cultural barriers can still prevent farmers from being decision-makers such as ethnic and community's social system of decision (Carr & Onzere, 2018; Hansen et al., 2019). The delay of delivery could also be a major barrier to the use of the information for the less equipped farmers as time could be too short to change cultural practices before the event occurred, resulting in no alternative strategy being left for farmers (Bacci et al., 2023;

Makaudze, 2005). Furthermore, it is also important to control the farmers' use of other climate services in their decision making to isolate the impact of a specific CS use (Camacho et al, 2019). Generally speaking, it is interesting to note that the use of the CS varies also according to the crops cultivated but also across the rain season depending on the sensitivity to weather conditions of the decision being made (from 83% of use in June to 17% on October for a delivery rate higher than 96% of information reception) (Yegbemey et al., 2022).

To overcome the last technical barriers and reducing the non-user rate some papers used brokers, working hand in hand with field advisors or NGOs to provide help for the service activation and the understanding of the indicators, as well as the potential adaptation options for cultural decisions of farmers (Manjunath et al., 2024; Sanfo et al., 2022; Yegbemey et al., 2023). It is a well-known practice recommended by the literature (Harvey et al., 2019). Indeed, impacts evaluations in this review proved that trainings improve farmers' CS uptake in comparison to untrained farmers and lead to positive impacts on yields (Bacci et al., 2023; Tarchiani et al., 2021). In Niger, in the experience, only 59% of untrained farmers were using CS whereas 98% of trained farmers used it (Bacci et al., 2023).

Targeting farmers needs working with scientists and experts from different disciplines (climatologists, agronomists, sociologists, economists etc.) is also favoring CS uptake by delivering contextualized and more accurate information (Carr et al., 2020b). Therefore, several papers tried to deliver specific forecasts indicators and advice according to the cultivated crops, the type of livestock or the type of lands cultivated (such as slopes and soil fertility) using interdisciplinary coproduction (Manjunath et al., 2024; Sanfo et al., 2022; Yegbemey et al., 2023). As forecast accuracy is usually considered a main component of farmers 'uptake (Bacci et al., 2023; Tarchiani et al., 2021), therefore participation of weather scientists to the evaluation is of importance. However, a disconnection between forecasts accuracy perception and measure is observed. Yegbemey et al. (2022), found that if 85% of the information sent was accurate whereas farmers perceived it as 60% accurate. Despite this disconnection, farmers in the experiment still considered information as important for their decision-making (96%). Indeed, there is only weak evidence that forecasts accuracy has impacts in our paper's selection (Coughlan de Perez et al., 2024; Miller et al., 2023).

Finally, since CS are with rare exceptions (Chiputwa et al., 2022; Tarchiani et al., 2021) often evaluated in a one-year farming season, another issue can arise, especially for seasonal climate forecasts. In some regions, farmers expectations are often made for a "normal" year following a shared and well-known calendar (Müller-Mahn et al., 2020). Therefore, when forecasts predict a normal year, treated farmers do not change expectations. Without additional information such as agrometeorological advice, the treatment and control farmers are likely to take the same decisions. In this case, it is difficult to distinguish the users from the non-users and there should be no effect of the treatment.

3.5. Conclusion

The goal of this review was mainly to take stock of the methods used to rigorously quantify the impacts of CS. Most of the papers were published recently and used experimental or quasi-experimental methods in developing countries. Quantifying impacts for CS is not simple. Depending on the control of the evaluator to the CS access different problems can emerge: i) spillovers in the control group and, ii) selection bias in the access and the use of the information. Therefore, econometric methods need to be applied to build a credible counterfactual. Instrument variable approaches allow controlling for spillovers among farmers, but further research could be done to quantify their extent as what some authors called a second level of impacts for farmers (i.e. undirect benefits of an intervention).

Controlling access and relevance along the CS implementation process are necessary conditions to avoid selection biases in the information usage and to reduce non-compliance rate. Knowledge brokering is also proved to be effective on uptake and evaluations on CS trainings lead to positive impacts. More participatory approaches could be useful for evaluators to captures the impact pathways that link outcomes to impacts and to understand complex decision making context.

In terms of quantified results, papers mainly focus on yields and farm management variables (cost/benefit) with positive impacts. Cash crops are less studied and so is breeding with only one evaluation on this latter sector. Social and environmental impacts are yet to be explored, but first results are promising for reducing quantities of fertilizers or improving food safety. New metrics may emerge in the following years from the co-building literature to quantify qualitative existing measures on CS social and environmental impacts. This review also highlights the growing interdisciplinary collaboration in CS evaluations between climate and weather scientists, agronomists, sociologists, economists etc. Collaboration is useful for producing high-quality and user-based forecasts and advice. It allow us to be optimistic for advancing mixing evaluation methods to produce and quantify CS benefits, notably for the most unreachable farmers.

References of Chapter 3

Agyekum, T. P., Antwi-Agyei, P., & Dougill, A. J. (2022). The contribution of weather forecast information to agriculture, water, and energy sectors in East and West Africa : A systematic review. *FRONTIERS IN ENVIRONMENTAL SCIENCE*, *10*, 935696. https://doi.org/10.3389/fenvs.2022.935696

Bacci, M., Idrissa, O. A., Zini, C., Burrone, S., Sitta, A. A., & Tarchiani, V. (2023). Effectiveness of agrometeorological services for smallholder farmers : The case study in the regions of Dosso and Tillabéri in Niger. *Climate Services*, *30*, 100360. https://doi.org/10.1016/j.cliser.2023.100360

Born, L., Prager, S., Ramirez-Villegas, J., & Imbach, P. (2021). A global meta-analysis of climate services and decision-making in agriculture. *Climate Services*, *22*, 100231. https://doi.org/10.1016/j.cliser.2021.100231

Camacho, A., & Conover, E. (2019). The impact of receiving SMS price and weather information on small scale farmers in Colombia. *World Development*, *123*, 104596. https://doi.org/10.1016/j.worlddev.2019.06.020

Carr, E. R., Goble, R., Rosko, H. M., Vaughan, C., & Hansen, J. (2020a). Identifying climate information services users and their needs in Sub-Saharan Africa : A review and learning agenda. *Climate and Development*, *12*(1), 23-41. https://doi.org/10.1080/17565529.2019.1596061

Carr, E. R., Goble, R., Rosko, H. M., Vaughan, C., & Hansen, J. (2020b). Identifying climate information services users and their needs in Sub-Saharan Africa : A review and learning agenda. *Climate and Development*, *12*(1), 23-41. https://doi.org/10.1080/17565529.2019.1596061

Carr, E. R., & Onzere, S. N. (2018). Really effective (for 15% of the men) : Lessons in understanding and addressing user needs in climate services from Mali'. *Climate Risk Management*, *22*, 82-95. https://doi.org/10.1016/j.crm.2017.03.002.

Chiputwa, B., Blundo-Canto, G., Steward, P., Andrieu, N., & Ndiaye, O. (2022). Co-production, uptake of weather and climate services, and welfare impacts on farmers in Senegal : A panel data approach. *Agricultural Systems*, *195*, 103309. https://doi.org/10.1016/j.agsy.2021.103309

Coughlan de Perez, E., Anderson, W., Han, E., Masukwedza, G. I. T., & Mphonyane, N. (2024). Detectable use of ENSO information on crop production in Southern Africa. *Climate Services*, *36*, 100514. https://doi.org/10.1016/j.cliser.2024.100514

Fafchamps, M., & Minten, B. (2012). Impact of SMS-Based Agricultural Information on Indian Farmers. *The World Bank Economic Review*, *26*(3), 383-414. https://doi.org/10.1093/wber/lhr056

Gouroubera, M. W., Sabi, A. K., Comada, T. K. B., Dosso, F., Fatondji, S. A., Gouthon, M. B., & Houaga, R. P. (2024). Designing effective digital-based delivery of climate information for smallholder farmers : A mini meta-analysis on drivers and barriers. *CLIMATE POLICY*, *24*(10), 1443-1456. https://doi.org/10.1080/14693062.2023.2266475

Hansen, J. W., Vaughan, C., Kagabo, D. M., Dinku, T., Carr, E. R., Körner, J., & Zougmoré, R. B. (2019). Climate Services Can Support African Farmers' Context-Specific Adaptation Needs at Scale. *Frontiers in Sustainable Food Systems*, *3*, 21. https://doi.org/10.3389/fsufs.2019.00021

Harvey, B., Jones, L., Cochrane, L., & Singh, R. (2019). The evolving landscape of climate services in sub-Saharan Africa : What roles have NGOs played? *Climatic Change*, *157*(1), 81-98. https://doi.org/10.1007/s10584-019-02410-z

Madhuri. (2023). How do climate information services (CIS) affect farmers' adaptation strategies? A systematic review. *Climate Services*, *32*, 100416. https://doi.org/10.1016/j.cliser.2023.100416

Makaudze, E. (2005). *Do seasonal climate forecasts and crop insurance matter for smallholder farmers in Zimbabwe ? Using contingent valuation method and remote sensing applications*. The Ohio State University.

Manjunath, K. V., Maiti, S., Garai, S., Reddy, D. A., Bhakat, M., Aggarwal, A., & Mondal, G. (2024). Impact of temperature humidity index-based climate services for Murrah buffaloes of India on operational decision-making and economic outcome of the farm. *Climate Services*, *36*, 100522. https://doi.org/10.1016/j.cliser.2024.100522

Miller, S. J., Clarke, E., & Mathews, S. L. (2023). Little evidence of avoided yield loss in US corn when short-term forecasts correctly predict extreme heat. *Environmental Research Letters*, *18*(12), 124041. https://doi.org/10.1088/1748-9326/ad0bd5

Muller, L. C. F. E., Schaafsma, M., Mazzoleni, M., & Van Loon, A. F. (2024). Responding to climate services in the context of drought : A systematic review. *CLIMATE SERVICES*, *35*, 100493. https://doi.org/10.1016/j.cliser.2024.100493

Müller-Mahn, D., Moure, M., & Gebreyes, M. (2020). Climate change, the politics of anticipation and future riskscapes in Africa. *Cambridge Journal of Regions, Economy and Society*, *13*(2), 343-362. https://doi.org/10.1093/cjres/rsaa013

Mwangi, M., Kituyi, E., & Ouma, G. (2021). A systematic review of the literature on the contribution of past climate information services pilot projects in climate risk management. *SCIENTIFIC AFRICAN*, *14*, e01005. https://doi.org/10.1016/j.sciaf.2021.e01005

Nepal, M., Ashfaq, M., Sharma, B. R., Shrestha, M. S., Khadgi, V. R., & Soares, M. B. (2024). Impact of weather and climate advisories on agricultural outcomes in Pakistan. *SCIENTIFIC REPORTS*, *14*(1), 1036. https://doi.org/10.1038/s41598-023-51066-4

Onyeneke, C. J., Umeh, G. N., & Onyeneke, R. U. (2023). Impact of Climate Information Services on Crop Yield in Ebonyi State, Nigeria. *Climate*, *11*(1), Article 1. https://doi.org/10.3390/cli11010007

Paparrizos, S., Dogbey, R. K., Sutanto, S. J., Gbangou, T., Kranjac-Berisavljevic, G., Gandaa, B. Z., Ludwig, F., & van Slobbe, E. (2023). Hydro-climate information services for smallholder farmers : FarmerSupport app principles, implementation, and evaluation. *Climate Services*, *30*, 100387. https://doi.org/10.1016/j.cliser.2023.100387

Roudier, P., Alhassane, A., Baron, C., Louvet, S., & Sultan, B. (2016). Assessing the benefits of weather and seasonal forecasts to millet growers in Niger. *Agricultural and Forest Meteorology*, *223*, 168-180. https://doi.org/10.1016/j.agrformet.2016.04.010

Sanfo, S., Salack, S., Saley, I. A., Daku, E. K., Worou, N. O., Savadogo, A., Barro, H., Guug, S., Koné, H., Ibrahim, B., Rojas, A., Raimond, C., & Ogunjobi, K. O. (2022). Effects of customized climate services on land and labor productivity in Burkina Faso and Ghana. *Climate Services*, *25*, 100280. https://doi.org/10.1016/j.cliser.2021.100280

Sharma, U., Chetri, P., Minocha, S., Roy, A., Holker, T., Patt, A., & Joerin, J. (2021). Do phone-based short message services improve the uptake of agri-met advice by farmers? A case study in Haryana, India. *CLIMATE RISK MANAGEMENT*, *33*, 100321. https://doi.org/10.1016/j.crm.2021.100321

Simon, W. J., Krupnik, T. J., Aguilar-Gallegos, N., Halbherr, L., & Groot, J. C. J. (2021a). Putting social networks to practical use : Improving last-mile dissemination systems for climate and market information services in developing countries. *Climate Services*, *23*, 100248. https://doi.org/10.1016/j.cliser.2021.100248

Simon, W. J., Krupnik, T. J., Aguilar-Gallegos, N., Halbherr, L., & Groot, J. C. J. (2021b). Putting social networks to practical use : Improving last-mile dissemination systems for climate and market information services in developing countries. *Climate Services*, *23*, 100248. https://doi.org/10.1016/j.cliser.2021.100248

Suckall, N., & Soares, M. B. (2022). Evaluating the benefits of weather and climate services in South Asia : A systematic review. *REGIONAL ENVIRONMENTAL CHANGE*, *22*(3), 104. https://doi.org/10.1007/s10113-022-01947-7

Tall, A., Coulibaly, J. Y., & Diop, M. (2018). Do climate services make a difference? A review of evaluation methodologies and practices to assess the value of climate information services for farmers: Implications for Africa. *Climate Services*, *11*, 1-12. https://doi.org/10.1016/j.cliser.2018.06.001

Tarchiani, V., Coulibaly, H., Baki, G., Sia, C., Burrone, S., Nikiema, P. M., Migraine, J.-B., & Camacho, J. (2021). Access, Uptake, Use and Impacts of Agrometeorological Services in Sahelian Rural Areas : The Case of Burkina Faso. *Agronomy*, *11*(12), 2431. https://doi.org/10.3390/agronomy11122431

Tham-Agyekum, E. K., Bakang, J.-E. A., Abdul-Mumin, A., Mensah, W., Adarkwa, B. O., Duah, A., & Awuku, B. O. (s. d.). Harnessing climate information service use for cocoa farming sustainability in Ghana. *Climate and Development*, *0*(0), 1-14. https://doi.org/10.1080/17565529.2024.2359984

Vaughan, C., Hansen, J., Roudier, P., Watkiss, P., & Carr, E. (2019). Evaluating agricultural weather and climate services in Africa : Evidence, methods, and a learning agenda. *WIREs Climate Change*, *10*(4). https://doi.org/10.1002/wcc.586

Visman, E., Vincent, K., Steynor, A., Karani, I., & Mwangi, E. (2022). Defining metrics for monitoring and evaluating the impact of co-production in climate services. *Climate Services*, *26*, 100297. https://doi.org/10.1016/j.cliser.2022.100297

Vogel, J., Letson, D., & Herrick, C. (2017). A framework for climate services evaluation and its application to the Caribbean Agrometeorological Initiative. *Climate Services*, *6*, 65-76. https://doi.org/10.1016/j.cliser.2017.07.003

Warner, D., Moonsammy, S., & Joseph, J. (2022). Factors that influence the use of climate information services for agriculture : A systematic review. *Climate Services*, *28*, 100336. https://doi.org/10.1016/j.cliser.2022.100336

Westgate, M. J. (2019). revtools : An R package to support article screening for evidence synthesis. *Research Synthesis Methods*, *10*(4), 606-614. https://doi.org/10.1002/jrsm.1374

Yegbemey, R. N., Bensch, G., & Vance, C. (2023). Weather information and agricultural outcomes : Evidence from a pilot field experiment in Benin. *World Development*, *167*, 106178. https://doi.org/10.1016/j.worlddev.2022.106178

Yegbemey, R. N., & Egah, J. (2021). Reaching out to smallholder farmers in developing countries with climate services : A literature review of current information delivery channels. *Climate Services*, *23*, 100253. https://doi.org/10.1016/j.cliser.2021.100253

Appendix 3.A– Climate services analysis

Table 3.7 - Climate services analysis

References	CS Studied	Parameters	Advice	Channels	Frequency	Language	Target	Information source	Other information
Bacci et al. (2023)	SCF + Advice	Rainfall, Temperature JJA, Temperature JAS, Start of the rainy season onset, Dry spells, End of the rainy season, Length of the rainy season	Crops variety, Seeding period, Toposequences, Field preparation period	Seminars, Radios, Podcasts, Voice messages,Text messages, Emails, Website	Twice a year	Local language and French	Farmers, Extension workers	National Meteorological Services (NMS)	*n/a*
	10-day forecasts + Advice	Cumulative 10 days rainfall (mm), Number of rainy days, Number of rainy days above 20 mm, Maximum number of consecutive dry days, Number of dry periods of at least 5 consecutive dry days, Wind speed, Temperature (max, min)	Seeding timing, Weeding timing, Fertilization timing, Pesticides timing, Other cropping practices	Radios, Voice messages, Text messages, Emails, Website	Each 10 days during the cropping season				
	24-72 hour forecasts	Wind, Rainfall, Temperature	Meteorological warnings	Radios, TV, Website	Daily				

	Past 10-day reports	Cumulative 10 days rainfall (mm) past 10-day, Crops phenology past 10-day, Hydrological situation past 10-day, Market prices past 10-day, Livestock situation past 10-day, Pasture situation last 10-day	*n/a*	Radios, Voice messages, Text messages, Emails, Website	Each 10 days during the cropping season				
Camacho et al. (2019)	7-day forecasts	Temperature (Max Min), Probability of rainfall	*n/a*	Text messages (SMS)	Weekly	*Unspecified*	Farmers	Instituto de Hidrología, Metereología y Estudios Ambientales (IDEAM)	Market price information
	EWS	Frost, Floods, Droughts			*n/a*				
Chiputwa (2019, 2020, 2022)	SCF + Advice	Start of the rainy season, End of the rainy season, Total rainfall amount (Rainy, Normal, Deficit)	*Unspecified*	From Multidisciplinary Working Groups to Relais farmers and farmers through Radios, cell phone calls, Text messages (SMS) or word of mouth.	Yearly and Monthly updated during the rainy season (JJA)	Local language	Farmers, Extension workers	National Meteorological Agency (ANACIM)	*n/a*
	10-day forecasts + Advice	Dry spells, Trends in rainfall			Each 10 days during the cropping season				
	12-72 hour forecasts	Probability of rainfall	*n/a*		Daily, updated twice a day		Farmers		
	EWS	Thunderstorm, Off-season showers / rains, High winds, Floods, Droughts			One-shot				

Fafchamps et Minten (2012)	Weather forecasts *(Unspecified)*	Probability of rainfall, Humidity rate	Crop advice : choice of variety, pesticide, and fertilizer	Text messages (SMS)	75 to 100 SMS/month	English or Local Language	Farmers	Reuters Market Light (RML)	Market price information, Commodity news
Tarchiani et al. (2021)	SCF	Total rainfall amount (Below, Normal, Above)	*Unspecified*	Radio, Seminars, Extension workers, Text messages	Yearly	Local language	Farmers	National Agency for Meteorology (ANAM)	*n/a*
Sanfo et al. (2022)	SCF	Total rainfall amount (Below, Normal, Above)	Technical itinerary and advice	Voice messages	Monthly	French, English and Local languages	Farmers	*Unspecified*	*n/a*
	24h forecasts	Rainfall (Yes/No)			Daily				
	7-day forecasts	Probability of rainfall, Dry spells (>9 days), Heavy rain events			*Unspecified*				
Yegbemey et al. (2023)	SCF	Start of the rainy season, End of the rainy season, Length of rainy season	*n/a*	Text messages (SMS)	Once	Local language, French	Farmers	MeteoBenin	*n/a*
	3-day forecasts	Rainfall (mm)			Every-three days				
Manjunath et al. (2024)	5-day forecasts + Advice	Rainfall (mm), Temperature (Max, Min), Humidity rate (Max, Min, Temperature Humidity Index (THI)), Wind speed (kmph), Wind direction (Degree), Cloud cover (Octa)	Animal feed and fodder, Management practices, Health and disease management, Housing and shelter	Text messages (SMS, Whatsapp), Mobile application	Weekly	English	Breeders	India Meteorology Department (IMD), National Dairy Research Institute,	*n/a*

	EWS + Advice	*Unspecified (Heat stress ?)*							
Coughlan de Perez et al. (2024)	SCF	Probability of seasonal rainfall totals	*n/a*	*n/a*	*Unspecified*	*Unspecified*	*Unspecified*	International Research Institute for Climate and Society (IRI), European Center for Medium Range Weather Forecasting (ECMWF)	*n/a*
Miller et al. (2023)	1-7-day forecasts	Temperature (Max, Min)	*n/a*	*n/a*	*Unspecified*	English	*Unspecified*	National Digital Forecast Database (NDFD)	*n/a*
Nepal et al. (2024)	Weather forecasts *(unspecified)* + Advice	*Unspecified*	*Unspecified (crop-specific)*	Website, SMS, TV, Social Medias, Newsletters	Weekly, Every 10 days, monthly	National and Local language	Farmers	Pakistan Meteorological Department (PMD)	*n/a*
	SCF + Advice								
	3-day forecasts			Website	Daily				

Onyeneke et al. (2023)	SCF	*Unspecified*	*n/a*	TV, Radio, Agricultural workshops/shows, bulletins, Other publications, Extension workers, Social media, Cell phones, Farmer groups	Daily, Weekly, Seasonal	Unspecified	Farmers	Nigerian Meteorological Agency (NiMET)	*n/a*
	Weather forecasts *(unspecified)*								
Ouédraogo et al. (2023)	10-day forecasts + Advice	Rainfall, Dry spells, Wind	*Unspecified*	Radio	*Unspecified*	Local language	Farmers	*Unspecified*	*n/a*
	SCF + Advice	End of the rainy season, Length of rainy season, Start of the rainy season, Total rainfall amount (Below, Normal, Above), Dry spells		Workshops	Twice a season				
	24 hour forecasts + Advice	Rainfall, Wind		Radio	Daily				
Sharma et al. (2021)	Advice	*n/a*	Scheduling different farming operations, specifically irrigation, fertilizers and weedicides application.	SMS	*Unspecified*	*Unspecified*	Farmers	India Meteorological Department (IMD)	*n/a*

Appendix 3.B – Climate services trainings analysis

Table 2.8 - Climate services trainings analysis

Reference	Type	Frequency	Target
Bacci et al. (2023)	Information production	One-shot	National Meteorological Service
	Use, Dissemination, Data collection	Yearly	Extensionists
	Communication and translation	One-shot	Radio operators
	Use, Data collection	Yearly	Farmers
Chiputwa et al. (2022)	Communication and translation	One-shot	Radio operators
Tarchiani et al. (2021)	Use	n/a	Farmers
Manjunath et al. (2024)	Use	One-shot	Farmers
Yegbemey et al. (2023)	Use	One-shot	Farmers
Sanfo et al. (2022)	Information production, Use, Dissemination, Data collection	Several times	Farmers

Conclusion Générale

Cette thèse d'économie s'est attachée à enrichir la littérature dans le domaine des services climatiques, à travers trois Chapitres sur la demande, l'utilisation et l'impact des SC. L'ensemble de ces travaux de recherche accordent une place centrale à la valeur de ces services et à l'hétérogénéité individuelle dans les analyses. Les chapitres 1 et 2 sont focalisés sur les territoires du nord de la Côte d'Ivoire et basés sur des données propres collectées sur le terrain tandis que le Chapitre 3 repose sur un spectre géographique global.

Le Chapitre 1 utilise l'expérimentation de choix pour analyser la préférence relative des agriculteurs pour l'intégration des savoirs prévisionnels locaux. Ce chapitre a permis d'identifier une présence active de savoirs prévisionnels locaux au Nord de la Côte d'Ivoire avec des agriculteurs prêts à collaborer pour créer des services hybrides. L'inventaire a montré que les savoirs les plus répandus sont des prévisions de court terme, et plus rarement des prévisions saisonnières et des périodes sans pluies. Ils sont considérés en moyenne comme plus fiables que les prévisions scientifiques bien que cette fiabilité diminue en raison du nombre d'indicateurs disponibles, et d'une moindre transmission des connaissances locales. Les agriculteurs semblent engager leur réputation lorsqu'ils partagent leur prévision et leur savoir ce qui a tendance à réduire leurs diffusions. L'expérimentation de choix démontre en moyenne que l'intégration des savoirs au format de prévisions comparatives n'est pas déterminant pour le choix d'un service climatique, à l'exception des populations les plus âgées. Cependant, le peu d'accès des agriculteurs aux services climatiques dans la zone, le faible taux d'éducation formelle et la moindre pénétration des smartphones a tendance à orienter les préférences des agriculteurs dans cette expérimentation de choix vers une attention particulière sur les moyens de diffusion oraux. Ces résultats contribuent ainsi à la littérature multidisciplinaire sur l'hybridation des services climatiques sous un angle économique en utilisant des méthodes d'estimations avancées tenant compte de l'hétérogénéité individuelle. En matière de recommandations, les politiques publiques doivent multiplier les moyens de dissémination oraux afin de dépasser les barrières à l'accès des populations illettrées et les plus isolées. Par ailleurs, de plus amples recherches pourraient être mise en œuvre sur la complémentarité des savoirs locaux et des SC dans cette zone afin de mieux comprendre les formats de collaboration qui pourrait convenir à des populations prêtent à partager leurs savoirs et auxquelles, en particulier, les plus âgés accordent toujours une grande confiance.

Le Chapitre 2 analyse les décisions de semis de maïs des agriculteurs en fonction d'une probabilité de pauses sèches à travers une approche expérimentale. Les résultats démontrent que les agriculteurs adaptent leurs stratégies, ce qui améliore systématiquement les récoltes espérées par rapport à une situation sans prévision. Toutefois, même lorsque les probabilités sont très faibles, de nombreux agriculteurs restent prudents et ne consacrent pas la totalité de leurs semences à l'option risquée, en particulier les agriculteurs dont le ménage souffre d'insécurité alimentaire. Les choix des agriculteurs sont influencés par leur comportement antérieur en matière de semis et de chocs passés. Les caractéristiques individuelles et notamment psychologiques influencent également la manière dont les agriculteurs perçoivent et réagissent à la probabilité de pause sèche. Des variables telles que le locus de contrôle, la volonté d'adaptation et les pertes passées réelles de maïs modulent de manière significative les réponses de semis aux probabilités de pause sèche. Ce Chapitre contribue à la littérature sur les effets des services climatiques sur la prise de décision agricole en introduisant un modèle intra-individuel innovant, compréhensible et reproductible parmi les populations rurales peu instruites. Les principales limites de l'étude découlent du cadre expérimental et sont notamment l'exclusion de contraintes telles que la disponibilité de la main-d'œuvre et/ou du matériel, et de l'absence d'interactions sociales comme les effets d'imitation. En outre, nous supposons que les effets de la perte de tout ou partie d'une récolte de maïs peuvent être sous-estimés dans ce type de modélisation, étant donné l'importance de ces récoltes pour la sécurité alimentaire des ménages dans la région. Enfin, l'expérience suppose une fiabilité parfaite de l'information, ce qui n'est pas le cas dans le monde réel. D'un point de vue opérationnel, les résultats soulignent néanmoins le potentiel de l'utilisation de formats probabilistes pour communiquer des informations météorologiques à des agriculteurs peu alphabétisés.

Le Chapitre 3 proposait à travers une revue systématique de mettre en lumière les méthodologies actuelles utilisées dans l'évaluation ex post de SC. La plupart des articles ont été publiés récemment et ont utilisé des méthodes expérimentales ou quasi-expérimentales. En fonction du contrôle exercé par l'évaluateur sur l'accès au SC, différents problèmes émergent : i) les effets de contamination dans le groupe de contrôle et ii) le biais de sélection dans l'accès et l'utilisation de l'information. Des approches basées sur des variables instrumentales permettent de contrôler les effets de contamination parmi les agriculteurs, mais des recherches supplémentaires pourraient être menées pour quantifier leur étendue. Certains auteurs appellent notamment à poursuivre les recherches pour mesurer les bénéfices d'une intervention sur les contaminés. La détermination rigoureuse des groupes de contrôle et traité par l'évaluateur est également une condition nécessaire pour éviter les biais de sélection. Les impacts quantifiés se concentrent principalement sur les rendements et les variables de gestion agricole (coût/bénéfice). Les cultures de rente sont moins étudiées, de même que l'élevage, qui n'a fait l'objet que d'une seule évaluation. Malgré des premiers résultats prometteurs sur la réduction des quantités d'engrais ou l'amélioration de la sécurité alimentaire, les impacts sociaux et environnementaux sont encore peu étudiés. Les formations ont également tendance à accroitre l'effet positif des services climatiques Ce Chapitre met aussi en évidence la collaboration interdisciplinaire croissante dans les évaluations des SC entre les climatologues, les météorologues, les agronomes, les sociologues, les économistes, etc. Ce constat permet d'être optimiste quant à l'évolution de méthodes d'évaluation mixtes.

Enfin, cette thèse conclue à l'influence majeure de l'hétérogénéité individuelle sur la demande, l'utilisation et l'impact des SC. Les résultats appuient la nécessité de tenir compte des individualités des agriculteurs afin de maximiser les bénéfices potentiels des SC.

Résumé substantiel en français

En Afrique de l'Ouest, la variabilité croissante des précipitations représente une menace pour les ménages agricoles (Basse et al., 2024; Gaetani et al., 2020). Une hausse de la fréquence et de la longueur des pauses sèches à l'intérieur de la saison des pluies, ainsi que la recrudescence d'épisodes de pluies intenses sont perçus et mesurés dans le nord de la Côte d'Ivoire par (Boko-Koiadia Adjoua et al., 2016; Dekoula et al., 2018, 2019). L'agriculture étant principalement pluviale, ces changements climatiques sont à l'origine de pertes de récoltes et, in fine, d'un risque grandissant d'insécurité alimentaire (Roudier et al., 2011; Sultan et al., 2013, 2019). Face à ces changements climatiques, la mise à disposition de services climatiques (SC) aux agriculteurs afin qu'ils anticipent les chocs météorologiques et adaptent leurs décisions apparait comme essentielle. Inscrits à l'agenda international du développement (Accord de Paris, article 7, alinéa c; Objectif de développement durable 13, cible 13.3), les SC se définissent comme tout service (applications, bulletins radio, sms etc.) comprenant des prévisions météorologiques de court-terme (1 à 15 jours), saisonnières (tendance sur 3 mois) ou encore des projections climatiques (jusqu'à un siècle) visant à guider les usagers dans leurs prises de décisions.

Cette thèse s'intéresse à la demande, l'utilisation et l'impact des services climatiques pour les agriculteurs du nord de la Côte d'Ivoire. Afin de mieux comprendre la demande locale, nous explorons, dans un premier temps, les préférences pour les SC à travers une expérimentation de choix auprès de 245 agriculteurs du nord de la Côte d'Ivoire. Ce premier chapitre accorde une attention particulière à la valorisation de l'intégration des savoirs locaux dans les SC. Ces savoirs étant encore peu documentés en Afrique de l'Ouest (Nyadzi, 2021a) , cette thèse se propose également d'inventorier les connaissances des agriculteurs en la matière. Dans un second temps, nous nous intéressons à la l'utilisation et de l'impact potentiel des prévisions météorologiques à travers une approche expérimentale. Cette approche a pour objectif de tester, auprès de 313 agriculteurs, l'adaptation des semis de maïs en réponse à une prévision de pause sèche. Nous mesurons ici, l'impact de cette prévision météorologique sur les rendements potentiels et explorons les facteurs qui influencent la prise de décision des agriculteurs. Enfin, la question de la quantification des impacts des SC en agriculture est analysée au cours d'un troisième chapitre consacré à une revue méthodologique et systématique des évaluations quantitatives publiées dans la littérature scientifique. Ce chapitre, contrairement aux précédents, est construit à partir d'articles publiés dans différentes géographies du monde.

Cette recherche doctorale, réalisée dans le cadre d'une convention CIFRE et financée par l'Agence Française de Développement (AFD), s'inscrit en cohérence avec les actions de l'institution dans la région, notamment à travers deux projets portant sur le renforcement de la Société d'Exploitation et de Développement Aéroportuaire, Aéronautique et

Météorologique (SODEXAM) et sur l'appui à la filière cotonnière. Les données empiriques mobilisées dans deux chapitres proviennent d'enquêtes menées en collaboration avec l'entreprise Ivoire Coton, qui a facilité l'accès à ses producteurs encadrés. Ces campagnes de collecte, financées par l'AFD, ont été conduites avec l'appui de consultants locaux (CIRES et Hervé Kakou) et en coordination avec la SODEXAM, afin de garantir la pertinence scientifique et opérationnelle de la recherche.

Ce résumé substantiel en français présentera dans l'ordre les trois chapitres qui composent cette thèse, à savoir :

1. **Les savoirs prévisionnels locaux au sein des services climatiques : une expérimentation de choix**
2. **Des prévisions sur le terrain : une probabilité de pause sèche peut-elle influer sur les comportements de semis des agriculteurs ?**
3. **Quantifier les impacts ex-post des services climatiques pour les agriculteurs : une revue méthodologique**

Ce résumé détaillera pour chaque chapitre la question de recherche, la méthodologie utilisée, les résultats et principales recommandations issues de cette recherche.

Chapitre 1 : Les savoirs prévisionnels locaux au sein des services climatiques : une expérimentation de choix

Dans plusieurs régions d'Afrique subsaharienne, voir des fourmis se déplacer dans une même direction est souvent considéré comme un signe annonciateur de pluie dans les jours suivants (Gbangou, 2021; Paparrizos et al., 2023; Roncoli et al., 2002). Les populations rurales continuent d'utiliser ce type de savoir prévisionnel local parallèlement aux services climatiques (SC) pour anticiper les événements météorologiques et orienter leurs décisions agricoles (Antwi-Agyei et al., 2013, 2015, 2021; Mafongoya & Ajayi, 2017; Nyadzi, 2021b)

Pour être pleinement efficaces, les services climatiques doivent être perçus par les utilisateurs comme crédibles, pertinents et légitimes, tout en répondant à un ou plusieurs besoins spécifiques (Carr et al., 2020; Carr & Onzere, 2018; Cash et al., 2003). Cependant, dans certaines régions, les savoirs locaux sont jugés plus fiables et légitimes que les prévisions scientifiques (Ebhuoma & Simatele, 2019). Cela soulève d'importantes questions quant à la conception de services climatiques adaptés aux préférences des utilisateurs. Ce chapitre explore l'intérêt des agriculteurs pour des services climatiques hybrides combinant prévisions scientifiques et locales, à partir d'une expérience de choix menée dans le nord de la Côte d'Ivoire.

Les savoirs prévisionnels locaux (SPL) renvoie ici aux indicateurs environnementaux observés localement par les populations pour formuler des prévisions météorologiques à court terme et saisonnières (Gbangou, 2021). Il repose sur des observations de terrain et se rapporte à la biodiversité (par exemple, les stades phénologiques des plantes, les comportements des animaux) ou à des éléments abiotiques (par exemple, les formations nuageuses, les étoiles, la température et le vent). Cette définition exclut délibérément les dimensions spirituelles, bien que les savoirs spirituels et observationnels ne soient pas toujours distincts, ni au sein des communautés ni dans la littérature (D. Nakashima et al., 2018; D. J. Nakashima et al., 2012; Nyadzi, 2021b; Roncoli, 2006; Roncoli et al., 2002). Le savoir local constitue un héritage intergénérationnel propre à un territoire donné (Mutasa, 2015). Il demeure toutefois dynamique, évoluant grâce à l'innovation, aux échanges interculturels et à la transmission entre générations (Dudgeon & Berkes, 2003; D. J. Nakashima et al., 2012). En Afrique de l'Ouest, notamment dans les pays francophones, les SPL restent peu documentés (Nyadzi, 2021a). Ce chapitre propose le premier inventaire connu du SPL dans le nord de la Côte d'Ivoire.

Les expérimentations combinant savoirs scientifiques et locaux au sein de services climatiques hybrides se multiplient ces dernières années (Gbangou, 2021; Masinde et al., 2018; Nyadzi et al., 2020; Paparrizos et al., 2023). Ces travaux, majoritairement conduits par des climatologues, montrent que les SPL peuvent améliorer la précision des prévisions et favoriser l'adoption d'innovations par les populations rurales. Par exemple, Nyadzi et al. (2020) démontrent qu'en combinant prévisions scientifiques et locales au Ghana, l'acceptation par les utilisateurs est renforcée et les résultats deviennent plus fiables que lorsque seule une source (SPL ou prévisions scientifiques) est utilisée. Néanmoins, cette littérature n'a pas encore examiné si l'intégration des SPL influence les choix des agriculteurs entre différents services climatiques, ni établi une valorisation économique de ces savoirs.

Les expériences de choix constituent un outil particulièrement adapté pour combler ce gap scientifique et sont de plus en plus mobilisées dans la littérature pour éclairer les politiques publiques (Kotu et al., 2022; Owuor et al., 2019; Wang et al., 2021). En présentant aux répondants une série de scénarios hypothétiques, elles permettent d'analyser les préférences pour des composantes spécifiques d'un service, telles que le type de prévision, l'intégration de SPL ou le canal de diffusion privilégié (par exemple, radio versus SMS). Elles permettent également d'estimer la propension à payer pour chaque composante. Bien que la plupart des études sur les préférences des utilisateurs pour les services climatiques reposent sur la méthode d'évaluation contingente (Amegnaglo et al., 2017; Makaudze, 2005; Zongo et al., 2015). l'usage des expériences de choix dans ce domaine est en pleine expansion (Prasada, 2020; Rahaman & Iqbal, 2021; Tesfaye et al., 2019, 2023). Cependant, à notre connaissance, aucune étude n'a encore appliqué cette méthode pour évaluer les préférences relatives à l'intégration du SPL dans les services climatiques. L'analyse de données a ensuite été effectuée à l'aide un modèle Mixed Logit (MIXL). Ce modèle permet de traiter l'hétérogénéité individuelle de façon continue.

Les résultats de l'inventaire des SPL indiquent la présence active des savoirs prévisionnels locaux dans le nord de la Côte d'Ivoire. L'ensemble des détenteurs de SPL ont exprimé leur volonté de collaborer avec les météorologues afin d'intégrer leurs connaissances dans des services climatiques hybrides. Ces formes de savoir concernent principalement les prévisions à court terme et, dans une moindre mesure, les prévisions saisonnières et celles relatives aux pauses sèches. Elles sont majoritairement détenues par des agriculteurs âgés et sont, en moyenne, perçues comme plus fiables que les prévisions scientifiques. Toutefois, cette perception de fiabilité tend à diminuer, en raison d'une réduction de la disponibilité des indicateurs — liée principalement aux changements environnementaux — et d'un affaiblissement de la transmission intergénérationnelle des savoirs.

L'expérience de choix montre que, en moyenne, l'intégration du SPL n'est pas un facteur déterminant dans la sélection d'un service climatique par les agriculteurs. Cependant, l'accès limité aux services climatiques dans la zone d'étude, combiné à un faible niveau d'éducation formelle et à une faible pénétration des smartphones, tend à restreindre les préférences exprimées par les agriculteurs. Néanmoins, les résultats révèlent une hétérogénéité des préférences : l'intégration des SPL au format d'une prévision supplémentaire est critère de sélection de service climatique pour les agriculteurs plus âgés.

Ce chapitre apporte trois contributions principales à la littérature. Premièrement, il présente le premier inventaire systématique des savoirs prévisionnels locaux dans le nord de la Côte d'Ivoire, région jusque-là non documentée. Deuxièmement, il fournit des preuves empiriques sur les préférences des agriculteurs quant à l'intégration des SPL dans les services climatiques, à l'aide d'une expérience de choix, méthode encore inédite sur ce sujet. Troisièmement, il quantifie l'importance relative des SPL par rapport à d'autres attributs des services (tels que le type de prévision et le mode de diffusion), générant ainsi des connaissances utiles à la conception de services climatiques centrés sur les utilisateurs en Afrique de l'Ouest.

En termes de recommandations de politiques publiques, ce chapitre montre que les décideurs publics doivent prioriser l'amélioration de l'accès aux prévisions scientifiques car elle demeure la principale préoccupation des populations locales. À cet effet, les efforts devraient se concentrer sur la diversification des canaux de diffusion, en particulier oraux, afin d'atteindre plus efficacement les populations analphabètes et géographiquement isolées. Au-delà de la radio, la large disponibilité des téléphones mobiles de base (par opposition aux smartphones) ouvre la possibilité d'utiliser des boîtes vocales accessibles par appel téléphonique. Bien que la diffusion des prévisions par des intermédiaires issus de coopératives soit fortement valorisée par les agriculteurs, elle comporte un risque réputationnel. Ce risque existe déjà avec les SPL, puisque les agriculteurs engagent implicitement leur réputation dans les prévisions qu'ils partagent. Ainsi, toute mise en œuvre de services climatiques doit être accompagnée de formations visant à renforcer la compréhension de l'incertitude des prévisions. Par ailleurs, des recherches complémentaires pourraient être menées dans cette région afin de mieux identifier les usages complémentaires des savoirs scientifiques et locaux, les agriculteurs continuant à accorder leur confiance aux SPL, mais — à l'exception des plus âgés — ne valorisant pas nécessairement leur intégration dans les services climatiques.

Après avoir traité de la demande pour les services climatiques dans la région, nous nous intéressons dans un second temps à l'usage et l'impact potentiel des prévisions de pauses sèches. En effet, le premier chapitre a notamment démontré une légère préférence pour les prévisions saisonnières. Ce type de prévision est encore peu disponible dans la région, en particulier les prévisions de pauses sèches. Cet aléa est perçu par les populations locales comme gagnant en fréquence et en intensité ces dernières années. Il a un impact particulièrement négatif sur les semis de maïs, un aliment essentiel de l'alimentation locale.

Chapitre 2 : Des prévisions sur le terrain : une probabilité de pause sèche peut-elle influer sur les comportements de semis des agriculteurs ?

Le changement climatique modifie les régimes pluviométriques en Afrique de l'Ouest et accroît la probabilité de pauses sèches dans la partie occidentale du Sahel au cours des prochaines saisons des pluies (Basse et al., 2024; Gaetani et al., 2020). Dans une région où l'agriculture est majoritairement pluviale, cette tendance représente une menace majeure pour les agriculteurs, en augmentant le risque de pertes de récoltes et d'insécurité alimentaire (Roudier et al., 2011 ; Sultan et al., 2019 ; Sultan & Gaetani, 2016). Dans ce contexte, les services climatiques (SC) jouent un rôle essentiel en permettant aux agriculteurs d'anticiper les aléas météorologiques. Parmi les décisions agricoles influencées par ces services, le choix de la date de semis revêt une importance particulière (Born et al., 2021). Ce chapitre choisit d'adopter une approche expérimentale afin d'analyser le rôle de l'information météorologique dans les décisions de semis de maïs des agriculteurs.

Notre expérience de type « lab-in-the-field » a été menée dans dix villages de la région de la Bagoué, au nord de la Côte d'Ivoire, auprès de 314 agriculteurs. Dans cette zone, l'instabilité du début de la saison des pluies perturbe les calendriers agricoles traditionnels, les interruptions de pluie endommageant fréquemment le maïs au moment du semis (Adesina & Ouattara, 2000; Boko-Koiadia Adjoua et al., 2016 ; Dekoula et al., 2018, 2019). De plus, ces localités se caractérisent par de faibles taux d'alphabétisation, un accès limité aux services climatiques et un recours fréquent aux savoirs locaux pour anticiper la météo. En pratique, la notion de probabilité sous-jacente aux prévisions est souvent mal comprise par les populations peu alphabétisées, et de nombreux obstacles contextuels peuvent influencer l'adoption ou le rejet de l'information climatique et météorologique par les agriculteurs (Antwi-Agyei et al., 2021 ; Carr & Onzere, 2018 ; Kumar et al., 2021; Lemos et al., 2012)

Par ailleurs, les mécanismes qui sous-tendent la prise de décision des agriculteurs en réponse aux prévisions font l'objet d'un intérêt croissant dans la recherche multidisciplinaire (Guido et al., 2020; Kusunose & Mahmood, 2016; Müller-Mahn et al., 2020; Nyamekye et al., 2021; Roudier et al., 2014). Ces travaux apportent des éclairages qualitatifs approfondis sur la prise de décision, mais encore peu de preuves quantitatives, car ils reposent le plus souvent sur des ateliers participatifs. En dehors du secteur agricole, une seule expérience — à notre connaissance — a porté sur la gestion d'un barrage hydraulique à partir de prévisions saisonnières, offrant ainsi des éléments quantitatifs sur la prise de décision fondée sur l'information météorologique (Crochemore et al., 2021). Les approches expérimentales permettent de modéliser de manière structurée la prise de décision dans des contextes réels sur des horizons temporels étendus (mois, saisons ou années), tout en préservant la clarté et la simplicité (Crochemore et al., 2021; Leblois et al., 2014). En parallèle, l'économie comportementale contextualise également de plus en plus les cadres standards d'élicitation des préférences individuelles face au risque — tels que les *Listes de prix multiples* (LPM) (Brick et al., 2012; Holt & Laury, 2002) — en les adaptant aux décisions agricoles réelles. Dans la plupart des cas, ces expériences se présentent comme des sélections de variétés de cultures pour la saison à venir, avec des gains dépendant de la variabilité pluviométrique saisonnière (Julia Ihli et al., 2022; Kemeze et al., 2020; Schrieks et al., 2024). Ce chapitre s'inscrit dans cette littérature expérimentale émergente en apportant de nouvelles preuves empiriques sur la prise de décision des agriculteurs face à l'information météorologique.

Il accorde une attention particulière à la dimension comportementale de ces décisions, en reconnaissant que l'interprétation des prévisions dépend aussi des caractéristiques individuelles, lesquelles influencent la manière dont les agriculteurs réagissent à l'information. Comme pour toute information probabiliste, une même probabilité de pause sèche peut être perçue et interprétée différemment selon les individus (Tversky & Kahneman, 1992). Les travaux sur les chocs climatiques montrent que l'expérience personnelle de pertes passées peut accroître la perception subjective du risque de perte (Brown et al., 2018; Menapace et al., 2016). Avoir subi un événement extrême peu probable peut amener un individu à surestimer la probabilité que de tels événements se reproduisent (Tversky & Kahneman, 1974, 1992). Pour tenir compte de ces effets, notre analyse des mécanismes décisionnels inclut des variables liées à l'évaluation du risque de pause sèche, telles que la gravité des pertes de maïs subies lors de tels épisodes et leur fréquence perçue. De plus, des traits psychologiques tels que le locus de contrôle et l'auto-efficacité influencent la perception du risque (Schrieks et al., 2024), mais également la prise de décision en agriculture (Carter, 2016; Wuepper et al., 2023; Wuepper & Sauer, 2016), l'adoption technologique (Abay et al., 2017) et l'adaptation au changement climatique (Kreft et al., 2021; van Valkengoed et al., 2023). À notre connaissance, leur rôle dans le contexte des services climatiques demeure largement inexploré ; ces facteurs ont donc été intégrés à notre étude.

C'est sur cette base que nous avons élaboré un protocole expérimental adapté au contexte agricole, afin d'analyser la manière dont les agriculteurs réagissent aux probabilités de pauses sèches au moment du semis et d'identifier les facteurs influençant leur processus décisionnel. Ce protocole s'inspire du jeu d'investissement développé par Gneezy & Potters (1997). Cependant, notre objectif n'était pas de mesurer l'aversion individuelle au risque, mais d'évaluer si les agriculteurs ajustent leurs décisions de semis de maïs en fonction d'une probabilité de pause sèche et d'examiner les déterminants de ces ajustements. Au cours de l'expérience, chaque agriculteur devait répartir ses semis de maïs entre une période « habituelle » — associée à une probabilité donnée de pause sèche — et une période de semis

« tardive », garantissant des rendements plus faibles mais certains. En cas de pause sèche, l'ensemble du maïs semé pendant la période risquée était perdu. Les probabilités ont été tirées sans remise, aléatoirement sur cinq saisons et comparées à un scénario sans information. Afin de dépasser les difficultés potentielles de compréhension liées à la notion de probabilité, nous avons conçu des outils visuels, de manière à concentrer l'analyse sur les mécanismes de décision une fois cette information assimilée. Chaque agriculteur a répété cette séquence de décisions à deux reprises, ce qui permet d'évaluer si une exposition antérieure à une meme probabilité influence les choix l'agriculteur la seconde fois qu'il rencontre une même probabilité.

Les résultats montrent que les agriculteurs ajustent leurs stratégies de semis en fonction des informations météorologiques probabilistes, ce qui améliore systématiquement les rendements espérés par rapport à une situation sans information (+ 14% de rendements environ). Toutefois, même face à des probabilités très faibles de pauses sèches, de nombreux agriculteurs demeurent prudents et ne consacrent pas l'ensemble de leurs semences à l'option risquée. Les probabilités de pauses sèches apparaissent comme le principal facteur influençant les décisions de semis dans cette expérience. Néanmoins, les résultats indiquent que les réponses comportementales aux dépendent également d'une combinaison de facteurs psychologiques et expérientiels. Les agriculteurs présentant un locus de contrôle interne élevé se montrent moins réactifs aux probabilités moyennes et élevées de pauses sèches, traduisant une tendance à se fier davantage à leur propre jugement qu'à des informations externes. À l'inverse, les individus ayant déjà subi d'importantes pertes de maïs ou disposant d'un niveau d'éducation plus élevé ajustent davantage la quantité semée dans la période risquée en fonction des prévisions, témoignant d'une plus grande sensibilité aux signaux probabilistes.

Des schémas comportementaux distincts apparaissent également dans les stratégies d'allocation des semences. Les agriculteurs ayant une forte propension à l'adaptation adoptent plus volontiers une stratégie de type « tout ou rien », concentrant leurs semis exclusivement sur la période risquée ou sur la période sûre selon la prévision. En revanche, ceux dotés d'un locus de contrôle interne élevé ou confrontés à l'insécurité alimentaire ont tendance à répartir leurs semis entre les deux périodes, maintenant ainsi une stratégie de diversification indépendamment de la probabilité. Ces résultats suggèrent que l'adaptation ne dépend pas uniquement de l'information externe, mais est fortement influencée par les perceptions individuelles et les traits psychologiques.

Ce chapitre contribue à la littérature sur les effets des services climatiques sur la prise de décision agricole en introduisant un dispositif intra-individuel innovant. L'expérience proposée est à la fois facilement compréhensible et réplicable auprès de populations rurales faiblement alphabétisées dans les pays en développement.

D'un point de vue opérationnel, ces résultats soulignent le potentiel d'utilisation des formats probabilistes pour communiquer l'information météorologique aux agriculteurs faiblement alphabétisés. Ce type d'information pourrait générer des gains de productivité considérables, notamment s'il est associé à des mécanismes compensatoires tels que les assurances indicielles, afin de combler l'écart entre rendements potentiels et rendements réalisés. Enfin, dans la mesure où les caractéristiques individuelles influencent la manière dont les agriculteurs perçoivent et utilisent l'information météorologique, les futurs services climatiques devraient être adaptés aux profils individuels des agriculteurs pour en maximiser l'efficacité.

Après avoir traité de l'usage et l'impact potentiel des prévisions de pauses sèches, nous choisissons dans un troisième temps de poursuivre l'étude de la question de l'impact des services climatiques pour l'agriculture par une revue systématique des méthodologie utilisées dans le monde pour évaluer l'impact ex-post de ces services.

Chapitre 3 : Quantifier les impacts ex-post des services climatiques pour les agriculteurs : une revue méthodologique

Les services climatiques constituent des outils essentiels d'aide à la décision pour les agriculteurs dans le contexte du changement climatique. Ils génèrent des effets positifs sur l'exploitation agricole (Roudier et al., 2016), bien que la quantification de ces impacts soit complexe. En effet, l'impact d'un SC n'existe que lorsque l'information transmise conduit à des décisions agricoles — *outcomes* (par exemple, période de semis, variétés, cultures ou parcelles utilisées) — qui se traduisent par des bénéfices tangibles pour l'agriculteur — *impacts* (par exemple, augmentation des rendements, réduction des coûts d'intrants, etc.) (Bacci et al., 2023). Cependant, l'accès et l'utilisation des SC dépendent de caractéristiques propres à chaque agriculteur, telles que la possession d'un dispositif de diffusion (radio, téléphone, etc.), le niveau d'alphabétisation ou la capacité à prendre des décisions agricoles fondées sur l'information reçue. Ces facteurs, s'ils ne sont pas soigneusement pris en compte, peuvent affecter significativement l'adoption des SC, entraînant un grand nombre de non-utilisateurs et introduisant des biais de sélection au sein du groupe traité. Deuxièmement, il est difficile de quantifier la contribution relative des SC parmi la multitude de facteurs qui influencent les décisions des ménages agricoles et participent aux impacts observés (Vaughan et al., 2019). Enfin, la difficulté réside également dans la constitution d'un groupe de contrôle (c'est-à-dire un point de référence) permettant de mesurer les effets des SC. En effet, il est complexe de contrôler la variabilité climatique (Tall et al., 2018) et les effets de contamination (*spillovers*). Ces derniers posent un défi particulier, car l'information peut être reproduite et transmise par des réseaux informels (Simon et al., 2021) rendant difficile pour l'évaluateur d'identifier quels agriculteurs bénéficient effectivement du service et lesquels n'en bénéficient pas.

C'est pourquoi l'évaluation des SC a longtemps pris la forme d'évaluations contingentes, centrées sur la valeur de l'information plutôt que sur ses impacts, ou de modélisations ex ante (Vaughan et al., 2019). Les modélisations ex ante (simulations informatiques) permettent aux évaluateurs d'isoler plus aisément les effets des SC en contrôlant les facteurs externes. Elles ont principalement documenté les impacts des SC sur les rendements agricoles (Vaughan et al., 2019). Les évaluations ex post, portant sur des services existants ou expérimentaux, sont plus récentes et ont émergé dans le sillage de la littérature sur les impacts des technologies de l'information et de la communication (TIC) (Camacho & Conover, 2019). La question des indicateurs utilisés pour mesurer les impacts ex post devient ainsi un enjeu croissant pour les services climatiques, en raison notamment :

i) du développement d'analyses économétriques ex post intégrées aux projets de SC ;
ii) de l'essor des services co-construits avec les agriculteurs, dont les bénéfices ont longtemps été évalués de manière qualitative, mais pour lesquels émergent désormais des approches quantitatives et mixtes (Visman et al., 2022);
iii) et enfin, de l'intégration progressive des dimensions sociales et environnementales dans les méthodes d'évaluation ex post.

Récemment, plusieurs revues systématiques et méta-analyses se sont intéressées aux *outcomes* tels que les changements comportementaux dans la prise de décision (Born et al., 2021), la gestion des risques climatiques et les stratégies d'adaptation (Madhuri, 2023; Muller et al., 2024; Mwangi et al., 2021), ainsi qu'aux facteurs influençant l'utilisation des SC (Gouroubera et al., 2024; Warner et al., 2022), ou encore aux bénéfices et à la valeur de ces services sans se concentrer sur un type d'évaluation particulier (Agyekum et al., 2022; Suckall & Soares, 2022). À notre connaissance, aucune revue méthodologique spécifique n'a encore été consacrée à l'évaluation ex post des impacts des services climatiques.

Cette revue méthodologique, menée à l'échelle mondiale sans distinction géographique, analyse les approches quantitatives d'évaluation ex post actuellement utilisées pour mesurer de manière rigoureuse les impacts des services climatiques sur les agriculteurs.

La plupart des articles recensés ont été publiés récemment et mobilisent des approches expérimentales ou quasi-expérimentales dans les pays en développement. La quantification des impacts des SC demeure complexe. Selon le degré de contrôle de l'évaluateur sur l'accès au service, différents problèmes peuvent apparaître : i) des effets de diffusion (*spillovers*) au sein du groupe de contrôle, et ii) des biais de sélection dans l'accès et l'utilisation de l'information. Ainsi, des méthodes économétriques sont mobilisées afin de construire un contrefactuel crédible. Les approches par variables instrumentales permettent de contrôler les effets de contamination entre agriculteurs, mais des recherches supplémentaires sont nécessaires pour en mesurer l'ampleur, certains auteurs les considérant même comme un second niveau d'impact pour les agriculteurs (c'est-à-dire les bénéfices indirects d'une intervention).

Le contrôle de l'accès et de la pertinence tout au long du processus de mise en œuvre des SC constitue une condition indispensable pour éviter les biais de sélection dans l'utilisation de l'information. La traduction de savoirs (*knowledge brokering)* s'avère également efficace pour favoriser l'adoption, et les évaluations portant sur les formations aux SC mettent en évidence des effets positifs. Des approches plus participatives pourraient être utiles aux évaluateurs afin d'identifier les chaînes d'impact reliant les résultats intermédiaires aux impacts finaux et de mieux comprendre les contextes décisionnels complexes.

Sur le plan des résultats quantifiés, les études se concentrent principalement sur les rendements et les variables de gestion agricole (coûts/bénéfices), avec des effets positifs observés. Les cultures de rente sont encore peu étudiées, tout comme l'élevage, pour lequel une seule évaluation a été recensée. Les impacts sociaux et environnementaux demeurent encore largement inexplorés, mais les premiers résultats sont prometteurs, notamment en matière de réduction des quantités d'engrais ou d'amélioration de la sécurité alimentaire. De nouveaux indicateurs pourraient émerger dans les prochaines années, issus de la littérature sur la co-construction, afin de quantifier les dimensions qualitatives existantes des impacts sociaux et environnementaux des SC.

Conclusion

Cette thèse contribue à une meilleure compréhension de la demande, de l'usage et des impacts des services climatiques (SC) dans le contexte agricole ouest-africain, à travers l'étude du cas du nord de la Côte d'Ivoire. Elle s'appuie sur différentes approches (analyses expérimentales et revue systématique de la littérature) et met en évidence la place centrale des caractéristiques individuelles des agriculteurs pour ajuster l'offre de services climatiques existantes, en comprendre l'usage et obtenir de plus grands impacts sur le plan économique mais également socio-environnemental.

Les résultats des trois chapitres offrent une perspective sur la valeur des SC, depuis la conception jusqu'à l'évaluation de leurs impacts. Le premier chapitre souligne la persistance et la richesse des savoirs prévisionnels locaux (SPL) dans les communautés rurales, tout en montrant que leur intégration dans les SC ne constitue pas, à ce stade, une priorité pour la majorité des utilisateurs, dont les attentes portent d'abord sur l'amélioration de l'accès aux prévisions scientifiques par des prix attractifs et un moyen de diffusion oral. Le deuxième chapitre démontre, à travers une expérience de terrain, que les prévisions probabilistes relatives aux pauses sèches influencent effectivement les décisions de semis et les rendements potentiels, tout en révélant le rôle dans la prise de décisions d'autres facteurs tels que des facteurs psychologiques et l'expérience passée des agriculteurs en matière de quantité de semis aux saisons précédentes et de pertes de maïs subies. Enfin, le troisième chapitre met en lumière la diversité des approches méthodologiques mobilisées pour évaluer les impacts ex post des SC et leurs limites.

Pris dans leur ensemble, ces travaux soulignent que l'efficacité des services climatiques repose en partie sur son accessibilité, sa compréhension et sa pertinence pour les usagers. Ils invitent à concevoir des services plus inclusifs, adaptés aux contextes socio-économiques locaux et intégrant les dimensions comportementales de la prise de décision. Les résultats appellent également à un renforcement de la collaboration entre chercheurs, institutions météorologiques et acteurs du développement afin d'améliorer la diffusion, la compréhension et l'évaluation des services climatiques.

En définitive, cette recherche confirme que ces services, lorsqu'ils sont conçus de manière contextualisée, peuvent constituer un instrument stratégique de l'adaptation des agricultures pluviales d'Afrique de l'Ouest face à la variabilité des précipitations.

Références du résumé

Abay, K. A., Blalock, G., & Berhane, G. (2017). Locus of control and technology adoption in developing country agriculture : Evidence from Ethiopia. Journal of Economic Behavior & Organization, 143, 98-115. https://doi.org/10.1016/j.jebo.2017.09.012

Adesina, A. A., & Ouattara, A. D. (2000). Risk and agricultural systems in northern Côte d'Ivoire. Agricultural Systems, 66(1), 17-32. https://doi.org/10.1016/S0308-521X(00)00033-0

Agyekum, T. P., Antwi-Agyei, P., & Dougill, A. J. (2022). The contribution of weather forecast information to agriculture, water, and energy sectors in East and West Africa : A systematic review. FRONTIERS IN ENVIRONMENTAL SCIENCE, 10, 935696. https://doi.org/10.3389/fenvs.2022.935696

Amegnaglo, C. J., Anaman, K. A., Mensah-Bonsu, A., Onumah, E. E., & Amoussouga Gero, F. (2017). Contingent valuation study of the benefits of seasonal climate forecasts for maize farmers in the Republic of Benin, West Africa. Climate Services, 6, 1-11. https://doi.org/10.1016/j.cliser.2017.06.007

Antwi-Agyei, P., Dougill, A. J., & Abaidoo, R. C. (2021). Opportunities and barriers for using climate information for building resilient agricultural systems in Sudan savannah agro-ecological zone of north-eastern Ghana. Climate Services, 22, 100226. https://doi.org/10.1016/j.cliser.2021.100226

Antwi-Agyei, P., Dougill, A. J., Fraser, E. D. G., & Stringer, L. C. (2013). Characterising the nature of household vulnerability to climate variability : Empirical evidence from two regions of Ghana. Environment, Development and Sustainability, 15(4), 903-926. https://doi.org/10.1007/s10668-012-9418-9

Antwi-Agyei, P., Dougill, A. J., & Stringer, L. C. (2015). Barriers to climate change adaptation : Evidence from northeast Ghana in the context of a systematic literature review'. Climate and Development, 7(4), 297-309. https://doi.org/10.1080/17565529.2014.951013.

Bacci, M., Idrissa, O. A., Zini, C., Burrone, S., Sitta, A. A., & Tarchiani, V. (2023). Effectiveness of agrometeorological services for smallholder farmers : The case study in the regions of Dosso and Tillabéri in Niger. Climate Services, 30, 100360. https://doi.org/10.1016/j.cliser.2023.100360

Basse, J., Camara, M., Diba, I., & Diedhiou, A. (2024). Projected Changes in Dry and Wet Spells over West Africa during Monsoon Season Using Markov Chain Approach. Climate, 12(12), Article 12. https://doi.org/10.3390/cli12120211

Boko-Koiadia Adjoua, N., Cissé, G., Koné, B., & Séri, D. (2016). Variabilité Climatique Et Changements Dans L'environnement À Korhogo En Côte D'ivoire : Mythes Ou Réalité ? European Scientific Journal, ESJ, 12(5), 158. https://doi.org/10.19044/esj.2016.v12n5p158

Born, L., Prager, S., Ramirez-Villegas, J., & Imbach, P. (2021). A global meta-analysis of climate services and decision-making in agriculture. Climate Services, 22, 100231. https://doi.org/10.1016/j.cliser.2021.100231

Brick, K., Visser, M., & Burns, J. (2012). Risk Aversion : Experimental Evidence from South African Fishing Communities. American Journal of Agricultural Economics, 94(1), 133-152. https://doi.org/10.1093/ajae/aar120

Brown, P., Daigneault, A. J., Tjernström, E., & Zou, W. (2018). Natural disasters, social protection, and risk perceptions. World Development, 104, 310-325. https://doi.org/10.1016/j.worlddev.2017.12.002

Camacho, A., & Conover, E. (2019). The impact of receiving SMS price and weather information on small scale farmers in Colombia. World Development, 123, 104596. https://doi.org/10.1016/j.worlddev.2019.06.020

Carr, E. R., Goble, R., Rosko, H. M., Vaughan, C., & Hansen, J. (2020). Identifying climate information services users and their needs in Sub-Saharan Africa : A review and learning agenda. Climate and Development, 12(1), 23-41. https://doi.org/10.1080/17565529.2019.1596061

Carr, E. R., & Onzere, S. N. (2018). Really effective (for 15% of the men) : Lessons in understanding and addressing user needs in climate services from Mali'. Climate Risk Management, 22, 82-95. https://doi.org/10.1016/j.crm.2017.03.002.

Carter, M. R. (2016). What farmers want : The "gustibus multiplier" and other behavioral insights on agricultural development. Agricultural Economics, 47(S1), 85-96. https://doi.org/10.1111/agec.12312

Cash, D. W., Clark, W. C., Alcock, F., Dickson, N. M., Eckley, N., Guston, D. H., Jäger, J., & Mitchell, R. B. (2003). Knowledge systems for sustainable development. Proceedings of the National Academy of Sciences, 100(14), 8086-8091. https://doi.org/10.1073/pnas.1231332100

Crochemore, L., Cantone, C., Pechlivanidis, I. G., & Photiadou, C. S. (2021). How Does Seasonal Forecast Performance Influence Decision-Making? Insights from a Serious Game. Bulletin of the American Meteorological Society, 102(9), E1682-E1699. https://doi.org/10.1175/BAMS-D-20-0169.1

Dekoula, C. S., Kouame, B., N'goran, E. K., Yao, F. G., Ehounou, J.-N., & Soro, N. (2018). Impact De La Variabilité Pluviométrique Sur La Saison Culturale Dans La Zone De Production Cotonnière En Côte d'Ivoire. European Scientific Journal, ESJ, 14(12), 143. https://doi.org/10.19044/esj.2018.v14n12p143

Dekoula, C. S., Kouame, B., N'Goran, K. E., Ehounou, J.-N., Yao, G. F., Kassin, K. E., Kouakou, J. B., N'Guessan, A. E. B., & Soro, N. (2019). Variabilité des descripteurs pluviométriques intrasaisonniers à impact agricole dans le bassin cotonnier de Côte d'Ivoire : Cas des zones de Boundiali, Korhogo et Ouangolodougou. Journal of Applied Biosciences, 130(1), 13199. https://doi.org/10.4314/jab.v130i1.7

Dudgeon, R. C., & Berkes, F. (2003). Local Understandings of the Land : Traditional Ecological Knowledge and Indigenous Knowledge. In H. Selin (Éd.), Nature Across Cultures (Vol. 4, p. 75-96). Springer Netherlands. https://doi.org/10.1007/978-94-017-0149-5_4

Ebhuoma, E. E., & Simatele, D. M. (2019). "We know our Terrain" : Indigenous knowledge preferred to scientific systems of weather forecasting in the Delta State of Nigeria'. Climate and Development, 11(2), 112-123. https://doi.org/10.1080/17565529.2017.1374239.

Gaetani, M., Janicot, S., Vrac, M., Famien, A. M., & Sultan, B. (2020). Robust assessment of the time of emergence of precipitation change in West Africa. Scientific Reports, 10(1), 7670. https://doi.org/10.1038/s41598-020-63782-2

Gbangou, T. (2021). Harnessing Local Forecasting Knowledge on Weather and Climate in Ghana : Documentation, Skills, and Integration with Scientific Forecasting Knowledge'. Weather, Climate, and Society, 13(1), 23-37. https://doi.org/10.1175/WCAS-D-20-0012.1.

Gneezy, U., & Potters, J. (1997). An Experiment on Risk Taking and Evaluation Periods*. The Quarterly Journal of Economics, 112(2), 631-645. https://doi.org/10.1162/003355397555217

Gouroubera, M. W., Sabi, A. K., Comada, T. K. B., Dosso, F., Fatondji, S. A., Gouthon, M. B., & Houaga, R. P. (2024). Designing effective digital-based delivery of climate information for smallholder farmers : A mini meta-analysis on drivers and barriers. CLIMATE POLICY, 24(10), 1443-1456. https://doi.org/10.1080/14693062.2023.2266475

Guido, Z., Zimmer, A., Lopus, S., Hannah, C., Gower, D., Waldman, K., Krell, N., Sheffield, J., Caylor, K., & Evans, T. (2020). Farmer forecasts : Impacts of seasonal rainfall expectations on agricultural decision-making in Sub-Saharan Africa. Climate Risk Management, 30, 100247. https://doi.org/10.1016/j.crm.2020.100247

Holt, C. A., & Laury, S. K. (2002). Risk Aversion and Incentive Effects.

Julia Ihli, H., Chiputwa, B., Winter, E., & Gassner, A. (2022). Risk and time preferences for participating in forest landscape restoration : The case of coffee farmers in Uganda. World Development, 150, 105713. https://doi.org/10.1016/j.worlddev.2021.105713

Kemeze, F. H., Miranda, M. J., Kuwornu, J. K. M., & Anim-Somuah, H. (2020). Smallholder Farmer Risk Preferences in Northern Ghana:Evidence from a Controlled Field Experiment. The Journal of Development Studies, 56(10), 1894-1908. https://doi.org/10.1080/00220388.2020.1715945

Kotu, B. H., Oyinbo, O., Hoeschle-Zeledon, I., Nurudeen, A. R., Kizito, F., & Boyubie, B. (2022). Smallholder farmers' preferences for sustainable intensification attributes in maize production : Evidence from Ghana. World Development, 152, 105789. https://doi.org/10.1016/j.worlddev.2021.105789

Kreft, C., Huber, R., Wuepper, D., & Finger, R. (2021). The role of non-cognitive skills in farmers' adoption of climate change mitigation measures. Ecological Economics, 189, 107169. https://doi.org/10.1016/j.ecolecon.2021.107169

Kumar, U., Werners, S., Paparrizos, S., Datta, D., & Ludwig, F. (2021). Co-producing Climate Information Services with Smallholder Farmers in the Lower Bengal Delta : How forecast visualization and communication support farmers' decision-making. Climate Risk Management, 33, 100346. https://doi.org/10.1016/j.crm.2021.100346

Kusunose, Y., & Mahmood, R. (2016). Imperfect forecasts and decision making in agriculture. Agricultural Systems, 146, 103-110. https://doi.org/10.1016/j.agsy.2016.04.006

Leblois, A., Quirion, P., & Sultan, B. (2014). Price vs. weather shock hedging for cash crops : Ex ante evaluation for cotton producers in Cameroon. Ecological Economics, 101, 67-80. https://doi.org/10.1016/j.ecolecon.2014.02.021

Lemos, M. C., Kirchhoff, C. J., & Ramprasad, V. (2012). Narrowing the climate information usability gap. Nature Climate Change, 2(11), 789-794. https://doi.org/10.1038/nclimate1614

Madhuri. (2023). How do climate information services (CIS) affect farmers' adaptation strategies? A systematic review. Climate Services, 32, 100416. https://doi.org/10.1016/j.cliser.2023.100416

Mafongoya, P. L., & Ajayi, O. O. C. (2017). Indigenous knowledge systems and climate change management in Africa. CTA.

Makaudze, E. (2005). Do seasonal climate forecasts and crop insurance matter for smallholder farmers in Zimbabwe ? Using contingent valuation method and remote sensing applications. The Ohio State University.

Masinde, M., Mwagha, M., & Tadesse, T. (2018). Downscaling Africa's Drought Forecasts through Integration of Indigenous and Scientific Drought Forecasts Using Fuzzy Cognitive Maps. Geosciences, 8(4), 135. https://doi.org/10.3390/geosciences8040135

Menapace, L., Colson, G., & Raffaelli, R. (2016). A comparison of hypothetical risk attitude elicitation instruments for explaining farmer crop insurance purchases. European Review of Agricultural Economics, 43(1), 113-135. https://doi.org/10.1093/erae/jbv013

Muller, L. C. F. E., Schaafsma, M., Mazzoleni, M., & Van Loon, A. F. (2024). Responding to climate services in the context of drought : A systematic review. CLIMATE SERVICES, 35, 100493. https://doi.org/10.1016/j.cliser.2024.100493

Müller-Mahn, D., Moure, M., & Gebreyes, M. (2020). Climate change, the politics of anticipation and future riskscapes in Africa. Cambridge Journal of Regions, Economy and Society, 13(2), 343-362. https://doi.org/10.1093/cjres/rsaa013

Mutasa, M. (2015). Knowledge apartheid in disaster risk management discourse : Is marrying indigenous and scientific knowledge the missing link? Jàmbá: Journal of Disaster Risk Studies, 7(1), 10 pages. https://doi.org/10.4102/jamba.v7i1.150

Mwangi, M., Kituyi, E., & Ouma, G. (2021). A systematic review of the literature on the contribution of past climate information services pilot projects in climate risk management. SCIENTIFIC AFRICAN, 14, e01005. https://doi.org/10.1016/j.sciaf.2021.e01005

Nakashima, D. J., Galloway McLean, K., Thulstrup, H.D., Ramos Castillo, A., & Rubis, J.T. (2012). Weathering uncertainty : Traditional knowledge for climate change assessment and adaptation. UNESCO ; UNU-IAS.

Nakashima, D., Krupnik, I., & Rubis, J. T. (Éds.). (2018). Indigenous Knowledge for Climate Change Assessment and Adaptation (1re éd.). Cambridge University Press. https://doi.org/10.1017/9781316481066

Nyadzi, E. (2021a). Indigenous knowledge and climate change adaptation in Africa : A systematic review. CAB Reviews: Perspectives in Agriculture, Veterinary Science, Nutrition and Natural Resources, 16(029). https://doi.org/10.1079/PAVSNNR202116029

Nyadzi, E. (2021b). Techniques and skills of indigenous weather and seasonal climate forecast in Northern Ghana'. Climate and Development, 13(6), 551-562. https://doi.org/10.1080/17565529.2020.1831429.

Nyadzi, E., Werners, S., Biesbroek, R., & Ludwig, F. (2020). Combining Indigenous and Scientific Forecast for Improved Climate Services in Ghana [Other]. pico. https://doi.org/10.5194/egusphere-egu2020-22322

Nyamekye, A. B., Nyadzi, E., Dewulf, A., Werners, S., Van Slobbe, E., Biesbroek, R. G., Termeer, C. J. A. M., & Ludwig, F. (2021). Forecast probability, lead time and farmer decision-making in rice farming systems in Northern Ghana. Climate Risk Management, 31, 100258. https://doi.org/10.1016/j.crm.2020.100258

Owuor, M. A., Mulwa, R., Otieno, P., Icely, J., & Newton, A. (2019). Valuing mangrove biodiversity and ecosystem services : A deliberative choice experiment in Mida Creek, Kenya. Ecosystem Services, 40, 101040. https://doi.org/10.1016/j.ecoser.2019.101040

Paparrizos, S., Dogbey, R. K., Sutanto, S. J., Gbangou, T., Kranjac-Berisavljevic, G., Gandaa, B. Z., Ludwig, F., & Van Slobbe, E. (2023). Hydro-climate information services for smallholder farmers : FarmerSupport app principles, implementation, and evaluation. Climate Services, 30, 100387. https://doi.org/10.1016/j.cliser.2023.100387

Prasada, D. V. P. (2020). Climate-Indexed Insurance as a Climate Service to Drought-Prone Farmers : Evidence from a Discrete Choice Experiment in Sri Lanka. In W. Leal Filho & D. Jacob (Éds.), Handbook of Climate Services (p. 423-445). Springer International Publishing. https://doi.org/10.1007/978-3-030-36875-3_21

Rahaman, M. M., & Iqbal, Md. H. (2021). Willingness-to-pay for improved cyclone early warning services across coastal Bangladesh : Application of choice experiment. International Journal of Disaster Risk Reduction, 61, 102344. https://doi.org/10.1016/j.ijdrr.2021.102344

Roncoli, C. (2006). Ethnographic and Participatory Approaches to Research on Farmers' Responses to Climate Predictions. Climate Research, Vol. 33, 81-99. http://dx.doi.org/10.3354/cr033081

Roncoli, C., Ingram, K., & Kirshen, P. (2002). Reading the Rains : Local Knowledge and Rainfall Forecasting in Burkina Faso. Society & Natural Resources, 15(5), 409-427. https://doi.org/10.1080/08941920252866774

Roudier, P., Muller, B., d'Aquino, P., Roncoli, C., Soumare, M., Batté, L., & Sultan, B. (2014). The role of climate forecasts in smallholder agriculture : Lessons from participatory research in two communities in Senegal. Climate Risk Management, 2, 42-55. https://doi.org/10.1016/j.crm.2014.02.001

Roudier, P., Sultan, B., Quirion, P., & Berg, A. (2011). The impact of future climate change on West African crop yields : What does the recent literature say? Global Environmental Change, 21(3), 1073-1083. https://doi.org/10.1016/j.gloenvcha.2011.04.007

Schrieks, T., Botzen, W. J. W., Haer, T., & Aerts, J. C. J. H. (2024). Drought risk attitudes in pastoral and agro-pastoral communities in Kenya. Journal of Behavioral and Experimental Economics, 108, 102143. https://doi.org/10.1016/j.socec.2023.102143

Simon, W. J., Krupnik, T. J., Aguilar-Gallegos, N., Halbherr, L., & Groot, J. C. J. (2021). Putting social networks to practical use : Improving last-mile dissemination systems for climate and market information services in developing countries. Climate Services, 23, 100248. https://doi.org/10.1016/j.cliser.2021.100248

Suckall, N., & Soares, M. B. (2022). Evaluating the benefits of weather and climate services in South Asia : A systematic review. REGIONAL ENVIRONMENTAL CHANGE, 22(3), 104. https://doi.org/10.1007/s10113-022-01947-7

Sultan, B., Defrance, D., & Iizumi, T. (2019). Evidence of crop production losses in West Africa due to historical global warming in two crop models. Scientific Reports, 9(1), 12834. https://doi.org/10.1038/s41598-019-49167-0

Sultan, B., Roudier, P., Quirion, P., Alhassane, A., Muller, B., Dingkuhn, M., Ciais, P., Guimberteau, M., Traore, S., & Baron, C. (2013). Assessing climate change impacts on sorghum and millet yields in the Sudanian and Sahelian savannas of West Africa. Environmental Research Letters, 8(1), 014040. https://doi.org/10.1088/1748-9326/8/1/014040

Tall, A., Coulibaly, J. Y., & Diop, M. (2018). Do climate services make a difference? A review of evaluation methodologies and practices to assess the value of climate information services for farmers: Implications for Africa. Climate Services, 11, 1-12. https://doi.org/10.1016/j.cliser.2018.06.001

Tesfaye, A., Hansen, J., Kagabo, D., Birachi, E., Radeny, M., & Solomon, D. (2023). Modeling farmers' preference and willingness to pay for improved climate services in Rwanda. Environment and Development Economics, 28(4), 368-386. https://doi.org/10.1017/S1355770X22000286

Tesfaye, A., Hansen, J., Kassie, G. T., Radeny, M., & Solomon, D. (2019). Estimating the economic value of climate services for strengthening resilience of smallholder farmers to climate risks in Ethiopia : A choice experiment approach. Ecological Economics, 162, 157-168. https://doi.org/10.1016/j.ecolecon.2019.04.019

Tversky, A., & Kahneman, D. (1974). Judgment under Uncertainty : Heuristics and Biases. Science, 185(4157), 1124-1131.

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory : Cumulative representation of uncertainty. Journal of Risk and Uncertainty, 5(4), 297-323. https://doi.org/10.1007/BF00122574

van Valkengoed, A. M., Perlaviciute, G., & Steg, L. (2023). From believing in climate change to adapting to climate change : The role of risk perception and efficacy beliefs. Risk Analysis, n/a(n/a). https://doi.org/10.1111/risa.14193

Vaughan, C., Hansen, J., Roudier, P., Watkiss, P., & Carr, E. (2019). Evaluating agricultural weather and climate services in Africa : Evidence, methods, and a learning agenda. WIREs Climate Change, 10(4). https://doi.org/10.1002/wcc.586

Visman, E., Vincent, K., Steynor, A., Karani, I., & Mwangi, E. (2022). Defining metrics for monitoring and evaluating the impact of co-production in climate services. Climate Services, 26, 100297. https://doi.org/10.1016/j.cliser.2022.100297

Wang, Y., Wang, Z., Wang, Z., Li, X., Pang, X., & Wang, S. (2021). Application of Discrete Choice Experiment in Health Care : A Bibliometric Analysis. Frontiers in Public Health, 9, 673698. https://doi.org/10.3389/fpubh.2021.673698

Warner, D., Moonsammy, S., & Joseph, J. (2022). Factors that influence the use of climate information services for agriculture : A systematic review. CLIMATE SERVICES, 28, 100336. https://doi.org/10.1016/j.cliser.2022.100336

Wuepper, D., Bukchin-Peles, S., Just, D., & Zilberman, D. (2023). Behavioral agricultural economics. Applied Economic Perspectives and Policy, 45(4), 2094-2105. https://doi.org/10.1002/aepp.13343

Wuepper, D., & Sauer, J. (2016). Explaining the performance of contract farming in Ghana : The role of self-efficacy and social capital. Food Policy, 62, 11-27. https://doi.org/10.1016/j.foodpol.2016.05.003

Zongo, B., Diarra, A., Barbier, B., Zorom, M., Yacouba, H., & Dogot, T. (2015). Farmers' Perception and Willingness to Pay for Climate Information in Burkina Faso. Journal of Agricultural Science, 8(1), 175. https://doi.org/10.5539/jas.v8n1p175