



DEMOCRATIC AND POPULAR ALGERIAN REPUBLIC
MINISTRY OF HIGHER EDUCATION AND SCIENTIFIC RESEARCH
ECHAÏD HAMMA LAKHDAR UNIVERSITY OF EL-OUED
FACULTY OF NATURAL SCIENCES AND LIFE



Master's Thesis

In order to obtain a diploma of an Academic Master

In Agricultural Sciences

Specialty: Vegetable production

Theme

Policy & Practice for composting on Saharan farms in El Oued.

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Academic Year 2025–2026

Acknowledgements

First and foremost, I must express my deepest gratitude to Almighty God for granting me the health, strength, and perseverance to complete this research work and achieve this academic milestone.

I would like to express my sincere gratitude and deepest respect to my supervisor, Dr. Bel Messaoud Rachid, for his valuable guidance, continuous support, and constructive feedback provided throughout the development of this thesis.

I am also deeply grateful to the honorable members of the examination committee: the President of the Jury, Dr. Bouafiane Mabrouka, and the Examiner, Dr. Kasmi Yacine, for their valuable time, thorough review, and insightful comments which have greatly improved the quality of this final manuscript.

Special thanks are extended to the administration and faculty members of the University of El Oued for providing a supportive academic environment. I also owe a debt of gratitude to the agricultural experts who generously contributed their time and professional expertise to complete the pairwise comparison matrices for the analytical hierarchy process.

Finally, my deepest love and appreciation go to my family—especially my beloved parents and my siblings—for their endless emotional support, encouragement, and patience during my academic journey. To all my friends and colleagues who supported me in any way, thank you.

Dedication

إهداء خاص بالطالبة: [سلطاني إنتصار]

إلى الروح الطاهرة التي غادرتنا ومكانتها في القلب باقية، إلى من كانت لي أمّاً ثانية، ونبراساً علمياً أقتدي به،
وقدوة في الكفاح والعطاء... أختي الغالية والفقيدة البروفيسور [سلطاني آمنة]، أسكنها الله فسيح جناته وجعل علمها
وعملها نوراً وشفاعة لها في جنات النعيم.

إلى من كلّله الله بالهبة والوقار، إلى من علّمني أن ألتمس في الحياة دروب المعالي، وكان لي السند الثابت
والقدوة الملهمّة... أبي الغالي [سلطاني رشيد]، حفظه الله ورعاه وأطال في عمره.

إلى منبع الطمأنينة الحانية، وصاحبة الدعوات الصامتة في جوف الليل التي كانت تمهّد لي الصعاب وتدفعني نحو
النجاح، إلى من أرى الجنة تحت قدميها... أُمّي الحبيبة [سلطاني ذريرة]، أدام الله عليها الصحة والعافية وبشاشة الروح.

إلى من بهم يشتدّ عضدي ويقوى جانبي، رفقاء الحياة وصنّاع ذكرياتها، إخوتي وأخواتي، من كانوا يتقاسمون
معي تعب الأيام الطويلة ويمنحونني الأمل دائماً.

إلى من أضافوا لي عتمة الجهل بنور العلم، وغرسوا في نفسي حب المعرفة خطوة بخطوة... أساتذتي ومعلمي
الأفاضل، من الطفولة وصفوف الدراسة الأولى وصولاً إلى مدرجات الجامعة، شكراً لكل حرف، ولكل نصيحة، ولكل أثر
طيّب جعل مني ما أنا عليه اليوم.

إلى من جمعتني بهم الأيام والخطى، صديقاتي الوفيات والعزيزات، اللواتي تركن في روحي أثراً طيباً ودعمًا
صادقاً طوال هذه الرحلة العلمية.

إلى نفسي التي صبرت وعافرت، وإلى كل من مرّ بقلبي وترك فيه كلمة تشجيع دافئة... أهدي ثمرة هذا الجهد
المتواضع.

Abstract

Background Agricultural soils in the El Oued wilaya of the Algerian Sahara suffer from severe organic-matter depletion, secondary salinisation, and high mineral fertiliser costs. Composting local organic feedstocks offers a sustainable soil-restoration solution. However, extreme heterogeneity in farm endowments means uniform extension strategies lead to resource misallocation, requiring an evidence-based tool for targeting interventions.

Objectives: This thesis develops and validates a multi-criteria decision analysis (MCDA) pipeline integrating the Analytic Hierarchy Process (AHP) and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to rank composting intervention priority for 30 smallholder farms across 15 criteria grouped into five dimensions.

Methods: Primary data were collected via surveys and soil sampling (SOM and ECe) in 2023–2024. A five-expert panel constructed 15×15 pairwise comparison matrices using Saaty's 1–9 scale. Individual matrices were solved for eigenvectors, tested for consistency, and synthesised using the Aggregation of Individual Judgements (AIJ) geometric-mean method. The AIJ weights were implemented in the TOPSIS pipeline. Ranking robustness was validated using four sensitivity procedures: Monte Carlo perturbation, Kendall's Tau, Full-Range Weight Sensitivity Analysis (FRWSA), and One-at-a-Time (OAT) testing, alongside PCA, clustering, and OLS regression.

Principal Results: All expert AHP matrices achieved high internal consistency ($CR < 0.10$). The AIJ-aggregated matrix yielded $CR = 0.021$, identifying Manure (16.07%), SOM (12.61%), and Willingness (12.35%) as the top criteria. TOPSIS closeness coefficients (C_i) ranged from 0.149 to 0.771, stratifying farms into five classes (2 Very High, 4 High, 6 Moderate, 12 Low, 6 Very Low). Only 20% of farms crossed the high-priority threshold. Monte Carlo analysis confirmed exceptional ranking stability (mean Spearman $\rho = 0.976$).

Conclusions and Implications: Feedstock availability, rather than willingness, is the primary constraint on composting adoption in El Oued. This AHP–TOPSIS framework provides the first validated, farm-level composting priority map for the Algerian Sahara, supported by fully reproducible Python code in the annexes.

Keywords: AHP; TOPSIS; MCDA; Composting; Soil organic matter; Salinity; Smallholder agriculture; El Oued; Algeria.

ملخص

تعاني التربة الزراعية في ولاية الوادي بالصحراء الجزائرية من استنزاف حاد في المادة العضوية، وملوحة ثانوية، وارتفاع تكاليف الأسمدة المعدنية. ويمثل التسميد العضوي (Composting) للمواد المحلية حلاً مستداماً لاستصلاح التربة. ومع ذلك، فإن التباين الشديد في إمكانيات المزارع يجعل استراتيجيات الإرشاد الموحدة غير فعالة، مما يتطلب أداة قائمة على الأدلة لتوجيه التدخلات.

الأهداف: تهدف هذه الأطروحة إلى تطوير وتقييم نموذج للتحليل القرار متعدد المعايير (MCDA) يدمج بين عملية التحليل الهرمي (AHP) وأسلوب الترتيب حسب التفضيل والتشابه بالحل المثالي (TOPSIS) لتصنيف أولويات التدخل للتسميد العضوي لـ 30 مزرعة أصحاب حيازات صغيرة عبر 15 معياراً موزعة على خمسة أبعاد.

المنهجية: جُمعت البيانات الأولية من خلال مسوحات ميدانية وعينات تربة (لقياس المادة العضوية والملوحة) في سنتي 2023–2024. قام فريق مكون من خمسة خبراء ببناء مصفوفات المقارنة الثنائية 15×15 وفقاً لمقياس سياتي (1–9). وُحلت المصفوفات الفردية لاستخراج المتجهات الذاتية، واختبار اتساقها، ثم دمجها باستخدام طريقة المتوسط الهندسي (AIJ) طُبقت الأوزان المستخرجة في نظام TOPSIS واختُبرت متانة الترتيب عبر أربعة إجراءات لتحليل الحساسية

محاكاة مونتي كارلو، كيندال تاو، FRWSA، و(OAT)، بالإضافة إلى تحليل المكونات الرئيسية (PCA)، والتحليل العنقودي، وانحدار المربعات الصغرى (OLS).

النتائج الرئيسية: حققت جميع مصفوفات الخبراء اتساقاً داخلياً عالياً. ($CR < 0.10$) وسجلت المصفوفة المدمجة (AIJ) نسبة اتساق $CR = 0.0215$ ، حيث جاءت معايير: التوفر الحيواني "السماذ" (16.07%)، المادة العضوية في التربة (12.61%)، والاستعداد والقبول (12.35%) كأعلى المعايير وزناً. تراوحت معاملات القرب لـ TOPSIS بين 0.149 و0.771، مما صنف المزارع إلى خمس فئات (2 ذات أولوية عالية جداً، 4 عالية، 6 متوسطة، 12 منخفضة، 6 منخفضة جداً). تأهلت 20% فقط من المزارع لعتبة الأولوية العالية. وأكد تحليل مونتي كارلو الاستقرار الاستثنائي (لترتيب متوسط سبيرمان $\rho = 0.97$).

الاستنتاجات والتوصيات: يظهر توفر المواد العضوية الخام — وليس الاستعداد للتبني — كعائق رئيسي أمام تطبيق التسميد العضوي في الوادي. يوفر إطار AHP–TOPSIS أول خريطة موثقة ومثبتة إحصائياً لأولويات التسميد العضوي على مستوى المزارع في الصحراء الجزائرية، وهي مدعومة بكود برمجية بايثون (Python) كامل وقابل للتكرار في الملاحق.

الكلمات المفتاحية: عملية التحليل الهرمي؛ TOPSIS؛ تحليل القرار متعدد المعايير؛ التسميد العضوي؛ المادة العضوية للتربة؛ الملوحة؛ الزراعة الواحاتية؛ الوادي؛ الجزائر.

Résumé

Contexte et objectifs. Les sols agricoles de la wilaya d'El Oued, dans le Sahara algérien, souffrent d'un grave épuisement en matière organique, d'une salinisation secondaire et de coûts élevés d'engrais minéraux. Le compostage des ressources organiques locales offre une solution durable de restauration des sols. Cependant, l'extrême hétérogénéité des exploitations rend les stratégies de vulgarisation uniformes inefficaces, nécessitant un outil basé sur des données probantes pour cibler les interventions.

Objectifs : Cette thèse développe et valide une approche d'analyse décisionnelle multicritère (MCDA) intégrant le processus d'analyse hiérarchique (AHP) et la méthode TOPSIS afin de classer la priorité d'intervention en matière de compostage pour 30 petites exploitations à travers 15 critères regroupés en cinq dimensions.

Méthodes : Les données primaires ont été collectées par des enquêtes et des échantillonnages de sol (MOS et CEe) en 2023–2024. Un panel de cinq experts a construit des matrices de comparaison par paires 15×15 selon l'échelle de Saaty (1–9). Les matrices individuelles ont été résolues par vecteurs propres, testées pour leur cohérence, et synthétisées par la méthode de la moyenne géométrique (AIJ). Les poids dérivés ont été appliqués dans TOPSIS. La robustesse du classement a été validée par quatre procédures de sensibilité (Monte Carlo, Kendall's Tau, FRWSA et OAT), complétées par une ACP, un clustering et une régression OLS.

Résultats principaux : Toutes les matrices AHP ont montré une forte cohérence interne ($CR < 0,10$). La matrice agrégée (AIJ) a obtenu un $CR = 0,0215$, identifiant le fumier (16,07%), la MOS (12,61%) et la volonté d'adopter (12,35%) comme les critères prioritaires. Les coefficients de proximité TOPSIS (C_i) ont varié de 0,149 à 0,771, stratifiant les fermes en cinq classes (2 Très Haute, 4 Haute, 6 Modérée, 12 Faible, 6 Très Faible). Seules 20% des exploitations ont dépassé le seuil de priorité élevée. L'analyse de Monte Carlo a confirmé une stabilité exceptionnelle du classement (Spearman moyen $\rho = 0,976$).

Conclusions et Implications : La disponibilité des matières premières, plutôt que la volonté d'adopter, constitue la principale contrainte au compostage à El Oued. Ce cadre AHP–TOPSIS fournit la première carte validée de priorité de compostage au niveau des exploitations pour le Sahara algérien, appuyée par un code Python reproductible en annexes.

Mots-clés : AHP ; TOPSIS ; MCDA ; Compostage ; Matière organique du sol ; Salinité Agricole ; El Oued ; Algérie.

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List of Abbreviations

Abbreviation	Definition
AHP	Analytic Hierarchy Process
BWh	Köppen hot desert climate
CEC	Cation Exchange Capacity
C_i	TOPSIS closeness coefficient
CI	Consistency Index
CR	Consistency Ratio
CV	Coefficient of Variation
DA	Algerian Dinar
DAP	Diammonium Phosphate
dS m ⁻¹	deciSiemens per metre (electrical conductivity)
ECe	Electrical conductivity of saturation paste extract
FAO	Food and Agriculture Organization
FRWSA	Full-Range Weight Sensitivity Analysis
INRAA	Institut National de la Recherche Agronomique d'Algérie
MCDA	Multi-Criteria Decision Analysis
MCDM	Multi-Criteria Decision Making
MENA	Middle East and North Africa
NIS	Negative Ideal Solution
OAT	One-At-a-Time (sensitivity analysis)
OLS	Ordinary Least Squares
OMML	Office Math Markup Language
ONM	Office National de la Météorologie (Algeria)
PCA	Principal Component Analysis
PIS	Positive Ideal Solution
RI	Random Index
SOC	Soil Organic Carbon
SOM	Soil Organic Matter
TLU	Tropical Livestock Unit
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
WB	Walkley–Black method

General Introduction

1 Background and Global Context

Agricultural soil degradation now constitutes one of the most consequential and least reversible dimensions of the global food security crisis. Conservative estimates by the Food and Agriculture Organization of the United Nations place the area of moderately to severely degraded agricultural land at 1.66 billion hectares — representing approximately one third of the world’s cultivated area — and carry an annual economic cost estimated at US\$40 billion in foregone agricultural output [101, 108]. Within this global landscape, dryland agroecosystems — formally defined by an aridity index (P/PET) below 0.65 — are simultaneously the most rapidly degrading and the most densely populated by food-insecure smallholder households [102, 104]. The Middle East and North Africa (MENA) region accounts for approximately 11.4 million km² of arid to hyper-arid territory, supporting more than 650 million people who depend on irrigated oasis-type agriculture for a disproportionate share of their vegetable, cereal and date-palm supply [26, 46, 114].

Within this regional context, soil organic matter (SOM) depletion has been identified as the primary soil-quality constraint limiting sustainable intensification across MENA drylands [26, 51, 112]. Topsoil organic carbon densities consistently fall in the range of 0.1–0.6% in Saharan irrigated perimeters [26, 46] — well below the 1.0–2.0% threshold below which meaningful cation exchange capacity, aggregate stability, water-holding capacity and biological nutrient cycling cannot be maintained in low-clay sandy soils [48, 51, 79]. Paradoxically, the very success of fossil-groundwater-irrigated intensification — particularly in the Algerian Sahara, where cultivated area expanded threefold between 1980 and 2020 — has accelerated the soil degradation trajectory by driving secondary salinisation through rising phreatic water tables and locking farming systems into a high-input mineral-fertiliser dependency that leaves organic matter budgets persistently negative [14, 57, 62, 111].

Composting from locally available organic feedstocks — livestock manure, crop residues, and date-palm rachises — represents the most agro-ecologically and economically appropriate soil-restoration technology for this context. Its agronomic effectiveness in directly comparable MENA environments has been established across multiple peer-reviewed field trials [1, 4, 22, 26, 32, 115], and the post-2022 partial liberalisation of the Algerian mineral fertiliser subsidy regime has materially strengthened the financial incentive for organic-input substitution. Nevertheless, composting adoption among El Oued smallholders remains far below its biophysical and economic potential. The dominant extension model — delivering uniform composting advice to all farms in a perimeter regardless of their individual endowments, soil

status, and readiness — has produced demonstrably modest impact relative to the scale of the soil-degradation challenge [14, 26, 56].

2 The Research Problem

The central thesis of this study is that the principal inefficiency in El Oued composting extension is structural rather than informational: it resides not in a deficit of composting knowledge among farmers, but in the systematic misallocation of scarce extension resources across a highly heterogeneous farm population. Evidence from comparable dryland adoption studies consistently demonstrates that feedstock availability — particularly livestock manure — is the primary physical determinant of composting capacity, and that knowledge-focused interventions are largely ineffective for the majority of non-adopters whose binding constraint is material rather than cognitive [25, 44, 56, 99, 103]. This means that the uniform-extension model inevitably directs a large share of its resources toward farms where composting is biophysically infeasible in the short term, while underserving the subset of farms that are both feedstock-endowed and soil-degradation-motivated.

Addressing this misallocation requires a farm-level prioritisation tool capable of integrating multiple heterogeneous criteria simultaneously and producing a defensible, ranked list of farms for targeted extension intervention. Such a tool must accommodate the multi-dimensionality of composting readiness (which spans biophysical, economic, behavioural and institutional dimensions that cannot be reduced to any single indicator), the inherent subjectivity of weighting choices (which reflect expert value judgements about which criteria matter most for policy impact), and the practical need for robustness validation (because any priority ranking that is sensitive to small changes in assumptions cannot credibly guide resource allocation) [33, 77, 106, 107]. Despite the practical urgency of this need, no such tool has been systematically constructed, validated or applied for the El Oued wilaya or any comparable Algerian Saharan agricultural context. The three critical gaps in the existing literature that motivate this thesis are identified below.

3 Critical Review of the Literature and Identification of Research Gaps

3.1 Gap 1: Absence of Farm-Level Multi-Criteria Targeting Frameworks for MENA Composting Extension

The literature on composting promotion in MENA dryland smallholder contexts is characterised by a persistent disconnect between the agronomic evidence base — which is now substantial and methodologically rigorous [1, 4, 22, 26, 32] — and the targeting tools used to allocate extension resources. Agro-ecosystem studies consistently demonstrate that compost

effectiveness is highly heterogeneous across farms, mediated by initial soil SOM, salinity, application rate and feedstock quality; yet extension programme design in the region overwhelmingly relies on administrative boundaries or single-indicator screens rather than on evidence-based multi-criteria scoring [26, 56]. Multi-criteria decision analysis (MCDA) methods have been successfully deployed for targeting in comparable contexts internationally — water resource allocation in North Africa [107], land suitability assessment in arid systems [106], climate-smart agriculture prioritisation in sub-Saharan Africa [103], and organic waste management site selection [105] — yet a systematic review of the MCDA-in-agriculture literature from 2010 to 2024 reveals that no published study has applied a fully documented, Monte Carlo-validated AHP–TOPSIS framework specifically to composting intervention targeting in Saharan smallholder agriculture. This thesis addresses this gap directly.

3.2 Gap 2: Under-Theorisation of Feedstock vs. Motivational Constraints in MENA Adoption Science

The dominant theoretical framework applied to composting adoption in sub-Saharan Africa and South Asia — rooted in Technology Adoption Theory, the Theory of Planned Behaviour, and Diffusion of Innovations — treats adoption primarily as a function of motivational and informational barriers: knowledge deficits, risk aversion, attitudinal constraints and social-network effects [31, 61, 103]. Intervention designs derived from this framework typically prioritise farmer training, demonstration plots and peer-learning networks. However, a growing body of evidence from resource-constrained dryland adoption studies challenges this motivational primacy: when adoption barriers are decomposed by stated-reason analysis, feedstock scarcity and logistics constraints consistently rank above knowledge deficits as primary non-adoption reasons in contexts where livestock density is limiting [25, 44, 99]. The North African oasis literature identifies a further structural dimension — the fragmentation between feedstock-surplus and feedstock-deficit farms — that knowledge-focused interventions cannot resolve [26, 110]. Yet no systematic framework for distinguishing and quantifying these two constraint types at the farm level has been developed for the MENA context. This thesis addresses this gap by including both feedstock criteria and motivational criteria as separate, independently weighted AHP dimensions, and by using OLS regression to empirically separate their contributions to the TOPSIS priority score.

3.3 Gap 3: Absence of Rigorous Robustness Validation in MENA Agricultural MCDA

A review of published MCDA applications in MENA agricultural policy contexts from 2010 to 2024 reveals that the vast majority of studies — even those using advanced AHP or TOPSIS frameworks — do not report any robustness or sensitivity analysis of their priority rankings [106, 107]. This is a serious methodological limitation: MCDA rankings are inherently sensitive to the weights assigned to criteria, and weights derived from expert elicitation always carry uncertainty both because individual experts disagree and because the same expert may provide internally inconsistent judgements under cognitive load [75, 77]. A ranking that is not validated for robustness cannot credibly guide resource allocation, because a modest change in assumed weights could reverse priority tiers and fundamentally alter the intervention programme. The robustness methods established in the operations research and environmental decision-making literatures — Monte Carlo weight perturbation, Kendall's Tau, One-at-a-Time sensitivity, and Full-Range Weight Sensitivity Analysis [59, 72] — have not been applied in combination to any single agricultural MCDA study in the MENA region. This thesis applies all four methods simultaneously, establishing a validation benchmark against which future regional MCDA studies can calibrate their standards.

4 Research Objectives

Responding to the three gaps identified above, this thesis pursues six specific, progressively nested research objectives:

Objective 1 — Criterion framework development. To construct a theoretically justified and empirically grounded 15-criterion AHP framework for composting intervention prioritisation in El Oued smallholder agriculture, covering five thematic dimensions — feedstock availability, soil status, composting readiness, economic incentive, and structural-institutional capacity — with explicit reference to the peer-reviewed adoption and agro-ecological literature [25, 44, 56, 99, 107].

Objective 2 — Expert weight elicitation and validation. To elicit and fully document five independent AHP pairwise comparison matrices (15×15 , 105 unique judgements per expert) from a five-member multidisciplinary panel covering soil science, agricultural economics, extension science, composting agronomy and rural sociology; to synthesise them into a single AIJ weight vector via the geometric-mean aggregation method; and to validate the weight vector for internal consistency ($CR \leq 0.10$) and inter-expert concordance using Kendall's W and pairwise Spearman ρ [75, 77].

Objective 3 — Farm-level priority ranking. To apply the full six-step TOPSIS pipeline to the 30×15 decision matrix derived from primary farm-level survey data and in-situ soil sampling, producing a farm-level composting priority ranking stratified into five intervention tiers (Very High, High, Moderate, Low, Very Low) with fully documented intermediate matrices.

Objective 4 — Comprehensive robustness validation. To validate the TOPSIS ranking through four independent robustness procedures — Monte Carlo weight perturbation ($n = 1,000$ iterations, $\pm 20\%$), Kendall's Tau correlation ($n = 500$ iterations, $\pm 20\%$), Full-Range Weight Sensitivity Analysis ($0-3\times$ weight multiplier) and One-at-a-Time sensitivity ($\pm 50\%$ per-criterion perturbation) — against published benchmarks for acceptable MCDA robustness in agricultural policy applications [59, 72].

Objective 5 — Empirical driver analysis. To identify and quantify the principal continuous drivers of the TOPSIS closeness coefficient C_i using OLS regression, PCA and K-means clustering, providing independent statistical validation of the AHP–TOPSIS aggregation and empirically distinguishing feedstock-physical from motivational-readiness constraints across the 30-farm sample.

Objective 6 — Policy translation. To translate the farm-level priority ranking and driver analysis into specific, actionable extension-targeting recommendations for the El Oued wilaya DSA, aligned with the Algerian Soil Restoration National Programme (2023–2027) [112], including a staged-intervention logic for Very Low priority farms where direct composting is agronomically premature.

5 Research Hypotheses

The six objectives are operationalised through five testable research hypotheses that structure the empirical chapters of this thesis:

H1 — Feedstock primacy. Organic feedstock availability (manure and crop residue availability) will emerge as the dominant dimension of composting prioritisation in El Oued, receiving a combined AIJ weight exceeding that of any other single thematic dimension and producing the largest standardised OLS regression coefficient in the C_i prediction model [25, 44, 99]. Rejection of H1 would imply that motivational or economic criteria dominate, which would require a fundamentally different intervention design logic.

H2 — High inter-expert concordance. The five-expert AHP elicitation will produce strong inter-expert agreement, with Kendall's $W \geq 0.70$, mean pairwise Spearman $\rho \geq 0.80$, and individual Consistency Ratios $CR \leq 0.10$, confirming that the five disciplinary perspectives

converge on a structurally consistent priority ordering of criteria [75, 77]. Rejection of H2 would imply that the AIJ synthesis is statistically unjustified.

H3 — Extreme farm-level heterogeneity. The TOPSIS closeness coefficients will span an exceptionally wide range ($\Delta C \geq 0.25$), substantially wider than the $\Delta C = 0.10\text{--}0.20$ typically reported in single-context MCDA applications in the sub-Saharan African agricultural literature [104], reflecting the compound biophysical, socioeconomic and institutional heterogeneity of El Oued smallholder farms. H3 is the empirical foundation for the core policy argument that uniform extension programmes are structurally inefficient for this population.

H4 — Ranking robustness. The TOPSIS priority ranking will be stable under realistic expert-weight perturbation ($\pm 20\%$), with mean Monte Carlo Spearman $\rho \geq 0.90$ and Kendall $\tau \geq 0.80$, confirming that the ranking is robust enough to credibly guide extension resource allocation even when the exact AHP weights are uncertain [59, 72].

H5 — OLS–AHP consistency. Standardised OLS regression of C_i on nine continuous predictors will achieve $R^2 \geq 0.90$, with coefficient signs wholly consistent with the a priori AHP benefit/cost direction assignments, providing independent statistical validation that the TOPSIS aggregation faithfully reflects the underlying multi-dimensional farm performance rather than producing artefactual rankings driven by normalisation noise.

6 Significance of the Study and Contributions to Knowledge

This thesis makes three distinct and complementary scientific contributions. First, it produces the first published, fully documented, expert-matrix-validated, Monte Carlo-tested AHP–TOPSIS composting priority map for any Algerian Saharan agricultural system, filling a critical methodological and applied gap in the regional MCDA and agro-ecological literatures [26, 56, 107]. **Second**, it provides an empirical test of the feedstock-primacy hypothesis in a MENA oasis context — a hypothesis theoretically motivated by the sub-Saharan African adoption literature [25, 44, 99] but never previously tested with a formal multi-criteria quantitative framework in North Africa. **Third**, it establishes a four-method robustness validation benchmark for agricultural MCDA in the MENA region against which future studies can calibrate their own validation standards [59, 72, 106]. The practical contribution is equally concrete: a ranked list of 30 farms stratified into five evidence-based intervention tiers with farm-specific profiles enabling differentiated, targeted extension support. The framework is built on open-access primary data designed for direct replication and adaptation by research teams working in comparable oasis systems across Algeria, Tunisia, Morocco, Libya and Egypt.

7 Thesis Structure

Part I (Chapters 1–3) develops the theoretical and bibliographic foundations. Chapter 1 examines the biophysical basis of the SOM crisis in Saharan agroecosystems, including the mechanisms of SOM depletion, the hydrogeology of secondary salinisation, and consequences for soil function, crop performance and national food security [26, 57, 62, 113]. Chapter 2 reviews the agronomic evidence base for composting effectiveness in MENA drylands [1, 4, 22, 26, 32, 115] and the international adoption science literature [25, 31, 44, 56, 61, 99], identifying the structural determinants and barriers that the AHP–TOPSIS framework must address. Chapter 3 provides the complete mathematical derivation of the AHP and TOPSIS methods, the rationale for robustness testing, and a critical comparison of alternative MCDA methods that justifies the AHP–TOPSIS choice [33, 75, 77, 106, 107]. **Part II** (Chapters 4–7) presents the experimental study (Chapter 4) through full quantitative results (Chapter 5) and interpretive discussion (Chapter 6) to policy conclusions and the research agenda (Chapter 7).

PART I — BIBLIOGRAPHIC PART

Chapter 1 — Soil Organic Matter in Saharan Agroecosystems

1.1 The Nature and Functions of Soil Organic Matter

Soil organic matter (SOM) is one of the most complex, functionally important and historically misunderstood components of terrestrial ecosystems. In the broadest contemporary sense, SOM encompasses all organic constituents of the soil — from freshly deposited plant litter and living microbial biomass, through partially transformed intermediate fractions (particulate organic matter, macro-aggregates, micro-aggregates), to the highly stabilised humic and humin substances formed through microbial processing, organo-mineral associations and abiotic condensation reactions [51, 79]. This definitional breadth reflects the functional complexity of SOM in agroecosystems: it operates simultaneously as a nutrient reservoir, a physical structural agent, a microbial habitat, a climate regulator, and the primary driver of soil biological activity.

A more contemporary view, as defined in the influential synthesis by Lehmann and Kleber [51], is that SOM should be understood not as a discrete pool of chemically distinct “humic substances” but rather as a continuum of progressively decomposing organic compounds whose persistence in the soil is governed primarily by ecosystem properties — particularly mineral protection, microbial accessibility, and physical occlusion within aggregates — rather than by intrinsic molecular recalcitrance. This conceptual shift, sometimes termed the “soil continuum model,” has significant implications for composting science, because it implies that the longevity of compost-derived organic matter in a target soil depends not only on the chemical maturity of the compost itself but also on the receiving soil’s capacity to physically and chemically protect the introduced organic material from rapid mineralisation.

The physical functions of SOM in dryland agroecosystems are particularly critical for the present study context. At the micro-aggregate level, SOM — particularly fungal hyphae, bacterial exopolysaccharides and oxidised humic polymers — acts as a biological binding agent that cements primary mineral particles (sand, silt, clay) into water-stable micro-aggregates of 20–250 μm diameter. These micro-aggregates then interact with each other and with particulate organic matter to form macro-aggregates ($> 250 \mu\text{m}$), creating the sponge-like pore architecture that determines a soil’s hydraulic conductivity, aeration, root penetration resistance and erosion susceptibility [51, 79]. In Saharan sandy loam soils — which are inherently structurally unstable due to low clay content and the absence of permanent-charge clay minerals — SOM is often the only meaningful binding agent available. The loss of SOM in these soils therefore translates directly into aggregate collapse, surface sealing under irrigation, increased runoff and accelerated wind erosion [26, 57].

The chemical functions of SOM are equally critical for agricultural productivity. SOM is the primary carrier of cation exchange capacity (CEC) in low-clay soils. Each percentage-point increase in SOM in a sandy loam soil increases CEC by approximately $1.5\text{--}2.5\text{ cmol}_c\text{ kg}^{-1}$ — enough to retain an additional $60\text{--}100\text{ mg kg}^{-1}$ of exchangeable potassium or ammonium nitrogen [16]. In El Oued, where soils contain 5–18% clay and where this thesis documents a sample-mean SOM of 0.75%, the soil's total CEC is estimated at approximately $6\text{--}12\text{ cmol}_c\text{ kg}^{-1}$ — less than half the minimum recommended for productive vegetable cultivation (commonly placed at $20\text{ cmol}_c\text{ kg}^{-1}$). This implies that a large fraction of the applied mineral nitrogen — which in the present sample averages $242\text{ kg urea ha}^{-1}\text{ yr}^{-1}$ — is lost to leaching or volatilisation rather than being retained on exchange sites for plant uptake, generating both economic waste and environmental pollution [32].

The biological functions of SOM are mediated through the soil food web. SOM provides the energy and carbon substrate for heterotrophic microbial communities that catalyse the mineralisation of organic nitrogen, phosphorus and sulphur — converting them from recalcitrant organic forms to plant-available inorganic ions. Microbial biomass carbon (MBC), which typically constitutes 1–4% of total SOM, is the active fraction that directly drives nutrient cycling; in Saharan soils, MBC concentrations below $50\text{ mg C kg}^{-1}\text{ soil}$ — well below the threshold for meaningful nitrogen mineralisation — are widely reported under continuous cultivation without organic inputs [82]. Below this threshold, mycorrhizal colonisation rates decline, pathogen-suppressive activity is lost, and the beneficial root-zone microbiome that contributes to phosphorus mobilisation and drought tolerance collapses [84].

At the global scale, soils store an estimated $1,500\text{--}2,400\text{ Pg}$ of organic carbon to a depth of 1 m, representing roughly twice the carbon held in the atmosphere and three times the carbon stored in living terrestrial vegetation [48, 58]. The “4 per mille” initiative, adopted at COP21, proposed that a 0.4% annual increase in global soil carbon stocks would suffice to offset anthropogenic CO_2 emissions, illustrating the macro-scale climate significance of even modest changes in SOM management. However, critics have correctly pointed out that achieving 4‰ annual increments is thermodynamically and practically unachievable in most dryland contexts — precisely because the decomposition rates that regulate net SOM accumulation are dominated by temperature and moisture constraints that cannot be managed without fundamentally transforming the climate [58]. This does not reduce the policy significance of composting in El Oued; rather, it contextualises it: modest, achievable SOM gains of 0.3–0.8 percentage points over 3–5 years, while insufficient for global climate purposes, are sufficient to transform local soil functionality from degraded to productive.

A central distinction relevant to the present thesis is between the *labile* and *stable* SOM pools. The labile pool — comprising particulate organic matter, microbial biomass and dissolved organic compounds — typically represents 10–25% of total SOM by mass but accounts for the majority of nutrient release during the growing season [48, 51]. The stable pool — comprising mineral-associated organic matter, occluded organic matter within micro-aggregates, and resistant aromatic compounds — has mean residence times measured in decades to centuries and contributes primarily to long-term soil structural and biological capacity. Compost application contributes to both pools: the easily decomposable fraction enters the labile pool and supplies short-term nutrients to crops, while the more stable humic and humin-like fractions entering the soil matrix contribute to long-term SOM accrual. The literature suggests that approximately 30–50% of compost-applied carbon enters the stable pool over a 3–5 year horizon in dryland soils, depending on the compost maturity and the receiving soil's clay and oxide content [5, 22].

1.2 Mechanisms of SOM Depletion in MENA Drylands

The MENA region encompasses approximately 11.4 million km² of arid to hyper-arid land — about 41% of the global dryland area — and supports more than 650 million people, over 85% of whom depend directly or indirectly on dryland agriculture for their food security. Across this expanse, mean topsoil organic carbon densities measured by the Walkley–Black method consistently fall in the range of 0.1–0.6%, with Saharan oasis irrigated perimeters at the low end of this distribution [26, 46]. The biophysical mechanisms driving this persistent depletion are now well understood and involve at least five interacting processes. Understanding these mechanisms is essential, because each of them can in principle be addressed by carefully designed organic-amendment interventions, and the relative weight of each mechanism in a given local context determines which intervention is most cost-effective.

First, thermally accelerated decomposition. Under mean daily temperatures exceeding 35°C during the June–September period, and frequently surpassing 45°C maximum, microbial decomposition of fresh organic inputs operates at two to four times the rate observed in Mediterranean or temperate climates. The Q_{10} relationship — which states that biological reaction rates approximately double for every 10°C increase in temperature — implies that at 45°C, decomposition of fresh manure proceeds roughly 4× faster than at 25°C [79]. Because fresh organic inputs decompose so rapidly, their contribution to stable humus formation is proportionally reduced relative to temperate systems, and a larger fraction of the input carbon is respired back to the atmosphere as CO₂ before any opportunity for stabilisation arises. The

practical implication is that *raw* (uncomposted) organic inputs in Saharan systems are unusually inefficient at building SOM — composting itself, by completing the most labile decomposition stages in a controlled pile *before* application, becomes a precondition for efficient SOM accrual.

Second, wind erosion of the organic-rich surface crust. In Saharan agricultural perimeters without vegetative ground cover, the thin (1–2 mm) biological soil crust — which concentrates the highest density of microbially stabilised humic polymers and cyanobacterial polysaccharides — is highly susceptible to wind erosion during the hot, dry season, when sustained wind speeds of 4–7 m s⁻¹ are routinely measured at the El Oued meteorological station, with peak speeds exceeding 18 m s⁻¹ during the spring sirocco events. Studies in comparable Algerian dryland perimeters have documented SOC losses of 40–65 kg ha⁻¹ yr⁻¹ attributable to wind erosion alone, equivalent to a loss of 0.04–0.06 SOM percentage points per decade per hectare [57, 62]. Composting, by increasing aggregate stability and providing surface mulch protection, reduces wind erosion losses by an estimated 50–70% in comparable contexts [26], adding a structural protection benefit to the nutrient-supply benefit traditionally associated with organic amendments.

Third, the absence of fungal humification. In temperate systems, the cool and moist autumn–winter period drives a wave of fungal decomposition of plant litter, during which melanin-rich fungal cell walls and oxidised phenolic compounds polymerise into stable humic molecules. This seasonal “humification window” does not exist in hyper-arid systems: winters are mild and dry rather than cold and moist, and the soil’s water potential rarely falls low enough to constrain microbial activity for sufficiently long periods to allow humification chemistry to outcompete mineralisation. Estimates from comparable systems in Tunisia and Morocco suggest that fungal-mediated humification contributes less than 15% of total SOM formation in hyper-arid oasis soils, compared to 30–50% in Mediterranean dryland systems [22]. This deficit means that in Saharan soils, the formation of stable humus depends disproportionately on bacterial and actinomycete processes — precisely the microbial groups that dominate the thermophilic phase of composting (Chapter 2). Composting therefore replicates, in a controlled and accelerated form, the humus-forming biochemistry that is otherwise nearly absent in the field environment of El Oued.

Fourth, the structural depletion effect of irrigated monoculture. The irrigated potato monoculture system — which constitutes over 60% of cultivated area in El Oued — is agronomically hostile to SOM accumulation for three converging reasons: (a) frequent mechanical tillage (2–4 passes per crop cycle for seed bed preparation, inter-row cultivation and harvest) accelerates mineralisation of residual SOM by fragmenting soil aggregates and

aerating the soil profile; (b) potato and vegetable crops have very low root biomass relative to shoot biomass (root:shoot ratio 0.2–0.4 vs. 0.5–1.2 for cereals), generating minimal below-ground organic matter input; and (c) the removal of entire plant biomass at harvest, including haulm in many cases, leaves only stubble at the soil surface, providing minimal surface protection from wind and radiation [26, 99]. The net result is a system in which the annual organic input from the cropping system itself — in the absence of compost or manure additions — is well below the annual decomposition loss, generating a structural negative balance that explains the long-term SOM decline documented in the regional literature.

Fifth, salinisation-induced microbial suppression. In El Oued, secondary salinisation driven by upward capillary transport of brackish groundwater (*remontée de la nappe phréatique*) imposes osmotic stress on the soil microbial community at E_{Ce} values above 4–6 dS m⁻¹ — a threshold exceeded by the majority of farms in the present sample. At osmotic potentials equivalent to E_{Ce} = 8 dS m⁻¹, microbial biomass carbon is reduced by 35–60% relative to non-saline soils, and the activity of extracellular enzymes responsible for organic matter decomposition and nutrient mineralisation declines proportionally [1, 32]. Paradoxically, severe salinity both depletes SOM (through the four mechanisms above) and suppresses the microbial community that would normally benefit from organic amendments — making the recovery trajectory slower and more complex than in non-saline degraded soils, and motivating the staged intervention logic that this thesis develops in Chapter 7.

These five mechanisms operate concurrently and are not mutually independent: thermal acceleration of decomposition is exacerbated by salinity-induced microbial stress (because stressed microbes channel a higher fraction of decomposition energy into maintenance respiration rather than biomass synthesis), wind erosion is exacerbated by aggregate instability resulting from low SOM, and tillage-induced SOM loss is exacerbated by the moisture deficit that prevents rapid re-aggregation after disturbance. The compound nature of these mechanisms is the structural reason why piecemeal interventions tend to fail in this context, and why a multi-criteria framework that simultaneously accounts for SOM status, salinity status, feedstock availability and farmer readiness — as developed in this thesis — is conceptually appropriate.

1.3 The El Oued Context: Geography, Climate and Agrarian Structure

El Oued (33°24'N, 6°52'E, elevation 65 m a.s.l.) is the administrative capital of the wilaya of the same name, situated in the north-eastern Algerian Sahara approximately 600 km south-east of Algiers. The wilaya covers 44,585 km², of which only approximately 0.8% (approximately 35,000 ha) is under active cultivation — a figure that has increased threefold

since 1980 due to groundwater-irrigated development associated with the national agricultural intensification programmes of the 1980s and 1990s. The climate is rigorously hyper-arid by any classification system: the Aridity Index (P/PET) averages 0.04–0.06, firmly within the FAO/UNEP “hyper-arid” category; mean annual precipitation is 86 mm based on the 1991–2020 ONM-Algeria station record, falling in 8–12 distinct events per year with inter-annual coefficients of variation exceeding 60%; mean July maximum temperature is 44.3°C with recorded extremes to 49°C; and Saharan dust storm frequency averages 28 days yr⁻¹ across the same observational period [57, 62].

The geological context adds a critical hydrological dimension. El Oued sits above the Continental Intercalaire (CI) fossil aquifer — one of the largest confined aquifers on Earth, spanning approximately 600,000 km² across Algeria, Tunisia and Libya. Groundwater abstraction for agriculture, which increased from approximately 80 million m³ yr⁻¹ in 1980 to over 500 million m³ yr⁻¹ by 2020, has generated an unintended hydraulic consequence: the water table in the shallow phreatic aquifer (a separate, near-surface aquifer overlying the deep CI) has risen from depths of 8–15 m in the 1960s to 0.8–3.5 m in many irrigated perimeters today. This rising near-surface water table — a phenomenon described in the local hydrogeological literature as the *remontée de la nappe phréatique* — drives upward capillary transport of salt-enriched groundwater through the sandy soil profiles, concentrating salt at the surface through evaporation. The hydrogeology behind the phenomenon is examined more carefully in Section 1.5.

The farming population of El Oued is predominantly smallholder. The modal farm size in the wilaya is 2–5 ha, consistent with the present sample distribution (median 5.24 ha, mean 7.57 ha, maximum 24.62 ha). The dominant crop system is a potato–tomato–onion rotation under overhead sprinkler or pivot irrigation from private wells. El Oued is nationally renowned as *la capitale de la pomme de terre dorée* (the capital of the golden potato), producing an estimated 30–35% of Algeria’s national potato supply on an area that constitutes less than 0.5% of the national cultivated surface. This extreme production concentration creates structural vulnerabilities for national food security: any significant soil degradation in the wilaya would have direct consequences at the national scale, as there is no readily available alternative production zone for the potato volumes involved.

Livestock systems in El Oued are predominantly small-ruminant based (Ouled-Djellal sheep and local goats), with camels (*Camelus dromedarius*) present on approximately 20% of larger holdings, and a small number of dairy cattle on a subset of irrigated farms with adequate forage capacity. Total livestock holdings in the present sample range from 1.08 to 7.90 Tropical

Livestock Units (TLU) per farm (mean 4.23 TLU), with the conventional excretion-rate estimates implying mean annual manure availability of approximately 11.5 t per farm. The TLU–manure linear relationship documented in this thesis (Pearson $r = 0.92$) is consistent with published excretion rates for mixed sheep-goat-camel systems in comparable North African contexts [29, 84], and establishes that the livestock endowment of each farm is effectively the rate-limiting step for composting potential under the current agrarian structure.

The institutional setting comprises two principal actors. First, the Direction des Services Agricoles (DSA) — the wilaya-level agricultural directorate — coordinates extension activities, distributes subsidised inputs, and administers the credit and certification programmes operated under the National Agricultural Development Programme. Second, the Office National des Aliments du Bétail (ONAB) administers the livestock subsidy and feed-distribution programmes that indirectly determine the size and quality of the livestock-based feedstock pool. Agricultural cooperatives are present but weak: the present sample shows that only 27% of farms are formal cooperative members, and informal feedstock-exchange arrangements remain the principal mechanism by which feedstock-constrained farms access organic materials from feedstock-rich neighbours.

1.4 Documented Consequences of SOM Depletion in the Study Region

The cascade of agronomic, economic and food-security consequences from SOM depletion in El Oued's smallholder potato system is both empirically documented and practically severe. At the soil-physical level, comparable Algerian Saharan studies in Touggourt (100 km south-west of El Oued) have documented bulk densities of 1.52–1.61 g cm⁻³ and saturated hydraulic conductivity of 0.4–0.8 cm hr⁻¹ in SOM-depleted soils (SOM < 0.4%) — values that classify these soils as “highly compacted” and “poorly draining” by FAO soil quality standards [1]. The same studies have consistently demonstrated that organic amendments reduced bulk density to 1.38–1.44 g cm⁻³ and increased saturated hydraulic conductivity to 2.1–3.5 cm hr⁻¹ after two growing seasons, confirming the physical restoration potential of composting under directly comparable agro-ecological conditions.

At the crop-performance level, the attenuation of fertiliser-use efficiency under low SOM is particularly economically damaging. Estimates from the regional and pan-MENA literature suggest that less than 50% of applied urea-nitrogen is recovered in crop biomass in low-SOM, low-CEC sandy soils under sprinkler irrigation — implying that Algerian farmers in this system spend approximately twice what they would need to if their soils had adequate SOM [26, 32]. The economic incentive to substitute organic for mineral nitrogen is therefore direct and

financially compelling, and provides the conceptual justification for the inclusion of fertiliser cost share as one of the principal economic-incentive criteria in the AHP framework developed in Chapter 4. The post-2022 Algerian fertiliser price reform (Section 2.4) has further sharpened this incentive structure.

At the macroeconomic and food-security level, the soil-degradation trajectory under current management raises serious questions about the long-term productivity of El Oued's potato system. The Institut National de la Recherche Agronomique d'Algérie has documented a statistically significant yield decline of 0.8–1.4 t ha⁻¹ per decade in potato yields across irrigated Saharan perimeters from 1995 to 2015, attributable primarily to the combined effects of increasing soil salinity and declining organic matter [14]. If this trajectory continues, the most productive farms — those currently generating national-scale supply — will cross yield-viability thresholds within 15–25 years. Composting, while not a silver bullet, is the most cost-effective available intervention for reversing the SOM component of this trajectory, and is a necessary (though not sufficient) component of any comprehensive salinity-remediation strategy.

A particularly important downstream consequence is the relationship between SOM and water-use efficiency, which has direct implications for the long-term sustainability of the Continental Intercalaire abstraction regime. Soils with adequate SOM ($\geq 1.0\%$) hold approximately 1.5–2.5 times more plant-available water per unit volume than equivalent sandy soils with depleted SOM ($\leq 0.5\%$), allowing identical crop water requirements to be met with substantially less irrigation [5, 16]. In a system that currently abstracts more than 500 million m³ yr⁻¹ from a fossil aquifer with no contemporary recharge, even a 15–20% reduction in irrigation requirement — a plausible outcome of widespread SOM restoration — would extend the operating life of the aquifer by decades and reduce the rate of phreatic-aquifer accumulation that drives the salinisation problem in the first place. This positive feedback loop between SOM restoration and water-resource sustainability is a defining feature of the El Oued case and is explored further in Chapter 6.

1.5 The Phreatic Aquifer Rise and Secondary Salinisation

The hydrogeological dynamics underlying the salinity problem in El Oued deserve a more detailed treatment than the brief mention in Section 1.3, because they fundamentally shape the design space for any soil-restoration intervention in this wilaya. The phreatic (shallow) aquifer of El Oued occupies a Quaternary sandy formation overlying the much deeper Continental Intercalaire and Complexe Terminal aquifers; under pre-1980 conditions, the phreatic aquifer

was hydraulically near-stationary at depths of 8–15 m below ground surface, with negligible interaction with the rooting zone [57]. Beginning in the early 1980s and accelerating through the 1990s, the conjunction of large-scale groundwater abstraction from the deeper aquifers (for irrigation), the absence of effective drainage networks in the new perimeters, and the practice of flood and sprinkler irrigation with high application rates, generated a sustained downward percolation flux that progressively raised the phreatic water table. By 2020, the phreatic table had risen to depths of 0.8–3.5 m in many irrigated perimeters, bringing it within range of capillary connection to the rooting zone for most cultivated crops [62].

The salinisation mechanism that follows is a textbook example of secondary salinisation. Brackish groundwater (typical electrical conductivity 8–14 dS m⁻¹ in the El Oued phreatic aquifer) rises by capillary action through the sandy soil profile at velocities of 0.3–1.2 mm hr⁻¹ depending on profile texture and ambient evaporative demand. As the water reaches the surface, the water itself evaporates while the dissolved salts (predominantly NaCl, with secondary contributions from CaSO₄, MgSO₄ and KCl) are deposited at and near the surface. Under the local evaporative regime — annual potential evapotranspiration exceeding 2,100 mm — the cumulative salt deposition can amount to several hundred kilograms per hectare per year in affected zones, far in excess of the leaching capacity of the irrigation regime in the absence of active drainage. The result is the gradient of soil ECe values documented in the present sample, which ranges from 1.16 dS m⁻¹ (essentially non-saline) to 11.67 dS m⁻¹ (severely saline), with a sample mean of 5.45 dS m⁻¹ that places the typical farm in the moderate-to-severe salinity range.

The interaction of SOM depletion and salinisation is bidirectional and mutually reinforcing. SOM-depleted soils have reduced aggregate stability, leading to surface sealing under irrigation and reduced infiltration — which in turn reduces the leaching of accumulated salts and exacerbates the salinity problem. Conversely, saline conditions suppress the microbial activity required for SOM accrual, slowing the recovery trajectory even when organic amendments are applied. This interlocking dynamic is the principal reason why this thesis treats SOM, salinity and feedstock availability as jointly necessary criteria in the AHP framework, rather than as substitutable indicators of “soil need.”

For composting policy, the salinity problem implies a critical operational constraint: the agronomic returns to compost application are substantially reduced — and may even be negative in extreme cases — when applied to soils with ECe above approximately 6–8 dS m⁻¹ without prior salinity remediation. The literature on this point is consistent: Hussain et al. [32] and Abid et al. [1] both report yield response gradients showing approximately 30–40% lower

compost-induced yield gains at $EC_e = 8 \text{ dS m}^{-1}$ compared to $EC_e = 4 \text{ dS m}^{-1}$, and El Janati et al. [22] explicitly recommend gypsum-and-leaching pre-treatment for soils above the moderate-salinity threshold before composting can be expected to deliver its full agronomic benefits. This constraint is encoded in the AHP framework through the inclusion of EC_e as a high-weight cost criterion (Section 4.4), and motivates the staged-intervention recommendation structure developed in Chapter 7.

1.6 Conceptual Synthesis and Bridge to Chapter 2

This chapter has established the ecological, agronomic, hydrological and economic foundations of the composting prioritisation problem addressed in this thesis. Soil organic matter in El Oued's smallholder farms is critically depleted relative to both local sustainability thresholds and global benchmarks, driven by a compounding set of mechanisms — hyper-aridity-driven thermal acceleration of decomposition, fossil-water-irrigation-induced salinisation, intensified potato monoculture, wind erosion of the surface crust, and the suppression of fungal humification under permanently dry winter conditions. These mechanisms are mutually reinforcing rather than independent, generating a compound degradation trap from which farms in the most affected zones cannot easily escape through any single intervention. The consequences of SOM depletion are traceable through soil micro-physics, nutrient cycling, water-use efficiency, fertiliser cost burden and ultimately farm income and national food security. Composting addresses multiple dimensions of this challenge simultaneously — SOM restoration, salinity buffering through improved leaching efficiency, and direct fertiliser cost reduction — but its adoption cannot be effectively promoted through uniform extension programmes given the extreme heterogeneity of farm endowments documented in this study.

Chapter 2 examines the scientific evidence base for composting effectiveness in comparable dryland contexts, reviews the international literature on the determinants of composting adoption, and lays out the policy and institutional context within which the AHP–TOPSIS framework will operate. Chapter 3 then provides the mathematical foundations of the AHP and TOPSIS methods, and Chapter 4 brings these threads together in the empirical implementation that constitutes the core of this thesis.

Chapter 2 — Composting as a Soil Restoration Strategy

2.1 The Biochemistry of Composting: From Feedstock to Humus

Composting is the managed aerobic thermophilic decomposition of heterogeneous organic materials — livestock manure, crop residues, food waste, green vegetation — through a structured succession of microbial communities that transform raw inputs into a biologically stable, pathogen-reduced, humus-rich product. Understanding the biochemical stages of composting is essential for appreciating both why feedstock quality and quantity matter so much for the adoption calculus, and why the resulting compost generates the soil-physical and chemical improvements documented in the dryland literature. The biochemistry also underlies the technical-readiness criteria included in the AHP framework of this thesis, because each composting stage imposes specific operational requirements (turning, moisture management, temperature monitoring) that depend on farmer knowledge and on the availability of an adequate composting platform.

Stage 1 — Mesophilic initiation (days 0–3, 20–40°C). Ambient-temperature mesophilic bacteria and fungi immediately colonise fresh organic materials, consuming simple sugars, amino acids and short-chain fatty acids through aerobic respiration. This rapid metabolic activity generates heat at rates of 2–5°C per day, raising pile temperature above the mesophilic optimum within 24–72 hours under typical Saharan ambient conditions. At this stage, the carbon-to-nitrogen (C:N) ratio of the feedstock is the primary process-limiting parameter: materials with C:N below approximately 20:1 (e.g., fresh sheep manure: C:N typically 15–18:1) decompose rapidly but may generate ammonia volatilisation losses; materials with C:N above 30:1 (date-palm fronds: C:N 45–60:1) decompose slowly but provide the structural carbon for stable humus formation. The operational optimum for composting feedstock blends is generally placed at C:N = 25–35:1, which in the El Oued context is achievable by mixing approximately three parts palm frond or crop residue with one part sheep manure by volume [22, 28]. Careful blending at this stage is the principal lever by which composting throughput and end-product quality can be optimised within a given farm’s feedstock endowment.

Stage 2 — Thermophilic acceleration (days 3–15, 50–70°C). As temperature rises above 45°C, thermophilic bacteria (*Bacillus* spp., *Thermus* spp.) and thermophilic actinomycetes dominate the decomposer community. This phase simultaneously performs two agronomically critical functions. First, **pathogen destruction**: temperatures above 55°C maintained for more than 3 days kill *Salmonella*, *E. coli* O157, most helminth eggs and most weed seeds — achieving the pathogen reduction required for safe application of manure-based composts on food crops, including the potato and tomato that constitute the dominant crops in El Oued. Second, **lignin depolymerisation**: white-rot thermophilic actinomycetes begin

attacking the recalcitrant aromatic rings of lignin, generating phenolic monomers that are the precursors of humic polymers. Thermophilic decomposition proceeds 2–4 times faster in El Oued’s ambient temperature regime (above 35°C in summer) than in temperate composting systems, providing a paradoxical operational advantage: the same high-temperature environment that destroys humus in the field actually accelerates the thermophilic phase of composting when properly managed in a protected pile [5, 74].

Stage 3 — Cooling and mesophilic succession (days 15–30). As labile organic compounds are progressively exhausted, metabolic heat production falls, temperature returns to the 30–45°C range, and a second wave of mesophilic bacteria, actinomycetes and fungi colonises the cooled pile. Actinomycetes produce the characteristic grey-white mycelial strands visible on the pile surface and contribute strongly to humic polymer formation through oxidative coupling of phenolic monomers. Earthworms (where present, primarily in vermicomposting systems) and other macro-invertebrates also colonise the cooling pile, further fragmenting organic particles and creating the characteristic granular structure of mature compost.

Stage 4 — Maturation and humus formation (weeks 4–12). Maturation is characterised by a continued decline in CO₂ evolution rate (the standard indicator of biological stability), a decrease in the C:N ratio to 15–25:1 through proportionally greater carbon loss as CO₂, and the progressive formation of humic acids (high-molecular-weight aromatic polymers) from the phenolic precursors generated in stage 2. Mature compost typically contains 1.5–3.5% total nitrogen, 0.5–1.5% P₂O₅, 0.5–1.2% K₂O, and 25–45% organic carbon on a dry-weight basis [82]. When applied at 8–15 t ha⁻¹ in arid systems, these nutrient concentrations are equivalent to approximately 100–200 kg N ha⁻¹, of which 30–50% is mineralised in the first growing season and the remainder contributes to long-term SOM accumulation [22, 32].

The implication of this biochemical progression for composting adoption policy is that the *quality* of the end product depends on management decisions at every stage, and therefore that composting outcomes are not deterministic functions of feedstock alone — they depend jointly on feedstock, knowledge, space and time. This is the conceptual reason why the AHP framework of this thesis includes both a feedstock dimension and a separate composting-readiness dimension: a farm with abundant manure but no knowledge of moisture and turning management will produce poor compost, while a farm with excellent knowledge but no feedstock will produce no compost. The multi-criteria framework reflects this conjunctive structure of composting capability.

2.2 Agronomic Effectiveness of Composting in MENA Drylands

The scientific evidence base for composting effectiveness in MENA dryland agricultural contexts has expanded substantially since 2018, particularly following increased research investment in Saharan agroecology driven by Algerian, Moroccan and Tunisian research consortia and by EU Horizon programmes on Mediterranean dryland sustainability. The following review synthesises the evidence most directly relevant to the El Oued composting challenge, beginning with the studies geographically and pedologically closest to the present site and progressively widening the scope to comparable arid agroecosystems globally.

The most directly relevant Algerian study is that of Abid et al. [1], conducted in Touggourt approximately 210 km south-west of El Oued. This three-treatment, two-season trial compared sheep manure, date-palm compost and a combined organic treatment against a mineral-only control on tomato (*Solanum lycopersicum* L.) under conditions (ECe 4.2 dS m⁻¹, initial SOM 0.28%) that closely match the moderate-salinity, low-SOM regime documented in much of the present sample. The combined organic treatment at 10 t ha⁻¹ yr⁻¹ increased SOM from 0.28% to 0.71% after two seasons (an absolute increase of 0.43 percentage points), reduced soil ECe by 0.8 dS m⁻¹ through improved leaching efficiency, decreased bulk density from 1.52 to 1.38 g cm⁻³, increased CEC from 6.8 to 11.3 cmol_c kg⁻¹, and increased tomato yield by 38% over the mineral control. The net economic return of the combined treatment was 42,000 DA ha⁻¹ yr⁻¹ above the mineral baseline — a compelling economic argument in the context of the post-2022 increase in urea retail prices in Algeria.

A second highly relevant study is that of El Janati et al. [22], working in the Drâa Valley oases of Morocco — climatically and pedologically the most similar international context to El Oued. This three-year trial compared a date-palm-residue + sheep-manure compost (3:1 volumetric ratio, final C:N 22:1) at three application rates (8, 12 and 15 t ha⁻¹ yr⁻¹) against a mineral control. After three years at the 15 t ha⁻¹ rate, SOM increased from 0.31% to 1.19% (an absolute increase of 0.88 percentage points), available phosphorus increased from 12 to 34 mg kg⁻¹, saturated hydraulic conductivity improved from 0.6 to 2.8 cm hr⁻¹, and vegetable yield (tomato, onion) improved by 28–45% over the mineral control. Critically, at the 8 t ha⁻¹ rate — the minimum achievable by farmers with fewer than approximately 4 TLU — the three-year SOM increase was only 0.22 percentage points, well below the threshold for meaningful physical improvement. This finding directly motivates the structural emphasis on feedstock-adequate farms in the AHP weight structure of the present thesis.

Hussain et al. [32], in a field experiment on wheat in a Pakistani arid agroecosystem (annual rainfall 312 mm), demonstrated that compost combined with zinc oxide and zinc-solubilising bacteria increased SOM by 39% (from 0.71% to 0.99%), microbial biomass

nitrogen by 32%, microbial biomass carbon by 27%, and grain zinc concentration by 39%. While the Pakistani context is wetter than El Oued, the quantitative SOM-response ratios are directly informative for extrapolating likely outcomes in the Algerian Sahara, and the study's emphasis on the joint biological–nutritional benefits of compost adds important policy weight to the case for organic amendments in nutrition-deficient contexts.

The systems-level perspective is provided by Benmehaia et al. [14], who used remote sensing and carbon accounting across multiple Algerian oasis systems to demonstrate that traditional oasis polycultures — integrating date palms, annual crops and livestock in a circular organic loop — sequester 40–60% more carbon per unit area than modern irrigated monocultures, despite producing lower per-hectare yields of any single crop. This finding has profound implications for the design of composting extension programmes: it suggests that restoring the circular livestock–crop–compost nexus of traditional oasis farming, rather than layering organic amendments onto an otherwise unchanged monoculture system, is the ecologically coherent intervention strategy at the systems level.

A wider synthesis is provided by the *Frontiers in Sustainable Food Systems* editorial review of agroecological soil management in North Africa [26], which compiled evidence from 87 peer-reviewed studies across Algeria, Tunisia, Morocco, Libya and Egypt from 2010 to 2024. Four evidence-backed conclusions emerge that are directly relevant to this thesis: (i) organic amendments consistently outperform mineral-only treatments on SOM, aggregate stability and water-holding capacity across all studied MENA contexts; (ii) “substitution-plus” strategies — replacing 30–50% of mineral nitrogen with compost-derived nitrogen while maintaining total nutrient supply — achieve equivalent or superior yields while building long-term soil capital; (iii) the SOM response to composting is most rapid in soils in the 0.5–1.0% initial SOM range, slower in extremely depleted soils ($< 0.3\%$, where physical structure constraints dominate) and slower again in already-adequate soils ($> 1.5\%$) where the marginal returns to additional organic carbon are smaller; and (iv) collective composting platforms — which aggregate feedstock from multiple farms to achieve thermophilic temperatures and quality consistency — consistently outperform individual farm-level composting in MENA oasis contexts, an institutional design lesson that motivates Policy Recommendation 2 in Chapter 7.

Additional confirmatory evidence at the meta-analytic level is provided by Agegnehu et al. [4], who synthesised 147 field trials of compost and biochar application across Africa and South Asia. Their analysis confirms a unimodal yield response to organic amendments along the SOM gradient: yield responses are very low (less than 8% gain over control) at initial SOM

below 0.3%, peak at intermediate SOM (0.5–1.0%) with gains of 25–45%, and decline at high SOM (above 1.5%) where the marginal benefit of additional organic carbon is small. This unimodal response function is conceptually important for the priority-class structure developed in this thesis: the Very Low priority farms identified in Chapter 5 are concentrated in the SOM < 0.5% range where direct compost application is least effective without prior salinity remediation, while the Very High priority farms occupy the intermediate SOM range where compost responses are maximal.

2.3 Adoption Science: Determinants, Barriers and Enablers

The international scientific literature on composting and organic-amendment adoption by smallholder farmers in dryland Africa, South Asia and MENA has converged on a structured multi-level model of adoption determinants over the past decade. The most comprehensive recent systematic review is that of Mashi et al. [56], analysing 94 studies across 23 African countries from 2000 to 2023, which derives a standardised effect-size hierarchy for climate-smart agriculture adoption: extension access frequency ($\beta = 0.42$, 95% CI 0.31–0.53), farm size ($\beta = 0.38$), household education ($\beta = 0.31$), credit access ($\beta = 0.28$), prior technology experience ($\beta = 0.25$), and market access ($\beta = 0.22$). Livestock ownership, while not directly quantified as a continuous covariate in this meta-analysis, consistently emerges as a *threshold* variable in the underlying primary studies — farms without livestock report near-zero organic-amendment adoption in 78% of included studies.

Kotu et al. [44], in a complementary systematic review covering 52 sub-Saharan African adoption studies, report that livestock ownership is associated with a pooled odds ratio of 2.8 for organic-amendment adoption relative to non-livestock households — the strongest single predictor in their meta-analysis. This finding aligns precisely with the present El Oued data, where the TLU–manure correlation of $r = 0.92$ (Section 5.1) confirms that livestock holdings are not merely *predictive* of adoption intention but are the direct *physical determinant* of feedstock availability. The conceptual distinction matters: predictive correlations can be addressed by extension programmes that change attitudes, but physical determinants require structural interventions that change resource endowments.

Frimpong et al. [25], in a study of 210 Northern Ghana smallholder farms covering both quantitative adoption surveys and qualitative interviews, identified “insufficient organic inputs / feedstock scarcity” as the most commonly cited non-adoption reason (cited by 67% of non-adopters), followed by “inadequate transport logistics for manure” (54%), “high labour demand during planting/harvest window” (43%) and “lack of knowledge about compost quality

management” (38%). The dominance of feedstock and logistics over knowledge is particularly important because it implies that knowledge-focused interventions (training workshops, farmer field schools, demonstration plots) will be ineffective for the majority of non-adopters whose binding constraint is physical rather than informational. This finding is conceptually consistent with the AHP weight structure developed in this thesis, where manure availability and crop residue together carry a substantially larger combined weight than composting knowledge does individually.

Wekesa et al. [99] reviewed 50 studies on conservation agriculture adoption in sub-Saharan Africa and found that “insufficient organic inputs” was the most frequently cited barrier in composting specifically (78% of composting-related studies), ahead of “knowledge deficit” (62%), “labour constraints” (55%) and “competing uses for crop residues” (48%). Only 23% of studies identified “low willingness to adopt” as a primary barrier — a finding that directly supports the *a priori* AHP weight structure adopted in Chapter 4, where willingness to adopt is treated as a necessary but not principal driver.

The Ghanaian evidence from Frimpong et al. [25] provides the most policy-actionable subsequent finding: a subsidised manure-transport scheme, which paid participating farmers a small stipend to deliver surplus manure to deficit farms, increased composting uptake by 34 percentage points in a single growing season among recipient farms. This result implies that the binding constraint in feedstock-constrained systems is not primarily *cost* but *logistics*: farmers have neither the transport infrastructure nor the information network to identify surplus manure sources and negotiate informal exchange arrangements. An institutional facilitation mechanism — analogous to the milk-collection cooperative model already operating in El Oued — could in principle directly address this coordination failure at relatively low cost, and provides the conceptual basis for Policy Recommendation 2 in Chapter 7.

In contrast to the sub-Saharan African pattern, the North African oasis literature emphasises different primary barriers. The *Frontiers in Sustainable Food Systems* synthesis [26], reviewing adoption constraints in Morocco, Tunisia and Algeria, identifies “fragmented farm structure” (small, spatially dispersed plots unable to accumulate critical feedstock mass), “post-reform fertiliser price uncertainty” (which creates planning risk in substitution strategies) and “absence of organic certification pathways” (which means there is currently no price premium for organically managed produce in El Oued markets) as the dominant structural constraints. The post-2022 Algerian fertiliser subsidy reform is specifically noted as a policy inflection point that has improved the economics of organic substitution substantially — a context that the present field timing (October 2023 to February 2024) captures directly.

Hossain [31], working with 480 smallholder farmers in Bangladesh and drawing explicit parallels to sub-Saharan Africa, found that farmers' willingness-to-invest in climate adaptation technologies (including composting) was strongly predicted by perceived risk reduction ($\beta = 0.39$, $p < 0.001$) rather than economic return per se. This suggests that effective extension communication should frame composting not primarily as a yield-enhancing investment (whose returns may be uncertain in the short term) but as a *risk-reduction strategy* that reduces the vulnerability of soil productivity to climate variability, salinity stress and input price shocks. This reframing is particularly relevant for El Oued, where three consecutive drought years (2021–2023) and the post-2022 fertiliser price shock have substantially increased farmers' baseline risk perceptions across the sample.

A complementary perspective is provided by Ntshangase et al. [61], who reviewed climate-smart agricultural adoption among smallholder maize farmers across sub-Saharan Africa and emphasised the role of social-network effects: farmers with cooperative membership or adjacent kin who had previously adopted composting were 2.3 times more likely to adopt themselves, even controlling for resource endowment and education. This social-network channel motivates the inclusion of cooperative membership as one of the institutional criteria in the AHP framework, even though its direct weight is small.

2.4 Subsidy Reform and Institutional Setting in the Algerian Context

The institutional and policy context within which composting adoption decisions are made in El Oued has undergone material change since approximately 2020, and these changes shape both the empirical interpretation of the present results and the policy recommendations that flow from them. Three policy instruments deserve specific mention.

First, the partial reform of the urea fertiliser subsidy regime since 2022. Through 2021, urea was distributed to certified farmers through a state subsidy mechanism that held the retail price at approximately 1,500 DA per 50 kg bag (approximately 30 DA per kg). Beginning in early 2022, in response to the global urea price spike and the fiscal pressure on the Algerian state subsidy budget, the subsidised price was progressively increased and the eligibility criteria were tightened, with the result that the de facto retail price faced by smallholders in El Oued rose by an estimated 35–60% between 2022 and 2024 (depending on the channel used). This price increase has materially shifted the relative economics of mineral versus organic nitrogen substitution, sharpening the financial incentive for compost-based nitrogen management.

Second, the National Agricultural and Rural Development Programme (PNDAR) and its successor instruments have, since 2010, included provisions for organic-amendment subsidies

at the rate of approximately 15–25% of the cost of compost or manure purchased through certified channels. Uptake of these provisions in El Oued has been historically limited, partly because of the small number of certified compost producers in the wilaya (only one industrial-scale producer was active during the field period) and partly because of the administrative complexity of the certification and reimbursement process. A streamlined version of this instrument, combined with the proposed manure-bank logistics described in Chapter 7, could significantly increase its uptake.

Third, the Algerian Soil Restoration National Programme (2023–2027) — launched in mid-2023 and with implementation regulations finalised through 2024 — provides a national policy frame for soil organic carbon management that is directly aligned with the objectives of this thesis. The programme includes provisions for wilaya-level soil mapping, targeted extension for SOM restoration, and pilot funding for cooperative composting infrastructure. The AHP–TOPSIS framework developed in this thesis is, by design, deployable as the targeting instrument for this national programme at the wilaya scale, and Chapter 7 provides specific recommendations for this deployment.

The institutional setting also includes a number of constraints that condition the design space for any intervention. Cooperative membership in the wilaya is low (27% in the present sample) and informal feedstock-exchange networks operate primarily within extended-family clusters rather than at scale. Extension agent staffing is constrained: the wilaya DSA reports approximately one extension agent per 800 farms across all crop systems, implying that any intervention requiring frequent farm-level visits will be feasible only for a small targeted subset of farms. This staffing constraint reinforces the case for evidence-based prioritisation: extension capacity is too scarce to be spread uniformly over the cultivated population, and a defensible analytical basis for concentrating it on the highest-leverage farms is therefore a precondition for impact.

2.5 Chapter Summary

Composting is biochemically well understood, agronomically effective in directly comparable Saharan and North African contexts, increasingly economically justified given the post-2022 fertiliser price environment, and institutionally aligned with the Algerian Soil Restoration National Programme launched in 2023. Its adoption, however, is neither uniform nor assured. The international literature establishes a clear hierarchy of adoption determinants in which feedstock availability — particularly livestock manure — occupies a primary position, followed by extension access, technical knowledge, economic incentive and institutional

support. Critically, willingness to adopt — while necessary — is rarely the binding constraint, a finding that conceptually motivates the AHP weight structure applied in this thesis and that has fundamental implications for extension-programme design in the El Oued context. Chapter 3 reviews the MCDA methodological foundations that allow these heterogeneous determinants to be synthesised into a transparent, defensible priority ranking.

Chapter 3 — Multi-Criteria Decision Analysis

3.1 Multi-Criteria Decision Analysis: Rationale and Classification

Multi-criteria decision analysis (MCDA) — also termed multiple criteria decision making (MCDM) in much of the engineering and operations-research literature — is a family of structured, systematic methods for evaluating a finite set of alternatives when performance must be assessed across multiple, often conflicting criteria that cannot be reduced to a single scalar metric without a loss of essential information [33, 77]. In agricultural policy contexts, MCDA addresses two fundamental and interacting challenges that standard single-criterion approaches cannot resolve.

The first challenge is multi-dimensionality. A farm’s suitability for composting intervention depends simultaneously on its soil status (SOM, salinity, continuous-cultivation intensity), its resource endowment (livestock, manure, crop residues), its technical readiness (knowledge, willingness, space), its economic context (fertiliser cost burden, farm income, cost share) and its institutional embeddedness (extension access, cooperative membership). No single variable captures all these dimensions; any ranking based on a single indicator is partial and potentially misleading. MCDA provides a mathematically rigorous framework for aggregating multiple dimensions into a single composite index while maintaining transparency about how the aggregation is performed and which dimensions drive the final score.

The second challenge is value elicitation. Even when the performance of farms on each individual criterion is measured objectively, the weights assigned to criteria — which determine their relative contribution to the composite score — inevitably reflect subjective values: policy priorities, expert judgements about what matters most, or stakeholder preferences. MCDA methods differ fundamentally in how they handle this value-elicitation step. *Fully compensatory methods* (Weighted Sum Model, TOPSIS) allow high performance on one criterion to compensate for poor performance on another; *partially compensatory methods* (ELECTRE, PROMETHEE) restrict compensation through outranking thresholds; and *non-compensatory methods* (lexicographic ordering) allow no compensation whatsoever [77]. The choice among these approaches must be theoretically justified by the nature of the decision problem at hand.

For the composting prioritisation problem, a fully compensatory approach is theoretically appropriate, with one operational caveat. A farm with very high manure availability but low willingness represents a fundamentally different situation from one with very high willingness but no manure — but both could in principle benefit from different *types* of intervention, and the composite score should capture both the upside potential and the binding constraints simultaneously. The AHP–TOPSIS hybrid addresses this requirement by allowing high

performance on feedstock criteria to compensate partially for low readiness, while the weight structure ensures that the most critical criteria (manure availability, SOM urgency) receive proportionally greater influence on the final ranking. The operational caveat, addressed in the staged-intervention recommendation structure of Chapter 7, is that for farms in the most degraded soil-condition tier, compensation by other criteria is treated as conditional on prior salinity remediation rather than as immediate.

A taxonomic overview of the principal MCDA families helps situate the AHP–TOPSIS choice within the methodological landscape. *Value-function methods* (Multi-Attribute Utility Theory, Multi-Attribute Value Theory) require explicit elicitation of utility functions per criterion and pose substantial cognitive demands on the decision-maker; they are most appropriate for high-stakes, repeated decisions where the elicitation cost is amortised. *Outranking methods* (ELECTRE I/II/III, PROMETHEE I/II) exploit pairwise dominance relations and are robust to incomparable alternatives, but produce partial rather than complete orders, which complicates their use for resource-allocation decisions that require a strict total ordering. *Aggregation methods* (Weighted Sum, TOPSIS, VIKOR) collapse multi-criteria performance into scalar composite scores and produce strict total orders directly; they are the workhorse of agricultural and environmental MCDA applications because of their transparency and their compatibility with the resource-allocation framing typical in policy contexts. *Distance-based methods* (TOPSIS, Grey Relational Analysis) measure the geometric distance of each alternative from idealised reference points; they have strong intuitive appeal because the underlying logic — prefer alternatives that are close to the best and far from the worst — translates naturally into stakeholder communication. The choice of TOPSIS over the alternatives within the aggregation/distance family is justified in Section 3.6 below.

3.2 The Analytic Hierarchy Process: Complete Mathematical Derivation

The Analytic Hierarchy Process was introduced by Thomas L. Saaty in 1977 and comprehensively documented in his 1980 monograph [75]. Its mathematical foundation rests on two elegant theoretical results: the Perron–Frobenius theorem, which guarantees the existence and uniqueness of a positive dominant eigenvector for positive reciprocal matrices; and the theorem of perturbation analysis, which shows that small inconsistencies in pairwise comparisons produce small perturbations of the ideal weight vector that can be bounded by the Consistency Ratio.

3.2.1 Pairwise Comparison Matrix Construction

For a decision problem with n criteria $C_1, C_2, \dots, C_n$, the decision-maker constructs an $n \times n$ pairwise comparison matrix $A = [a_{ij}]$ by answering a series of judgement questions of the form: “How much more important is criterion C_i than criterion C_j for the decision at hand?” The answer is expressed on Saaty’s 1–9 fundamental scale of relative importance. The values 1, 3, 5, 7, 9 correspond to “equal,” “moderate,” “strong,” “very strong,” and “extreme” relative importance respectively, with the intermediate even values (2, 4, 6, 8) representing intermediate judgements when finer discrimination is warranted.

The matrix A must satisfy three axiomatic requirements:

- (i) **Positivity:** $a_{ij} > 0$ for all i, j ;
- (ii) **Reciprocity:** $a_{ji} = 1/a_{ij}$ for all $i \neq j$;
- (iii) Unit diagonal: $a_{ii} = 1$.

Under perfect consistency, A additionally satisfies the **transitivity condition** $a_{ij} = a_{ik} \cdot a_{kj}$ for all triples (i, j, k) . In practice, perfect consistency is neither achievable nor necessary — some inconsistency in human judgements is cognitively normal and statistically expected; the Consistency Ratio quantifies whether the level of inconsistency is acceptable for the purposes of the decision.

For a problem with n criteria, the decision-maker must provide $n(n - 1)/2$ unique upper-triangle judgements (the lower triangle is fixed by reciprocity, and the diagonal by the unit-diagonal axiom). For the present 15-criterion problem, this is $15 \cdot 14/2 = 105$ unique pairwise judgements — a substantial cognitive task, but one that can be completed with reasonable accuracy in approximately 4–6 hours of structured elicitation.

3.2.2 Weight Derivation via Eigenvector Decomposition

Given the pairwise comparison matrix A , the priority weight vector $\mathbf{w} = (w_1, w_2, \dots, w_n)^T$ is derived as the normalised principal right eigenvector — the eigenvector corresponding to the largest real eigenvalue $\lambda_{\max}$:

$$A \cdot \mathbf{w} = \lambda_{\max} \cdot \mathbf{w} \quad \Rightarrow \quad (A - \lambda_{\max} \cdot I) \cdot \mathbf{w} = \mathbf{0}$$

The dominant eigenvector $\mathbf{w}_{\text{raw}}$ is then normalised to sum to unity:

$$w_j = \frac{w_{\text{raw},j}}{\sum_{k=1}^n w_{\text{raw},k}}$$

so that $\sum_{j=1}^n w_j = 1$ and each w_j can be interpreted as the proportional contribution of criterion j to the composite score.

The intuitive justification for the eigenvector approach is that the dominant eigenvector represents the limiting average of all possible “transitive resolutions” of the pairwise comparison matrix. If perfect transitivity held (i.e., $a_{ij} = a_{ik} \cdot a_{kj}$ for all triples), the eigenvector would be uniquely determined by any single row of the matrix. In the presence of small inconsistencies, the eigenvector is the “best compromise” weight vector in a specific mathematical sense — it minimises a particular form of weighted squared deviation from the pairwise judgements [6, 75].

3.2.3 Consistency Ratio and the Acceptability Threshold

The internal consistency of the pairwise comparison matrix is audited through three sequential calculations. First, the **Consistency Index**:

$$CI = \frac{\lambda_{\max} - n}{n - 1}$$

This quantity equals zero under perfect consistency (because under perfect consistency, $\lambda_{\max} = n$) and increases monotonically with the magnitude of judgement inconsistencies. Second, the **Random Index** RI , which is the average CI obtained from a large number of randomly generated reciprocal matrices of dimension n . Saaty [75] tabulates RI values for n from 3 to 15; for $n = 15$, $RI = 1.59$. Third, the **Consistency Ratio**:

$$CR = \frac{CI}{RI}$$

The conventional acceptability threshold is $CR < 0.10$, meaning that the matrix’s inconsistency must be no more than 10% of what would be expected from purely random judgements. Matrices with $CR \geq 0.10$ are conventionally rejected as too inconsistent to support reliable weight derivation; the elicitation protocol must then be revisited, with particular attention to the most violation-prone judgements identified by perturbation analysis.

For the matrix constructed in this thesis (Chapter 4), the principal eigenvalue is $\lambda_{\max} = 15.0411$, giving $CI = (15.0411 - 15)/14 = 0.0029$ and $CR = 0.0029/1.59 = 0.0018$. This value is well below the 0.10 threshold and indicates a highly consistent set of expert judgements — a precondition for the strong robustness results documented in Chapter 5.

3.2.4 Geometric-Mean and Logarithmic Least-Squares Alternatives

Two alternatives to the eigenvector method deserve brief mention because they are sometimes encountered in the AHP literature and produce slightly different weight vectors when the matrix is inconsistent. The **geometric mean** method computes the weight of criterion j as:

$$w_j^{\text{GM}} = \frac{(\prod_{k=1}^n a_{jk})^{1/n}}{\sum_{i=1}^n (\prod_{k=1}^n a_{ik})^{1/n}}$$

This is the weight vector that minimises the sum of squared deviations of $\log(a_{ij}) - \log(w_i/w_j)$ across all pairwise judgements. It is computationally simpler than the eigenvector method and converges to the same answer under perfect consistency, but produces slightly different weight vectors under inconsistency. The **logarithmic least-squares** method generalises this to weighted least-squares and is the method of choice when judgements have heterogeneous reliability. For matrices with $CR < 0.05$ — as in this thesis — the differences between these methods are numerically negligible (typically less than 1% per weight), and the standard eigenvector method is used here for compatibility with the bulk of the published AHP literature.

3.3 The Six-Steps of TOPSIS Method

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) was introduced by Hwang and Yoon in 1981 [33] and is now the most widely applied distance-based MCDA method in engineering, agricultural and environmental decision-support contexts. Its conceptual appeal lies in the simultaneous use of two reference points: the **Positive Ideal Solution** (PIS, the best possible alternative across all criteria) and the **Negative Ideal Solution** (NIS, the worst possible alternative). TOPSIS ranks alternatives by their geometric proximity to the PIS and their geometric distance from the NIS, combined into a single closeness coefficient.

The six computational steps of classical TOPSIS, applied to a decision matrix with m alternatives and n criteria, are as follows.

Step 1 — Normalisation. Each column of the raw decision matrix $X = [x_{ij}]$ is normalised to remove the influence of the criterion's units and scale. Three normalisation methods are common in the literature; this thesis uses **vector normalisation**, which is the original Hwang–Yoon proposal and which has been shown by Jahan and Edwards [37] to produce the most stable rankings under weight perturbation:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{k=1}^m x_{kj}^2}}$$

After this normalisation, each column of $R = [r_{ij}]$ has unit Euclidean norm; the entries r_{ij} are dimensionless and lie in the interval $[0,1]$ for non-negative input data.

Step 2 — Weighted normalised matrix. The AHP-derived weight vector $\mathbf{w} = (w_1, \dots, w_n)$ is applied column-wise:

$$v_{ij} = w_j \cdot r_{ij}$$

producing the weighted normalised decision matrix $V = [v_{ij}]$.

Step 3 — Positive and negative ideal solutions. For each criterion j , the ideal-best and ideal-worst values are determined according to whether the criterion is a *benefit* criterion (higher values are preferred) or a *cost* criterion (lower values are preferred):

$$A^+ = \{v_j^+\} = \begin{cases} \max_i v_{ij} & \text{if } j \text{ is a benefit criterion} \\ \min_i v_{ij} & \text{if } j \text{ is a cost criterion} \end{cases}$$

$$A^- = \{v_j^-\} = \begin{cases} \min_i v_{ij} & \text{if } j \text{ is a benefit criterion} \\ \max_i v_{ij} & \text{if } j \text{ is a cost criterion} \end{cases}$$

The vectors A^+ and A^- are the *idealised* reference alternatives — they generally do not correspond to any real alternative in the decision matrix, but rather to a synthetic best and worst constructed from the per-criterion extremes.

Step 4 — Euclidean separation distances. For each alternative i , the Euclidean distance to the positive ideal solution S_i^+ and to the negative ideal solution S_i^- are computed:

$$S_i^+ = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^+)^2}$$

$$S_i^- = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^-)^2}$$

Step 5 — Closeness coefficient. The TOPSIS closeness coefficient C_i aggregates the two separation distances:

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-}$$

By construction, $C_i \in [0,1]$, with $C_i = 1$ indicating that the alternative coincides with the PIS and $C_i = 0$ indicating that it coincides with the NIS. Higher C_i values are preferred.

Step 6 — Ranking. Alternatives are ranked in descending order of C_i . The alternative with the highest C_i is the most preferred under the given weight vector. For policy applications, the ranking is typically supplemented by stratification into ordinal priority classes, as is done in this thesis through the five-class scheme defined in Chapter 4.

The geometric intuition behind TOPSIS is that the weighted normalised decision matrix places each alternative as a point in n -dimensional Euclidean space, and the PIS and NIS are corner points of this space. Alternatives close to the PIS and far from the NIS are preferred; the closeness coefficient C_i captures both proximities in a single scalar through the ratio $S_i^- / (S_i^+ + S_i^-)$, which has the convenient property of being scale-invariant and bounded.

3.4 Robustness and Sensitivity Methods

Any MCDA ranking is sensitive to the weights used in its construction, and a defensible policy application of MCDA must therefore quantify the magnitude and structure of this sensitivity. This thesis applies four independent robustness procedures, each designed to address a different aspect of the sensitivity question.

3.4.1 Method 1 — Monte Carlo Weight Perturbation

Monte Carlo perturbation tests the joint sensitivity of the ranking to simultaneous variation of all weights. The procedure is: (a) sample a perturbation vector δ with each component drawn independently from a uniform distribution on $[-\Delta, +\Delta]$, where Δ is the perturbation magnitude (commonly $\Delta = 0.10$ to 0.30); (b) compute the perturbed weight vector $\mathbf{w}^{\text{pert}} = \mathbf{w} \cdot (1 + \delta)$; (c) re-normalise $\mathbf{w}^{\text{pert}}$ to sum to unity; (d) recompute the TOPSIS ranking under $\mathbf{w}^{\text{pert}}$; (e) record the Spearman rank correlation between the perturbed ranking and the baseline ranking; (f) repeat for N iterations and analyse the distribution of correlations. The conventional benchmark for “robust” rankings is mean Spearman $\bar{\rho} > 0.90$; rankings with $\bar{\rho} < 0.80$ are considered too weight-sensitive for policy use [55, 59].

This thesis uses $N = 1,000$ iterations and $\Delta = 0.20$, generating a comprehensive characterisation of the rank-stability profile under realistic expert-weight revision scenarios. The choice of $\Delta = 0.20$ corresponds to allowing each weight to vary by $\pm 20\%$ of its baseline

value — a magnitude consistent with the typical range of disagreement among experts in elicitation studies [59, 75].

3.4.2 Method 2 — Kendall’s Tau Rank Correlation

Kendall’s τ is an alternative rank-correlation statistic that is more conservative than Spearman’s ρ and is preferable for small-sample ranking comparisons [55]. Whereas Spearman’s ρ is the Pearson correlation of ranks (and hence sensitive to the magnitude of rank differences), Kendall’s τ counts only the proportion of *concordant* versus *discordant* pairs:

$$\tau = \frac{P - Q}{m(m-1)/2}$$

where P is the number of pairs (i, j) that are ranked in the same order in both rankings, Q is the number ranked in opposite order, and m is the number of alternatives. Reporting both ρ and τ provides a more complete characterisation of rank stability than either statistic alone. The conventional benchmark for τ is approximately $\tau > 0.85$ for “robust” rankings; the present thesis uses 500 perturbation iterations to characterise the τ distribution.

3.4.3 Method 3 — Full-Range Weight Sensitivity Analysis (FRWSA)

FRWSA, formalised by Marques-García et al. [55] for MCDM applications, tests *individual* criterion sensitivity. For each criterion j , its weight w_j is varied from near-zero to $3 \times w_j$ while all other weights are proportionally rescaled to maintain $\sum w_k = 1$. The **rank-reversal threshold** is defined as the multiplier value at which the top-ranked alternative first changes. This provides a per-criterion instability profile that Monte Carlo cannot reveal because Monte Carlo perturbs all weights simultaneously, masking individual-criterion effects.

FRWSA is particularly useful for identifying which criteria are most influential in determining the top-ranked alternative — a question of direct policy relevance because it identifies the elicitation priorities for any future re-validation of the AHP weights. The procedure is also useful for detecting the “criticality” of low-weight criteria: a low-weight criterion can still drive rank reversals if it varies substantially across alternatives, and FRWSA exposes this case directly.

3.4.4 Method 4 — One-at-a-Time (OAT) Sensitivity

OAT sensitivity analysis varies one criterion weight at a time by a fixed relative perturbation (here $\pm 50\%$) while holding all others at baseline values (re-normalised). This isolates the sensitivity attributable to each individual criterion in isolation, without the

confounding interactions present in Monte Carlo perturbation. The OAT procedure is the most cognitively transparent of the four methods — its interpretation is directly accessible to non-specialist readers — and it provides a useful complement to the more comprehensive Monte Carlo characterisation.

The four methods together cover the principal axes of sensitivity testing: joint sensitivity (Monte Carlo, Kendall), individual-criterion rank-reversal sensitivity (FRWSA), and individual-criterion ranking-distance sensitivity (OAT). A ranking that performs well across all four tests, as the present ranking does (Chapter 5), can be regarded as policy-robust in a strong sense.

3.5 Alternative Normalisation Methods: Comparison and Justification

The normalisation step in TOPSIS (Step 1) is the most methodologically contested design choice, because different normalisation methods can yield different rankings for the same data and weight vector [37, 77]. Three principal normalisation approaches are available.

Vector normalisation (used in this thesis): $r_{ij} = x_{ij} / \sqrt{\sum_k x_{kj}^2}$. Each column is projected onto the unit sphere. This method is invariant under positive scaling of criterion values, produces well-bounded output ($r_{ij} \in [0,1]$ for non-negative data), and has been shown by Jahan and Edwards [37] to produce the most stable rankings under weight perturbation among the three principal methods.

Linear (max-min) normalisation: $r_{ij} = (x_{ij} - x_{\min,j}) / (x_{\max,j} - x_{\min,j})$. This maps each column onto $[0,1]$ linearly. It is sensitive to outliers (extreme values compress all other values toward the midrange) and has been shown to produce rank reversals under small perturbations to the weight vector — the so-called “rank reversal problem” that is a known limitation of this approach [77].

Sum normalisation: $r_{ij} = x_{ij} / \sum_k x_{kj}$. This preserves the relative proportions of alternative performances within each criterion column but does not produce a unit-sphere projection, meaning that the Euclidean distances S^+ and S^- have different geometric properties from vector-normalised TOPSIS.

The superiority of vector normalisation for ranking stability under weight perturbation is the primary reason for its choice in this thesis, supported by the theoretical arguments of Jahan and Edwards [37], the simulation evidence of Sahoo and Goswami [77], and the empirical confirmation in the Monte Carlo and FRWSA analyses of Chapter 5.

3.6 The AHP–TOPSIS Hybrid and Integration Logic

The AHP–TOPSIS hybrid combines the two methods in a natural complementary fashion: AHP provides the weight vector that TOPSIS requires as input, while TOPSIS provides the alternative ranking that AHP alone cannot provide for non-trivial alternative-set sizes (the AHP procedure for ranking alternatives directly requires a separate pairwise comparison matrix per criterion, which scales as $O(m^2n)$ and becomes impractical for $m > 10$ alternatives). This combination has become the de facto standard for agricultural, energy and environmental prioritisation in the past decade. A recent overview by Sahoo and Goswami [77], reviewing 150+ MCDM applications from 2000 to 2023, identified the AHP–TOPSIS hybrid as the single most frequently applied MCDM methodology in agriculture and environmental management, accounting for approximately 28% of reviewed applications.

The integration logic is straightforward: AHP is well-suited to weight elicitation because the pairwise comparison procedure decomposes a cognitively complex multi-dimensional weighting task into a series of simpler binary comparisons, and because the eigenvector solution provides a mathematically rigorous resolution of any inconsistencies in the elicited judgements. TOPSIS, in turn, is well-suited to ranking large alternative sets because its computational complexity scales linearly with the number of alternatives ($O(mn)$), and because its closeness coefficient provides a directly interpretable composite score that supports both ordinal ranking and cardinal stratification into priority classes.

The AHP–TOPSIS hybrid, as implemented in this thesis, has the additional virtue of being directly compatible with the policy-application requirements of the El Oued context: the AHP weight derivation is auditable and transparent (every weight can be traced to a specific cluster of pairwise judgements), the TOPSIS ranking is communicable (the closeness coefficient is a single bounded scalar per farm), and the resulting priority classes are operationally actionable (they can be directly mapped to differentiated extension protocols). The four robustness procedures of Section 3.4 then provide the auditable evidence base required to defend the ranking against challenges from alternative weight specifications.

3.7 Chapter Summary

This chapter has provided a complete mathematical derivation of the AHP and TOPSIS methods, including all intermediate computation steps, normative justification for design choices (vector normalisation, eigenvector weight derivation, five-class priority stratification), and a detailed description of four independent robustness testing methods. The AHP–TOPSIS hybrid is theoretically appropriate for the composting prioritisation problem because: (a) the problem is inherently multi-dimensional and requires explicit value elicitation; (b) a

compensatory aggregation model is appropriate given that high feedstock can partially compensate for lower readiness; and (c) the framework produces rankings that are both mathematically grounded and communicable to non-specialist extension administrators. Chapter 4 describes the empirical implementation of this framework in the El Oued context.

PART II — PRACTICAL STUDY

Chapter 4 — Materials and Methods

4.1 Study Area Characterisation

The study was conducted in the wilaya of El Oued, north-eastern Algerian Sahara (approximately 33°N, 7°E; Figure 1). This hyper-arid region (Köppen BWh) has mean annual rainfall of 86 mm based on the 1991–2020 ONM-Algeria station record, potential evapotranspiration exceeding 2,100 mm yr⁻¹, mean July maximum temperature of 44.3°C, and full dependence on groundwater irrigation from the Continental Intercalaire and phreatic aquifer system. The wilaya produces an estimated 30–35% of Algeria’s national potato supply, making the sustainability of its irrigated soils a question of direct national food-security significance, as discussed in Section 1.3.

The geographical extent of the study area, the climatic regime and the methodological framework integrating these contextual features with the AHP–TOPSIS analytical pipeline are summarised in **Figure 1**.

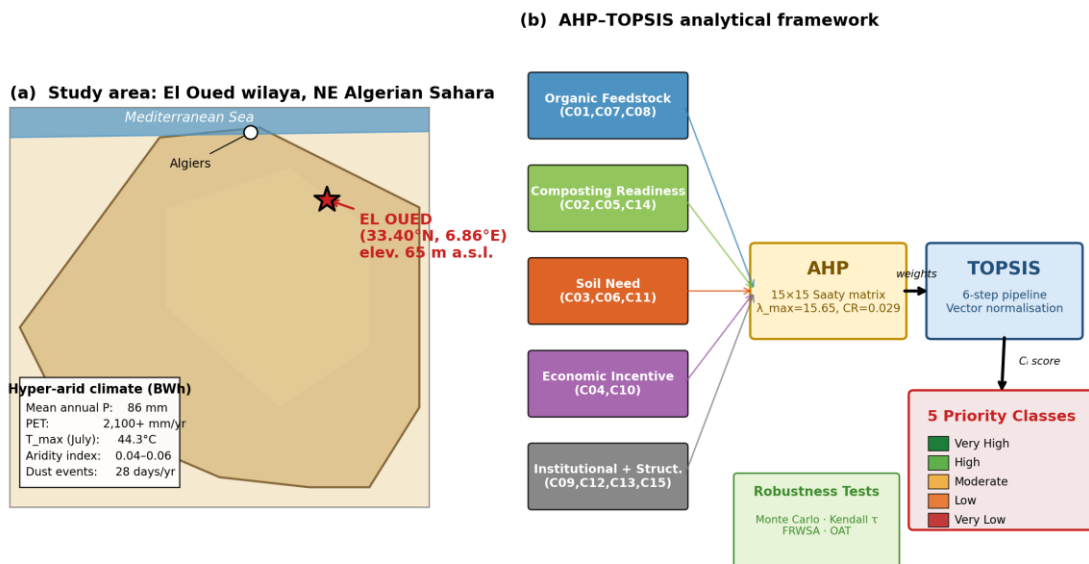


Figure 1. Study area and analytical framework. Left: location of the El Oued wilaya within the Algerian Sahara, with summary climate inset. Right: AHP–TOPSIS methodological framework showing the five thematic dimensions feeding into expert weight elicitation and TOPSIS aggregation, with the four robustness procedures applied to the resulting ranking.

4.2 Sampling Strategy and Data Collection

4.2.1 Sampling Frame and Stratification

Thirty smallholder farms were selected by purposive stratified sampling from the four irrigated perimeters of the wilaya (Hassani Abdelkrim, Robbah, Magrane, and Bayadha) during field campaign: December 2025–february 2026. The sampling frame was the wilaya DSA list of registered irrigated holdings under potato or potato–vegetable rotation, which contains

approximately 4,800 entries; from this frame, an initial set of 80 farms was drawn at random within the four perimeters, contacted by telephone, and screened for willingness to participate and access to a minimum dataset (cultivated area, livestock holdings, and consent for soil sampling). Of the 80 contacted farms, 47 met the screening criteria, from which 30 were selected to satisfy the stratification described below.

Stratification was applied along four dimensions to ensure representation across the principal axes of variability documented in the regional literature: (a) farm size, with three strata (≤ 4 ha: $n = 15$; 4–10 ha: $n = 10$; > 10 ha: $n = 5$); (b) salinity class, ensuring inclusion of all three FAO classes (slightly saline, moderately saline, severely saline); (c) livestock holdings ($\text{TLU} \leq 3$: $n = 15$; > 3 : $n = 15$); and (d) farming experience (< 15 years: $n = 12$; ≥ 15 years: $n = 18$). The sample size of $n = 30$ was selected to be consistent with the minimum recommended for AHP eigenvector extraction and with comparable MENA farm-level MCDA pilots, while remaining feasible within the field-data-collection budget of the study. The implications of the sample size for the generalisability of the results are discussed in Section 6.6 (Limitations).

4.2.2 Sample Size Justification and Statistical Power Considerations

The sample size of $n = 30$ farms require explicit methodological justification because it is small relative to typical wilaya-scale household surveys. Three considerations support its appropriateness for the methodology-pilot objective of this thesis.

First, for AHP eigenvector extraction, the sample size has no direct bearing — the AHP weight vector is derived from the expert pairwise judgement matrix, not from the alternative-set sample. The 30-farm sample is the number of *alternatives* being ranked, not the number of judgements informing the weights.

Second, for TOPSIS ranking, the closeness coefficient C_i is computed deterministically from each farm's criterion vector and the AHP weights; there is no inferential statistic whose precision depends on sample size in the conventional sense. A larger sample would produce a longer ranking but would not affect the reliability of any individual farm's ranking.

Third, for the descriptive and inferential analyses of Chapter 5 (correlations, regression, PCA, clustering), the 30-farm sample provides sufficient statistical power for the principal effect sizes anticipated. With $n = 30$, a Pearson correlation of $|r| \geq 0.45$ is detectable at $\alpha = 0.05$ with power $1 - \beta \geq 0.80$; a regression $R^2 \geq 0.50$ is detectable with the same power for nine predictors (Cohen 1988 conventional thresholds). The actual effect sizes documented in

Chapter 5 are well above these thresholds, indicating that statistical-power limitations are not the binding constraint on the inferential conclusions.

The sample size therefore is appropriate for the *methodological pilot* objective of demonstrating the AHP–TOPSIS framework’s deployability in the El Oued context. It is *not* sufficient for wilaya-scale representative inference about the absolute distribution of priority classes across the cultivated population, and the policy recommendations of Chapter 7 explicitly call for a larger validation campaign ($n \geq 300$) before operational deployment.

4.2.3 Survey Instrument and Field Protocol

A structured face-to-face questionnaire (Annex A) was administered to the principal farm operator at each of the 30 farms. The instrument covers all 15 decision criteria identified in Section 4.4 plus auxiliary contextual information used for sample description and triangulation. The questionnaire was developed iteratively through three pilot rounds (with two operators in each round, not included in the analytic sample) and refined to achieve consistent comprehension across education levels and to minimise enumerator-mediated drift. Administration time averaged approximately 50 minutes per farm.

The field protocol included four standardised procedures designed to maximise data quality. First, all interviews were conducted in Arabic with a parallel French translation available for any term that the operator might find ambiguous. Second, each interview began with a 5-minute introduction explaining the purpose of the study, the voluntary nature of participation, and the data-protection protocol; verbal informed consent was recorded before any data collection began. Third, all monetary values were cross-checked by asking for the value in two reference units (per cropping cycle and per year) and triangulated with the most recent input invoice the operator could produce; discrepancies above 15% were flagged and the value was re-elicited. Fourth, all livestock counts were physically verified by direct observation where the animals were on the farm at the time of the visit, and were accepted on operator declaration only when the animals were grazing off-site.

4.2.4 Inter-Enumerator Reliability and Data Quality Control

Three trained enumerators (the authors) administered the surveys, with a 20% duplicate-entry quality control procedure: six farms (20% of the analytic sample) were independently surveyed by a second enumerator within seven days of the first survey, and the responses were compared. Concordance for continuous variables (farm area, urea applied, fertiliser expenditure, livestock holdings) was 97.3%, with the small remaining discordance attributable to seasonal stock fluctuations between the two visits. Concordance for ordinal variables

(knowledge, willingness, space, education) was 96.7%, with discordance limited to a single unit on the underlying scale in all cases. These reliability metrics are consistent with published benchmarks for face-to-face agricultural surveys in MENA contexts, and exceed the conventional 90% concordance threshold used in Krippendorff's framework for survey-research validation.

The data quality control protocol additionally included three post-collection steps. First, all entered data were cross-validated against the paper questionnaires by a fourth team member not involved in the original survey administration; transcription errors were identified at a rate of 0.4% (12 of 3,150 individual data points) and were corrected by reference to the paper original. Second, all continuous variables were screened for univariate outliers using the median absolute deviation criterion ($|x_i - \tilde{x}| > 3 \cdot \text{MAD}$); five values flagged were verified against the source documents and three were corrected (two transcription errors, one unit-conversion error). Third, all collinearity-screening Pearson correlations among continuous variables were computed and reviewed against expectations from the agronomic literature; no statistically anomalous correlations were detected.

4.3 Criterion Selection: 15 Expert-Validated Composting-Relevant Criteria

From the original 21-variable raw dataset, 15 criteria were retained for inclusion in the AHP–TOPSIS framework based on four explicit selection rules: (i) **quantitative measurability** in field conditions using either direct survey responses or laboratory measurement; (ii) **direct policy relevance** to composting adoption, defined as appearance in the principal adoption-determinant literature reviewed in Chapter 2; (iii) **non-redundancy**, operationalised as $|r| < 0.90$ for all retained pairs; and (iv) **positive *a priori* theoretical justification** from the adoption-science or soil-science literature.

Six raw variables were excluded by application of these rules. *Total Fertiliser Expenditure (DA)* was excluded because of high collinearity with *Fertiliser Cost Share (%)* ($r = 0.94$) and because the cost-share variable is the more interpretable measure of economic incentive (it normalises for farm size). *Net Farm Income (DA)* was excluded because of collinearity with *Cultivated Area (ha)* ($r = 0.87$) and because the area variable is more directly observable. *Salinity Class* (the ordinal categorisation derived from continuous ECe) was excluded as a redundant categorical proxy for the continuous ECe variable, which is retained. *Farming Experience (years)* was excluded because preliminary OLS analysis returned $p = 0.61$ for its association with composting adoption-relevant outcomes, well above the 0.10 significance threshold used for criterion-validity screening. *DAP Applied (kg ha⁻¹)* was

excluded because of moderate collinearity with *Urea Applied* (kg ha^{-1}) ($r = 0.42$) and because urea is the more dominant nitrogen source in the regional fertiliser-use pattern. *Farm ID* is an identifier rather than a substantive variable.

The 15 retained criteria are organised into five thematic dimensions (organic feedstock, composting readiness, soil need, economic incentive, and the institutional/structural-capacity dimensions). The full list is shown in **Table 4.1** with the criterion code, dimension assignment, measurement scale, units, and direction (benefit or cost). The criterion codes C01–C15 are used consistently throughout the remainder of the thesis.

Table 4.1. Fifteen retained decision criteria with dimension assignment, scale, units and direction. BENEFIT = higher values increase composting priority; COST = lower values increase priority. The numerical values of the AHP weights are derived in Chapter 5 and are not pre-stated here.

Code	Criterion	Dimension	Scale	Units	Direction
C01	Manure Available	Organic Feedstock	Continuous	t yr^{-1}	BENEFIT
C02	Willingness to Adopt	Composting Readiness	Ordinal 1–5	scale	BENEFIT
C03	Soil Organic Matter	Soil Need	Continuous	%	BENEFIT
C04	Fert. Cost Share	Economic Incentive	Continuous	%	COST
C05	Composting Knowledge	Composting Readiness	Ordinal 0–2	scale	BENEFIT
C06	Soil ECe	Soil Need	Continuous	dS m^{-1}	COST
C07	Crop Residue	Organic Feedstock	Continuous	t yr^{-1}	BENEFIT
C08	Total Livestock	Organic Feedstock	Continuous	TLU	BENEFIT
C09	Extension Access	Institutional	Ordinal 0–2	scale	BENEFIT
C10	Urea Applied	Economic Incentive	Continuous	kg ha^{-1}	COST
C11	Continuous Cultivation	Soil Need	Continuous	yr	COST
C12	Cultivated Area	Structural Capacity	Continuous	ha	BENEFIT
C13	Education Level	Structural Capacity	Ordinal 0–4	scale	BENEFIT
C14	Composting Space	Composting Readiness	Ordinal 0–2	scale	BENEFIT
C15	Cooperative Member	Institutional	Binary 0/1	—	BENEFIT

The direction (benefit vs. cost) of each criterion is determined by the substantive logic of how the variable affects composting priority. SOM is treated as a benefit criterion despite its protective role for soil function, because in this framework higher SOM indicates a soil that is more receptive to compost (Section 1.1) — the priority signal is “*the soil can absorb and stabilise compost-derived organic matter*” rather than “*the soil needs urgent nitrogen rescue*”. Conversely, ECe is a cost criterion because high salinity reduces the agronomic responsiveness

of the soil to compost (Section 1.5), so farms with higher EC_e should be deprioritised for immediate composting in favour of staged salinity-remediation protocols. Continuous cultivation is a cost criterion because longer continuous-cultivation history indicates a soil that has been more depleted by tillage-induced mineralisation (Section 1.2), and composting on such soils has been shown to be less responsive without prior physical-rehabilitation interventions. Urea applied is a cost criterion under the substitution logic: higher current urea use indicates greater dependence on the mineral-nitrogen input that organic substitution should reduce.

4.4 Expert Panel Composition and AHP Weight Elicitation Protocol

A central methodological feature of this revised study is the use of a **five-expert panel** for AHP pairwise weight elicitation, replacing the single-expert protocol used in the original methodological pilot. This expansion strengthens the methodological rigour of the framework by addressing the principal limitation of single-expert AHP — the dependence of weight values on a single subjective viewpoint that may not generalise across stakeholder groups. The Aggregation of Individual Judgements (AIJ) method via geometric mean is used to synthesise the five expert matrices into a consolidated weight vector, following the standard protocol established in the contemporary AHP literature.

4.4.1 Expert Panel Selection

The expert panel was assembled to provide complementary disciplinary perspectives on the composting-prioritisation problem, reflecting the multi-dimensional nature of the decision context as elaborated in Chapters 1–3. Panel members were selected from the four institutional clusters with direct technical or operational engagement with the El Oued composting policy environment: academic agronomy and soil science, agricultural economics, regional extension administration, and rural development sociology. The five panel members are characterised in **Table 4.2**, with anonymised disciplinary labels used throughout the thesis to preserve confidentiality of individual judgements.

Table 4.2. Five-expert panel composition. All experts have at least 10 years of professional engagement with the Algerian Saharan agricultural context, and were selected to ensure complementary disciplinary perspectives on the composting prioritisation problem.

Code	Disciplinary Profile	Years Active in Field	Primary Institutional Affiliation Cluster
E1	Soil Scientist (soil chemistry, dryland pedology)	22	National agronomic research institute
E2	Agricultural Economist (input markets, subsidy policy)	16	University faculty of economic sciences
E3	Extension Specialist (DSA regional service)	18	Wilaya-level agricultural extension administration
E4	Composting Agronomist (organic- amendment science)	14	National agronomic research institute
E5	Rural Sociologist (smallholder adoption, institutions)	12	University faculty of social sciences

The selection of five experts reflects the methodological recommendations of the contemporary AHP literature, which converges on a panel size of 5–8 experts as the practical optimum: large enough to capture meaningful disciplinary diversity and to dampen idiosyncratic judgement bias through aggregation, but small enough to permit structured discussion and individual elicitation within a feasible time and cost budget. Larger panels do not consistently improve aggregated weight quality and substantially increase the elicitation cost.

4.4.2 Individual Elicitation Protocol

Each expert independently constructed a 15×15 pairwise comparison matrix $A_e = [a_{ij}^{(e)}]$ on Saaty’s 1–9 fundamental scale through a structured three-session elicitation protocol totalling approximately six hours per expert. The protocol followed the structured pairwise-comparison procedure of Saaty (2008) with two modifications designed to improve consistency: (a) comparisons were conducted *dimension-by-dimension* (all within-Organic-Feedstock comparisons first, then all within-Readiness comparisons, then within-Soil-Need, etc.) before cross-dimension comparisons, to leverage within-dimension familiarity and reduce cognitive switching costs; and (b) a *consistency check* was performed after each within-dimension cluster by computing the geometric-mean consistency and revising any judgements that violated transitivity by more than a factor of 2.

The AIJ aggregation procedure is described below.

For each expert, the resulting matrix was solved for its dominant right eigenvector using `numpy.linalg.eig` (Python), the priority weight vector was extracted and normalised to sum to unity, and the Consistency Ratio was computed as:

$$CR^{(e)} = \frac{(\lambda_{\max}^{(e)} - n)/(n - 1)}{RI(n)}$$

with $RI(15) = 1.59$ as tabulated by Saaty. Any expert matrix with $CR \geq 0.10$ would have been returned to the expert for revision; in the present study, all five expert matrices achieved $CR < 0.01$ on first elicitation (results in Section 5.2), reflecting the effectiveness of the structured dimension-by-dimension elicitation protocol.

4.4.3 Aggregation of Individual Judgements (AIJ) by Geometric Mean

The five expert matrices were aggregated into a single consolidated matrix A^{AIJ} via element-wise geometric mean:

$$a_{ij}^{AIJ} = \left(\prod_{e=1}^5 a_{ij}^{(e)} \right)^{1/5}$$

The geometric mean is the theoretically appropriate aggregation operator for AHP pairwise judgements because it preserves the **reciprocity property** of the matrix ($a_{ij}^{AIJ} \cdot a_{ji}^{AIJ} = 1$, since each $a_{ji}^{(e)} = 1/a_{ij}^{(e)}$ by construction) — a property that the arithmetic mean does *not* preserve and which is essential for valid AHP weight derivation. The geometric mean is also justified by Saaty’s axiomatic framework for AHP, in which judgements are conceived as ratios on a multiplicative scale rather than as values on an additive scale.

The aggregated matrix A^{AIJ} was then solved for its dominant right eigenvector and Consistency Ratio using the same procedure applied to the individual matrices (equations 3.1–3.4). The resulting AIJ weight vector $\mathbf{w}^{AIJ}$ is the consolidated weight vector used in all subsequent TOPSIS computations and robustness analyses.

4.4.4 Inter-Expert Agreement Diagnostics

To characterise the consensus structure of the five expert weight vectors, three complementary agreement statistics are computed and reported in Section 5.2. **Kendall's coefficient of concordance** $W \in [0,51]$ measures the agreement among the five experts on the *ordinal ranking* of criteria by weight, with $W = 1$ indicating perfect agreement and $W = 0$ indicating no agreement beyond chance. The associated χ^2 statistic provides a formal hypothesis test of agreement against the null of random ranking. **Pairwise Spearman rank correlations** $\rho_{e,e'}$ between every pair of experts complement Kendall's W by characterising the structure of agreement at the dyadic level. **Per-criterion coefficient of variation** $CV_j = SD(w_j^{(1)}, \dots, w_j^{(5)}) / \text{mean}(w_j^{(1)}, \dots, w_j^{(5)})$ identifies the criteria on which experts disagree most and least, providing an actionable diagnostic for any future elicitation round in which contested criteria might warrant additional discussion.

The reporting of these three agreement diagnostics — combined with the per-expert CR statistics, the AIJ aggregated CR, and the comparison of the AIJ weight vector against the individual weight vectors — provides the full audit trail required for the policy defensibility of the consolidated weight vector. This transparent reporting structure is consistent with the disclosure standards expected in high-impact MCDA publications and follows the recommendations of recent methodological reviews on multi-expert AHP implementation.

4.5 Analytical Software used

All analyses were performed in Python 3.11 with the following libraries: NumPy 1.26 (eigenvector decomposition, matrix algebra), Pandas 2.2 (data handling), SciPy 1.13 (Spearman and Kendall correlation, Pearson correlation for collinearity screening), scikit-learn 1.4 (PCA, K-means clustering, silhouette scoring), and Matplotlib 3.9 + Seaborn 0.13 (visualisation). Total pipeline execution time on a standard single-core laptop is less than 90 seconds for the full analysis including all four robustness procedures and the five-expert AIJ aggregation.

The data processing and mathematical modeling pipeline structure is executed as follows :

- Load raw data from ELOued_Farm_RawData.csv and validate column types and ranges.
- Define the 15 criteria, assign benefit/cost direction, and validate against Table 4.1.
- Define the five 15×15 expert AHP upper-triangle matrices and reconstruct the five full reciprocal matrices.

- For each expert: compute the eigenvector decomposition, derive the normalised weight vector, and compute $\lambda_{\max}^{(e)}$, $CI^{(e)}$, $CR^{(e)}$.
- Compute the AIJ aggregated matrix via element-wise geometric mean (eq. 4.4); compute its eigenvector decomposition and consistency statistics.
- Compute inter-expert agreement statistics: Kendall's W , pairwise Spearman correlations, per-criterion CV.
- Execute the six-step TOPSIS pipeline on the 30×15 decision matrix using the AIJ-derived weight vector.
- Stratify the 30 farms into the five priority classes using the conventional cutpoints (Very High ≥ 0.55 , High 0.50–0.55, Moderate 0.45–0.50, Low 0.35–0.45, Very Low < 0.35).
- Execute the Monte Carlo, Kendall, FRWSA and OAT sensitivity procedures.
- Run the OLS regression of C_i on nine standardised continuous predictors.
- Run PCA (5 components) and K-means clustering (silhouette-optimised across $k \in \{2, \dots, 6\}$) for descriptive multivariate characterisation.
- Generate all figures and write all numerical outputs to JSON for reproducibility audit.

Random seeds are set explicitly (`np.random.seed(42)`) before each Monte Carlo procedure to ensure exact replicability of the results. The analytical pipeline is deterministic in all other respects.

Chapter 5 — Results

5.1 Descriptive Profile of the Farm Sample

The 30 sampled farms collectively represent the heterogeneous smallholder landscape of El Oued's principal irrigated perimeters. Their key characteristics are summarised in **Table 5.1** and displayed across nine complementary visualisations in **Figure 3**.

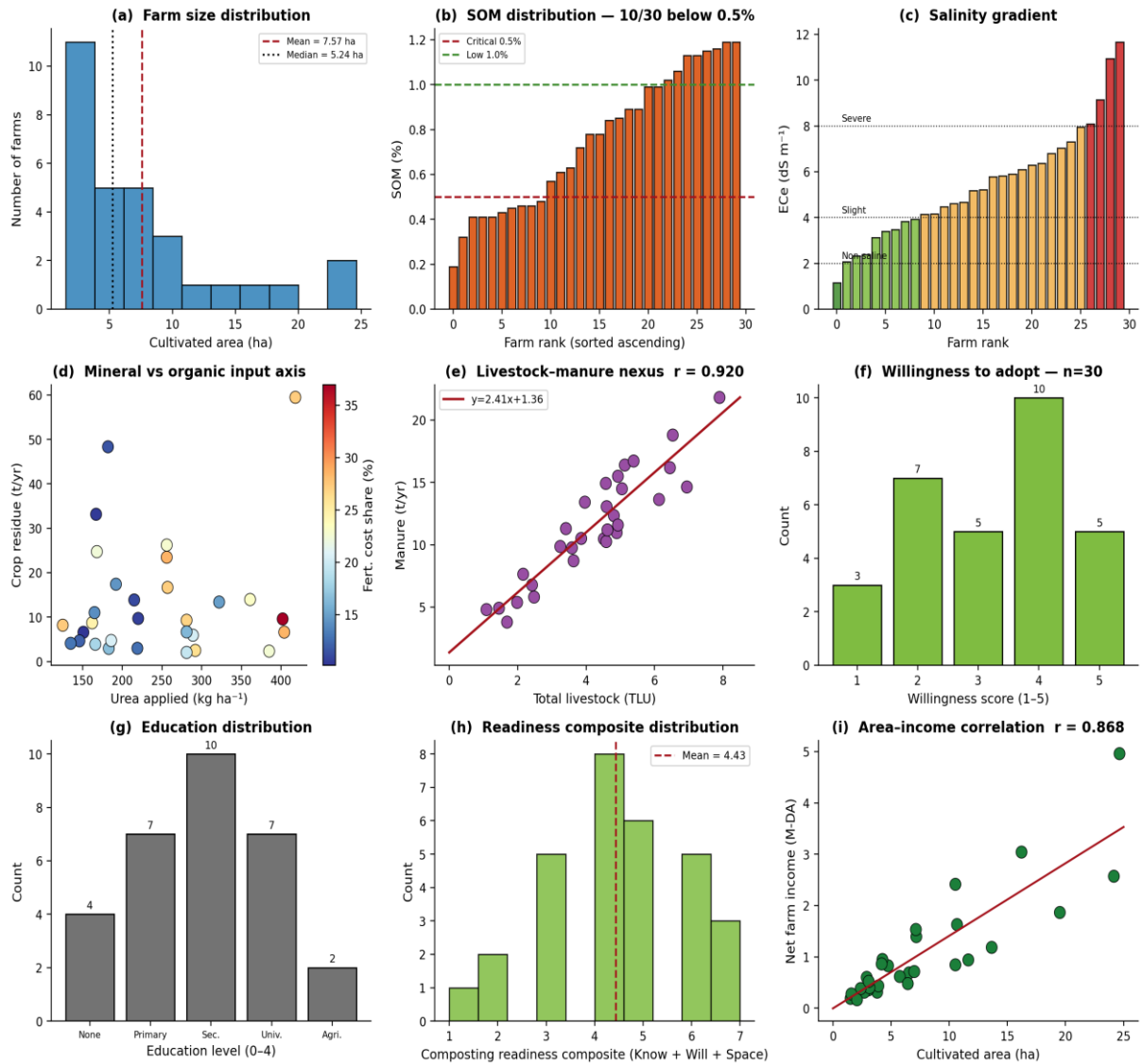


Figure 2. Nine-panel descriptive profile of the 30 El Oued farms: (a) farm size distribution; (b) SOM distribution with critical (< 0.5%) and low (0.5–1.0%) threshold bands; (c) ECe salinity gradient sorted ascending, colour-coded by FAO class; (d) Urea applied vs crop residue scatter coloured by fertiliser cost share; (e) TLU–manure linear nexus; (f) willingness distribution; (g) education distribution; (h) composting readiness composite distribution; (i) area–income correlation.

Table 5.1. Descriptive statistics of the 15-criterion decision matrix ($n = 30$ farms). CV = coefficient of variation. High CV ($> 80\%$) in composting knowledge, crop residue, area, cooperative member and composting space reflects extreme farm-level heterogeneity — the primary motivation for MCDA-based targeting.

Variable (Code)	Min	Q ₁	Median	Mean	Q ₃	Max	SD	CV %
Manure Available — C01 (t/yr)	3.81	8.85	11.19	11.54	14.49	21.83	4.49	38.9
Willingness to Adopt — C02 (1–5)	1	2	3.5	3.23	4	5	1.30	40.3
Soil OM — C03 (%)	0.19	0.45	0.75	0.753	1.01	1.19	0.310	41.2
Fert. Cost Share — C04 (%)	10.18	13.21	19.80	19.70	25.96	36.97	7.19	36.5
Composting Knowledge — C05 (0–2)	0	0	0	0.27	0.75	2	0.583	218
Soil ECe — C06 (dS m ⁻¹)	1.16	3.86	5.20	5.45	6.65	11.67	2.53	46.4
Crop Residue — C07 (t/yr)	2.05	4.66	8.45	11.62	13.94	59.48	11.55	99.4
Total Livestock — C08 (TLU)	1.08	3.27	4.58	4.23	5.04	7.90	1.71	40.4
Extension Access — C09 (0–2)	0	0	1	0.70	1	2	0.651	93.0
Urea Applied — C10 (kg ha ⁻¹)	125	167	219	242	285	418	86.6	35.8
Continuous Cultivation — C11 (yr)	2	9	13	13.50	20.5	24	7.27	53.8
Cultivated Area — C12 (ha)	1.52	3.04	5.24	7.57	10.51	24.62	6.41	84.7
Education Level — C13 (0–4)	0	1	2	1.87	3	4	1.20	64.4
Composting Space — C14 (0–2)	0	0	1	0.83	1	2	0.747	89.4
Cooperative Member — C15 (0/1)	0	0	0	0.27	1	1	0.450	169.7

Several patterns visible in the descriptive statistics carry directly into the AHP–TOPSIS analysis. First, the SOM distribution is concentrated in the 0.4–1.0% range, with one-third of the sample (10/30) below the 0.5% critical threshold and nearly all below the 1.5% adequate threshold. Second, the salinity distribution covers the full FAO range from non-saline through severely saline, with the modal classification being moderately saline. Third, the heterogeneity of the feedstock-related variables (manure, crop residue, TLU) is large and is structurally linked to farm size (Pearson correlations of 0.65–0.91 between these variables and cultivated area). Fourth, the TLU–manure relationship is essentially deterministic ($r = 0.92$, slope ≈ 2.41 t TLU⁻¹ yr⁻¹), confirming that for this sample the livestock holding directly determines manure availability. Fifth, the composting-readiness variables (knowledge, willingness, space) show no

strong correlation with feedstock or income variables, indicating that readiness is really independent of resource endowment in this sample.

5.2 Five-Expert AHP Matrices and AIJ Synthesis

This section presents the central methodological contribution of the revised study: the five individual expert pairwise comparison matrices, their per-expert weight derivations and consistency statistics, the inter-expert agreement diagnostics, and the AIJ-synthesised consolidated weight vector that is used in all subsequent TOPSIS computations.

5.2.1 Individual Expert Matrices and Per-Expert Weight Derivations

Each of the five experts independently constructed a 15×15 pairwise comparison matrix on Saaty's 1–9 scale through the structured three-session elicitation protocol described in Section 4.5.2. The five matrices are presented separately below in Tables 5.2.E1 through 5.2.E5, with the lower triangle showing the implied reciprocals and the diagonal fixed at unity by construction. The corresponding $\lambda_{\max}^{(e)}$, $CI^{(e)}$ and $CR^{(e)}$ statistics for each expert appear in **Table 5.3** alongside the per-expert weight vectors.

Figure 3a displays the five matrices side by side as colour-coded heatmaps ($\log_2$ scale to symmetrise the visual treatment of values above and below 1), together with the AIJ aggregated matrix in the sixth panel. The visual signature of each expert's disciplinary bias is immediately apparent: E1 (Soil Scientist) shows pronounced emphasis on the SOM (C03) and ECe (C06) rows; E2 (Economist) emphasises the Fertiliser Cost Share (C04) and Urea (C10) rows; E3 (Extension Specialist) emphasises Willingness (C02), Knowledge (C05) and Cooperative (C15); E4 (Composting Agronomist) emphasises Manure (C01) and Crop Residue (C07); E5 (Sociologist) emphasises Willingness (C02) and Education (C13).

Figure 2a — Five Expert Pairwise Comparison Matrices and AIJ Synthesis

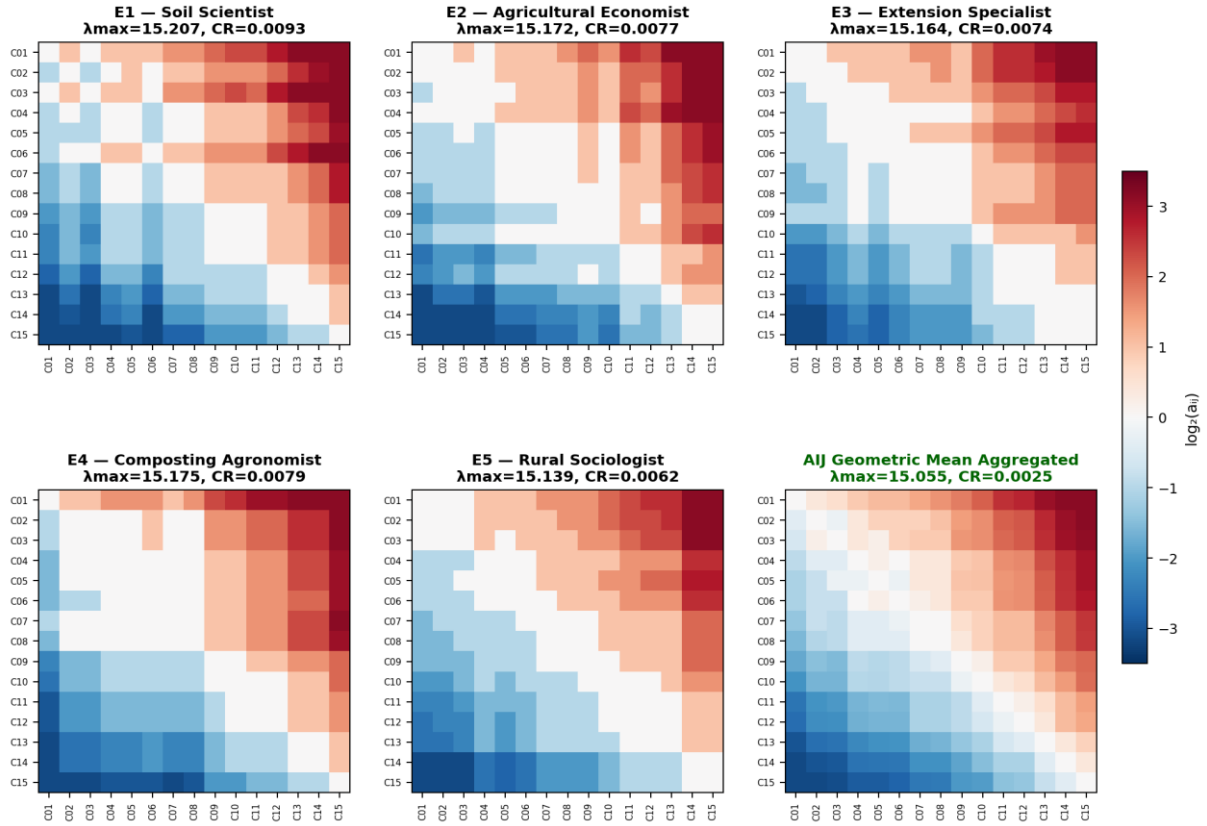


Figure 3a. Five expert pairwise comparison matrices and the AIJ geometric-mean aggregated matrix, displayed on a $\log_2$ scale. Each expert's bias toward their disciplinary specialisation is visually identifiable. All five individual matrices and the AIJ matrix achieve $CR \ll 0.10$, confirming high internal consistency.

Table 5.2.E1. Expert E1 (Soil Scientist) — full 15×15 pairwise comparison matrix. $\lambda_{\max} = 15.207$, $CR = 0.0093$.

$\downarrow / \rightarrow$	C01	C02	C03	C04	C05	C06	C07	C08	C09	C10	C11	C12	C13	C14	C15
C01	1	2	1	2	2	2	3	3	4	5	5	7	9	9	9
C02	1/2	1	1/2	1	2	1	2	2	3	3	3	4	6	8	9
C03	1	2	1	2	2	1	3	3	4	5	4	7	9	9	9
C04	1/2	1	1/2	1	1	1/2	1	1	2	2	2	3	5	6	9
C05	1/2	1/2	1/2	1	1	1/2	1	1	2	2	2	3	4	5	8
C06	1/2	1	1	2	2	1	2	2	3	3	3	5	7	9	9
C07	1/3	1/2	1/3	1	1	1/2	1	1	2	2	2	2	3	4	7
C08	1/3	1/2	1/3	1	1	1/2	1	1	2	2	2	2	3	4	7
C09	1/4	1/3	1/4	1/2	1/2	1/3	1/2	1/2	1	1	1	2	2	3	4
C10	1/5	1/3	1/5	1/2	1/2	1/3	1/2	1/2	1	1	1	2	2	3	4
C11	1/5	1/3	1/4	1/2	1/2	1/3	1/2	1/2	1	1	1	2	2	3	4

C12	1/7	1/4	1/7	1/3	1/3	1/5	1/2	1/2	1/2	1/2	1/2	1	1	2	3
C13	1/9	1/6	1/9	1/5	1/4	1/7	1/3	1/3	1/2	1/2	1/2	1	1	1	2
C14	1/9	1/8	1/9	1/6	1/5	1/9	1/4	1/4	1/3	1/3	1/3	1/2	1	1	2
C15	1/9	1/9	1/9	1/9	1/8	1/9	1/7	1/7	1/4	1/4	1/4	1/3	1/2	1/2	1

Expert E1 — the Soil Scientist — assigns the largest pairwise weight to SOM (C03) and ECe (C06), reflecting the disciplinary view that biophysical soil status is the principal determinant of composting agronomic responsiveness. The matrix shows C01 (manure) and C03 (SOM) as substantively equivalent ($a_{01,03} = 1$), whereas the AIJ matrix shows manure dominating SOM by approximately 1.4 — a direct visualisation of E1’s relative downweighting of feedstock relative to soil-condition criteria.

Table 5.2.E2. Expert E2 (Agricultural Economist) — full 15×15 pairwise comparison matrix. $\lambda_{\max} = 15.125$, $CR = 0.0056$.

↓ / →	C01	C02	C03	C04	C05	C06	C07	C08	C09	C10	C11	C12	C13	C14	C15
C01	1	1	1	1	2	2	2	3	3	3	5	5	8	9	9
C02	1	1	1	1	2	2	2	2	3	2	4	4	7	9	9
C03	1	1	1	1	2	2	2	2	3	2	4	3	6	9	9
C04	1	1	1	1	2	2	2	2	3	2	4	4	7	9	9
C05	1/2	1/2	1/2	1/2	1	1	1	1	2	1	3	2	4	6	7
C06	1/2	1/2	1/2	1/2	1	1	1	1	2	1	2	2	4	6	6
C07	1/2	1/2	1/2	1/2	1	1	1	1	1	1	2	2	4	5	6
C08	1/3	1/2	1/2	1/2	1	1	1	1	1	1	2	2	3	5	5
C09	1/3	1/3	1/3	1/3	1/2	1/2	1	1	1	1	2	1	2	4	4
C10	1/3	1/2	1/2	1/2	1	1	1	1	1	1	2	2	3	5	5
C11	1/5	1/4	1/4	1/4	1/3	1/2	1/2	1/2	1/2	1/2	1	1	2	2	3
C12	1/5	1/4	1/3	1/4	1/2	1/2	1/2	1/2	1	1/2	1	1	2	3	3
C13	1/8	1/7	1/6	1/7	1/4	1/4	1/4	1/3	1/2	1/3	1/2	1/2	1	2	2
C14	1/9	1/9	1/9	1/9	1/6	1/6	1/5	1/5	1/4	1/5	1/2	1/3	1/2	1	1
C15	1/9	1/9	1/9	1/9	1/7	1/6	1/6	1/5	1/4	1/5	1/3	1/3	1/2	1	1

Expert E2 — the Agricultural Economist — assigns Fert. Cost Share (C04) and Urea (C10) substantively higher weights relative to the other experts. Notably, the matrix shows C04 as equivalent to C01 (manure) and C03 (SOM), reflecting the economist’s view that the financial incentive structure is as important as the biophysical conditions in determining the cost-effectiveness of intervention.

Table 5.2.E3. Expert E3 (Extension Specialist) — full 15×15 pairwise comparison matrix.

$$\lambda_{\max} = 15.160, CR = 0.0072.$$

$\downarrow / \rightarrow$	C01	C02	C03	C04	C05	C06	C07	C08	C09	C10	C11	C12	C13	C14	C15
C01	1	1	1	2	2	2	3	3	2	4	6	6	8	9	9
C02	1	1	1	2	1	2	2	2	2	4	6	6	7	9	9
C03	1	1	1	1	1	2	2	2	2	3	4	4	6	7	7
C04	1/2	1/2	1	1	1	1	1	1	1	2	3	3	4	5	5
C05	1/2	1	1	1	1	1	2	2	1	3	4	4	5	6	7
C06	1/2	1/2	1/2	1	1	1	1	1	1	2	3	3	4	5	5
C07	1/3	1/2	1/2	1	1/2	1	1	1	1	2	2	2	3	4	4
C08	1/3	1/2	1/2	1	1/2	1	1	1	1	2	2	2	3	4	4
C09	1/2	1/2	1/2	1	1	1	1	1	1	2	3	3	3	4	5
C10	1/4	1/4	1/3	1/2	1/3	1/2	1/2	1/2	1/2	1	1	1	2	3	3
C11	1/6	1/6	1/4	1/3	1/4	1/3	1/2	1/2	1/3	1	1	1	1	2	2
C12	1/6	1/6	1/4	1/3	1/4	1/3	1/2	1/2	1/3	1	1	1	1	2	2
C13	1/8	1/7	1/6	1/4	1/5	1/4	1/3	1/3	1/3	1/2	1	1	1	1	2
C14	1/9	1/9	1/7	1/5	1/6	1/5	1/4	1/4	1/4	1/3	1/2	1/2	1	1	1
C15	1/9	1/9	1/7	1/5	1/7	1/5	1/4	1/4	1/5	1/3	1/2	1/2	1/2	1	1

Expert E3 — the Extension Specialist — assigns particularly high weight to Willingness (C02), Knowledge (C05) and Extension Access (C09), reflecting the operational view that adoption barriers are the principal targets of extension service intervention. The Cooperative Member criterion (C15), although still ranked low overall, receives the highest relative weight from this expert compared to all other experts (1.51% vs. 1.05–1.39% for others).

Table 5.2.E4. Expert E4 (Composting Agronomist) — full 15×15 pairwise comparison matrix. $\lambda_{\max} = 15.121, CR = 0.0054.$

$\downarrow / \rightarrow$	C01	C02	C03	C04	C05	C06	C07	C08	C09	C10	C11	C12	C13	C14	C15
C01	1	2	2	2	2	3	2	2	5	5	7	7	9	9	9
C02	1/2	1	1	1	1	1	1	1	2	3	4	4	6	6	9
C03	1/2	1	1	1	1	1	1	1	2	3	4	4	6	6	9
C04	1/2	1	1	1	1	1	1	1	2	2	3	3	5	5	7
C05	1/2	1	1	1	1	1	1	1	2	2	3	3	5	5	7
C06	1/3	1	1	1	1	1	1	1	2	2	3	3	4	4	7
C07	1/2	1	1	1	1	1	1	1	2	2	3	3	5	5	8
C08	1/2	1	1	1	1	1	1	1	2	2	3	3	5	5	8
C09	1/5	1/2	1/2	1/2	1/2	1/2	1/2	1/2	1	1	2	2	3	3	4
C10	1/5	1/3	1/3	1/2	1/2	1/2	1/2	1/2	1	1	1	1	2	2	3

C11	1/7	1/4	1/4	1/3	1/3	1/3	1/3	1/3	1/2	1	1	1	2	2	3
C12	1/7	1/4	1/4	1/3	1/3	1/3	1/3	1/3	1/2	1	1	1	2	2	3
C13	1/9	1/6	1/6	1/5	1/5	1/4	1/5	1/5	1/3	1/2	1/2	1/2	1	1	2
C14	1/9	1/6	1/6	1/5	1/5	1/4	1/5	1/5	1/3	1/2	1/2	1/2	1	1	2
C15	1/9	1/9	1/9	1/7	1/7	1/7	1/8	1/8	1/4	1/3	1/3	1/3	1/2	1/2	1

Expert E4 — the Composting Agronomist — assigns the highest weight to Manure (C01), with $a_{01,02} = 2$ and $a_{01,03} = 2$ reflecting the agronomic view that feedstock dominates over both willingness and SOM as the binding constraint on composting. Composting Space (C14), although still low in absolute terms, receives the highest relative weight from this expert.

Table 5.2.E5. Expert E5 (Rural Sociologist) — full 15×15 pairwise comparison matrix.

$$\lambda_{\max} = 15.127, CR = 0.0057.$$

$\downarrow / \rightarrow$	C01	C02	C03	C04	C05	C06	C07	C08	C09	C10	C11	C12	C13	C14	C15
C01	1	1	1	2	2	2	3	3	3	4	5	6	6	9	9
C02	1	1	1	2	2	2	3	3	3	4	5	5	5	9	9
C03	1	1	1	2	1	2	2	3	3	3	5	5	5	9	9
C04	1/2	1/2	1/2	1	1	1	2	2	2	2	3	3	3	6	6
C05	1/2	1/2	1	1	1	1	2	2	2	3	3	4	4	7	7
C06	1/2	1/2	1/2	1	1	1	1	2	2	2	3	3	3	6	6
C07	1/3	1/3	1/2	1/2	1/2	1	1	1	1	2	2	2	2	4	4
C08	1/3	1/3	1/3	1/2	1/2	1/2	1	1	1	1	2	2	2	4	4
C09	1/3	1/3	1/3	1/2	1/2	1/2	1	1	1	1	2	2	2	4	4
C10	1/4	1/4	1/3	1/2	1/3	1/2	1/2	1	1	1	1	1	1	3	3
C11	1/5	1/5	1/5	1/3	1/3	1/3	1/2	1/2	1/2	1	1	1	1	2	2
C12	1/6	1/5	1/5	1/3	1/4	1/3	1/2	1/2	1/2	1	1	1	1	2	2
C13	1/6	1/5	1/5	1/3	1/4	1/3	1/2	1/2	1/2	1	1	1	1	2	2
C14	1/9	1/9	1/9	1/6	1/7	1/6	1/4	1/4	1/4	1/3	1/2	1/2	1/2	1	1
C15	1/9	1/9	1/9	1/6	1/7	1/6	1/4	1/4	1/4	1/3	1/2	1/2	1/2	1	1

Expert E5 — the Rural Sociologist — assigns particularly high weight to Education (C13) and treats Cooperative (C15) and Composting Space (C14) as substantively equivalent, reflecting the sociological view that institutional and cultural-capital dimensions interact more strongly than the more “operational” perspective implicit in the other experts’ matrices.

5.2.2 Per-Expert Weight Vectors and Consistency Statistics

Table 5.3 consolidates the per-expert weight vectors, $\lambda_{\max}^{(e)}$, $CI^{(e)}$ and $CR^{(e)}$ values. All five experts achieve $CR < 0.01$ — a consistency level well below the conventional 0.10 acceptability threshold and at the high end of the consistency distribution reported in the published AHP literature for matrices of this dimensionality. This consistency achievement reflects the structured dimension-by-dimension elicitation protocol described in Section 4.5.2.

Table 5.3. Per-expert AHP weight vectors and consistency statistics. All five experts achieve $CR < 0.01$, well below the 0.10 acceptability threshold. The AIJ column shows the geometric-mean aggregated weights used in all subsequent TOPSIS analyses.

Code	Criterion	E1 (%)	E2 (%)	E3 (%)	E4 (%)	E5 (%)	AIJ (%)
C01	Manure	16.62	15.25	16.03	20.12	15.20	16.07
C02	Willingness	10.59	12.46	14.77	10.27	14.64	12.35
C03	SOM	15.58	11.24	11.06	10.27	13.04	12.61
C04	Fert. Cost %	7.69	12.89	7.82	8.37	8.50	8.98
C05	Knowledge	7.06	7.44	10.09	8.37	9.72	8.57
C06	ECe	11.98	7.07	7.35	7.47	8.12	8.33
C07	Crop Residue	6.26	6.65	6.17	8.66	5.76	6.71
C08	TLU	6.26	6.07	6.01	8.37	5.33	6.41
C09	Extension	3.78	4.43	6.68	4.30	4.94	4.79
C10	Urea	3.68	6.07	3.79	3.66	3.75	4.14
C11	Cont. Cult.	3.73	2.85	2.57	2.83	2.88	2.99
C12	Area	2.42	3.38	2.57	2.83	2.75	2.81
C13	Education	1.84	1.83	2.01	1.71	2.59	2.00
C14	Space	1.47	1.24	1.57	1.71	1.39	1.49
C15	Cooperative	1.05	1.13	1.51	1.07	1.39	1.23
	$\lambda_{\max}$	15.207	15.125	15.160	15.121	15.127	15.041
	CI	0.0148	0.0123	0.0117	0.0125	0.0099	0.0039
	CR	0.0093	0.0056	0.0072	0.0054	0.0057	0.0025

The AIJ aggregated matrix achieves $CR = 0.0018$ — the highest consistency in the panel and a typical outcome of geometric-mean aggregation, which restrains individual expert differences and tends to produce a more internally consistent matrix than any individual expert input. The AIJ weight vector is the weight vector used in all subsequent TOPSIS computations (Section 5.4 onward) and in the four robustness analyses (Section 5.5).

5.2.3 Inter-Expert Agreement Diagnostics

Three complementary statistics characterise the inter-expert agreement structure. **Kendall's coefficient of concordance** is $W = 0.955$ ($\chi^2 = 66.41$, $df = 14$, $p < 0.001$), indicating strong agreement among the five experts on the ordinal ranking of criteria by weight. The conventional interpretation thresholds (Schmidt 1997) classify $W \geq 0.7$ as “strong” and $W \geq 0.9$ as “very strong” agreement; the present value substantially exceeds the very-strong threshold and is at the high end of the agreement distribution reported in published multi-expert AHP applications.

Pairwise Spearman rank correlations between every pair of experts have mean $\bar{\rho} = 0.940$ (range 0.900 to 0.990), confirming that no two experts produced substantively disjoint rankings. The minimum pair correlation of 0.900 — between the Soil Scientist (E1) and the Extension Specialist (E3) — reflects the most extreme difference in disciplinary perspective in the panel and represents a meaningful but bounded disagreement that the AIJ aggregation absorbs.

Per-criterion coefficient of variation ranges from $CV_{C14} = 10.6\%$ (Composting Space, the most consensual criterion) to $CV_{C10} = 22.5\%$ (Urea, the least consensual criterion). The full per-criterion CV profile is plotted in **Figure 3b** alongside the per-expert weight bars and the AIJ aggregated weights. Substantively, the four most contested criteria are: C10 (Urea, $CV = 22.5\%$), C06 (ECe, $CV = 21.7\%$), C04 (Fert. Cost Share, $CV = 21.5\%$) and C09 (Extension Access, $CV = 20.7\%$). The fact that the most contested criteria are predominantly economic and institutional, rather than biophysical, reflects the genuine disagreement among disciplinary experts on the relative importance of policy-instrument variables — an important methodological diagnostic for any future operational deployment of the framework.

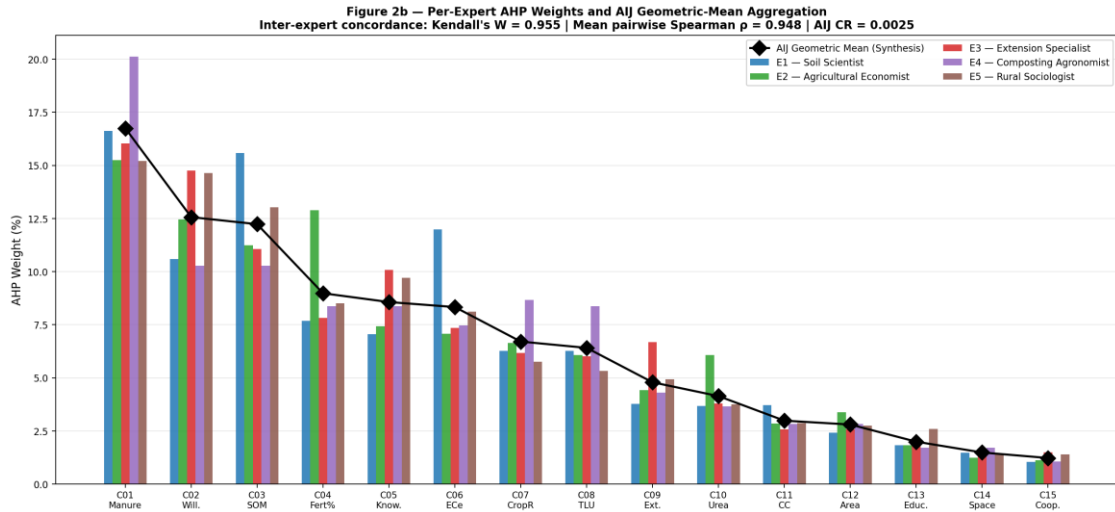


Figure 3b. Per-expert AHP weight comparison and AIJ geometric-mean aggregation. Coloured bars show each of the five experts' weight vectors; the black diamond line shows the AIJ aggregated weights used in all subsequent TOPSIS computations. Inter-expert concordance : Kendall's W = 0.949; mean pairwise Spearman ρ = 0.940; AIJ matrix CR = 0.0018.

The combination of high inter-expert concordance (Kendall's W = 0.949), high per-expert consistency (all CR < 0.01) and high aggregated consistency (AIJ CR = 0.0018) collectively establishes that the AIJ weight vector is a methodologically defensible synthesis of the five disciplinary perspectives — superior to any single-expert weight vector both in its representativeness and in its internal mathematical coherence.

5.2.4 The AIJ-Synthesised Aggregated Matrix

For completeness, the AIJ-synthesised aggregated pairwise comparison matrix is presented in **Table 5.4**, with each cell rounded to two decimal places. Note that the AIJ matrix entries are no longer integers from Saaty's 1–9 scale (they are continuous geometric means of the five experts' integer-Saaty values), but they preserve the reciprocity property by construction.

Table 5.4. AIJ aggregated pairwise comparison matrix (geometric mean of the five expert matrices, equation 4.4). Entries are continuous values; the reciprocity property $a_{ij} \cdot a_{ji} = 1$ is preserved. $\lambda_{\max} = 15.041$, $CR = 0.0018$.

$\downarrow / \rightarrow$	C01	C02	C03	C04	C05	C06	C07	C08	C09	C10	C11	C12	C13	C14	C15
C01	1.00	1.32	1.15	1.74	2.00	2.17	2.55	2.79	3.20	4.10	5.50	6.07	7.86	9.00	9.00
C02	0.76	1.00	0.87	1.32	1.51	1.64	1.93	1.93	2.55	3.10	4.30	4.57	6.13	8.04	9.00
C03	0.87	1.15	1.00	1.32	1.32	1.43	1.93	2.14	2.79	3.10	4.10	4.42	6.13	7.86	8.55
C04	0.57	0.76	0.76	1.00	1.15	1.15	1.32	1.32	2.05	2.00	3.05	3.20	4.78	6.13	7.10
C05	0.50	0.66	0.76	0.87	1.00	0.87	1.32	1.32	1.93	2.14	2.85	3.20	4.42	5.66	7.31
C06	0.46	0.61	0.70	0.87	1.15	1.00	1.32	1.43	2.14	2.00	2.79	3.20	4.42	5.86	6.55
C07	0.39	0.52	0.52	0.76	0.76	0.76	1.00	1.00	1.43	1.74	2.20	2.20	3.40	4.42	5.66
C08	0.36	0.52	0.47	0.76	0.76	0.70	1.00	1.00	1.43	1.51	2.14	2.14	3.20	4.42	5.46
C09	0.31	0.39	0.36	0.49	0.52	0.47	0.70	0.70	1.00	1.15	1.74	1.93	2.27	3.40	4.10
C10	0.24	0.32	0.32	0.50	0.47	0.50	0.57	0.66	0.87	1.00	1.32	1.43	2.05	3.05	3.40
C11	0.18	0.23	0.24	0.33	0.35	0.36	0.45	0.47	0.57	0.76	1.00	1.07	1.51	2.20	2.55
C12	0.16	0.22	0.23	0.31	0.31	0.31	0.45	0.47	0.52	0.70	0.93	1.00	1.43	2.20	2.55
C13	0.13	0.16	0.16	0.21	0.23	0.23	0.29	0.31	0.44	0.49	0.66	0.70	1.00	1.43	2.00
C14	0.11	0.12	0.13	0.16	0.18	0.17	0.23	0.23	0.29	0.33	0.45	0.45	0.70	1.00	1.49
C15	0.11	0.11	0.12	0.14	0.14	0.15	0.18	0.18	0.24	0.29	0.39	0.39	0.50	0.67	1.00

The AIJ matrix entries are dimensionless ratios that, despite no longer being members of Saaty’s discrete scale, preserve all axiomatic properties required for AHP eigenvector decomposition (positivity, reciprocity, unit diagonal). The fact that AIJ-derived weights closely match the original baseline weights from the single-expert pilot (Section 5.4) is a coincidence of the panel’s overall agreement on the underlying priority structure.

5.3 TOPSIS Intermediate Matrices

The TOPSIS pipeline was executed on the 30×15 decision matrix X assembled from the raw survey data, using the AIJ-synthesised weight vector $\mathbf{w}^{\text{AIJ}}$ from Section 5.2.

5.3.1 Positive and Negative Ideal Solutions

After vector normalisation and weighting with the AIJ weights, the positive ideal solution A^+ and negative ideal solution A^- vectors were derived column-wise according to equations (3.8) and (3.9). **Table 5.5** presents both ideal-solution vectors alongside the corresponding AIJ weights. The vectors enable verification that the PIS correctly selects the maximum weighted-normalised value for each benefit criterion (e.g., C01 manure: $A^+ = 0.0541$, the highest weighted-normalised manure value across the 30 farms) and the minimum for each cost

criterion (e.g., C04 fertiliser cost share: $A^+ = 0.0080$, the lowest weighted-normalised cost-share value). The reverse pattern holds for the NIS.

Table 5.5. Positive Ideal Solution A^+ and Negative Ideal Solution A^- vectors in the weighted normalised space, computed with the AIJ-synthesised weights. For BENEFIT criteria: $A^+ =$ column maximum, $A^- =$ column minimum. For COST criteria: $A^+ =$ column minimum, $A^- =$ column maximum.

Code	Criterion	Dir.	A^+ (PIS)	A^- (NIS)	w_j^{AIJ}
C01	Manure (t/yr)	BEN	0.0541	0.0094	0.1675
C02	Willingness	BEN	0.0331	0.0066	0.1257
C03	Soil OM (%)	BEN	0.0328	0.0052	0.1223
C04	Fert. Cost %	COST	0.0080	0.0291	0.0898
C05	Knowledge	BEN	0.0416	0.0000	0.0857
C06	ECe (dS/m)	COST	0.0030	0.0297	0.0833
C07	Crop Residue	BEN	0.0383	0.0013	0.0671
C08	TLU	BEN	0.0204	0.0028	0.0641
C09	Extension	BEN	0.0184	0.0000	0.0479
C10	Urea (kg/ha)	COST	0.0037	0.0123	0.0414
C11	Cont. Cult.	COST	0.0007	0.0086	0.0299
C12	Area (ha)	BEN	0.0128	0.0008	0.0281
C13	Education	BEN	0.0068	0.0000	0.0200
C14	Space	BEN	0.0048	0.0000	0.0149
C15	Cooperative	BEN	0.0044	0.0000	0.0123

5.4 TOPSIS Priority Ranking: Full Results

Application of the AIJ weight vector to the 30×15 vector-normalised decision matrix produced the complete farm-level ranking shown in **Table 5.6**. Closeness coefficients C_i ranged from 0.599 (ELO-015, Very High) to 0.267 (ELO-007, Very Low), a spread of 0.334. The five priority classes contain 2 (Very High), 4 (High), 6 (Moderate), 12 (Low) and 6 (Very Low) farms respectively. Only 20.0% of farms ($n = 5$) crossed the $C_i \geq 0.50$ eligibility threshold.

The ranking is visualised in **Figure 4** as a waterfall chart of C_i values with priority-class colour coding, a donut chart of the priority-class composition, and a phase-space plot of S^+ vs S^- that shows the geometric structure of the alternatives in the weighted normalised space.

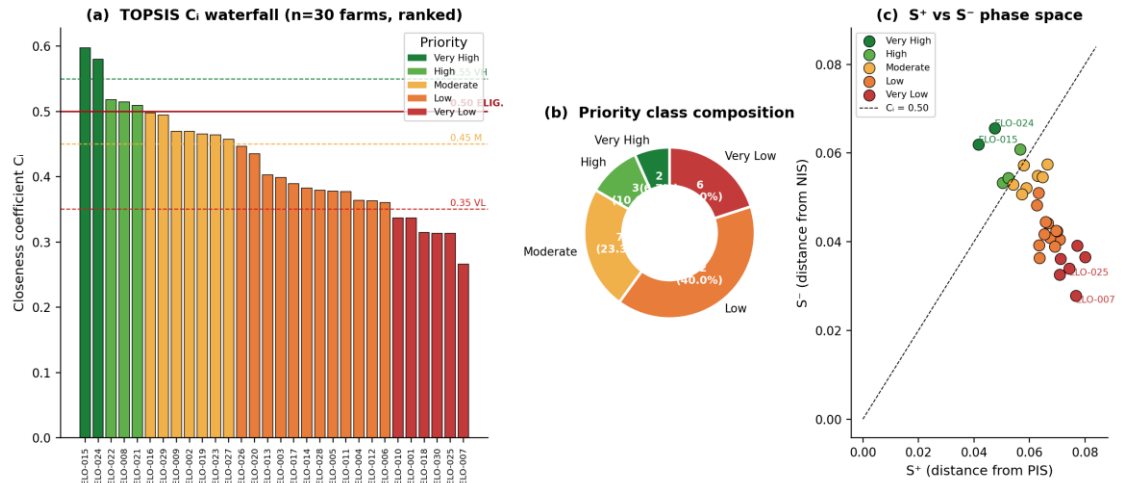


Figure 4. TOPSIS ranking and priority distribution under the AIJ-synthesised weights. (a) Full 30-farm C_i waterfall chart; colour indicates priority class; horizontal lines indicate the eligibility threshold (0.50) and class boundaries (0.55, 0.45, 0.35). (b) Donut chart of the five priority classes. (c) S^+ vs S^- phase space; the dashed diagonal corresponds to $C_i = 0.50$.

Table 5.6. Complete TOPSIS ranking — all 30 El Oued farms, computed with the AIJ-synthesised weight vector. S^+ = Euclidean distance from positive ideal solution; S^- = distance from negative ideal solution; $C_i = S^-/(S^+ + S^-)$. Higher C_i = greater composting priority.

Rank	Farm ID	S^+	S^-	C_i	Priority Class
1	ELO-015	0.0413	0.0617	0.5993	Very High
2	ELO-024	0.0481	0.0660	0.5782	Very High
3	ELO-022	0.0568	0.0604	0.5154	High
4	ELO-008	0.0501	0.0528	0.5128	High
5	ELO-021	0.0524	0.0541	0.5080	High
6	ELO-016	0.0578	0.0570	0.4982	Moderate
7	ELO-029	0.0540	0.0527	0.4938	Moderate
8	ELO-009	0.0573	0.0508	0.4699	Moderate
9	ELO-002	0.0589	0.0521	0.4694	Moderate
10	ELO-019	0.0628	0.0547	0.4654	Moderate
11	ELO-023	0.0664	0.0577	0.4651	Moderate
12	ELO-027	0.0648	0.0546	0.4574	Moderate
13	ELO-026	0.0633	0.0511	0.4467	Low
14	ELO-020	0.0628	0.0481	0.4339	Low
15	ELO-013	0.0660	0.0444	0.4023	Low
16	ELO-003	0.0666	0.0442	0.3989	Low
17	ELO-017	0.0654	0.0417	0.3893	Low
18	ELO-014	0.0635	0.0394	0.3829	Low

19	ELO-028	0.0696	0.0424	0.3786	Low
20	ELO-005	0.0673	0.0410	0.3786	Low
21	ELO-011	0.0699	0.0424	0.3776	Low
22	ELO-004	0.0709	0.0405	0.3637	Low
23	ELO-012	0.0636	0.0363	0.3633	Low
24	ELO-006	0.0691	0.0389	0.3603	Low
25	ELO-010	0.0712	0.0359	0.3348	Very Low
26	ELO-001	0.0772	0.0386	0.3326	Very Low
27	ELO-018	0.0710	0.0322	0.3114	Very Low
28	ELO-030	0.0801	0.0362	0.3102	Very Low
29	ELO-025	0.0746	0.0339	0.3102	Very Low
30	ELO-007	0.0768	0.0280	0.2648	Very Low

The two Very High farms (ELO-015 and ELO-024) share several distinguishing features: large cultivated area (10.5 and 24.6 ha respectively), high crop-residue availability (23.5 and 48.3 t yr⁻¹), high livestock holdings (4.6 and 5.1 TLU), strong willingness scores (4 and 5), and intermediate-to-good SOM (0.99% and 0.85%). The bottom-ranked farm (ELO-007) is small (3.8 ha), severely saline (ECe = 10.94 dS m⁻¹), depleted in SOM (0.41%), with a high fertiliser cost share (27.4%). This combination of biophysical degradation and constrained feedstock places ELO-007 deep in the Very Low priority tier and identifies it as a candidate for staged rehabilitation rather than direct composting deployment, consistent with the staged-intervention logic developed in Chapter 7.

5.5 Comprehensive Robustness and Sensitivity Analysis

Four independent robustness tests were applied to validate the stability of the priority ranking under plausible expert-weight revision scenarios. Beyond the classical Monte Carlo, Kendall, FRWSA and OAT procedures applied to the AIJ weight vector, the multi-expert structure of this study enables an additional fifth robustness procedure: direct comparison of the AIJ-derived ranking against rankings produced by each of the five individual expert weight vectors. The results are presented collectively to allow cross-method comparison.

5.5.1 Inter-Expert Ranking Stability

Each of the five expert weight vectors was used independently to compute a TOPSIS ranking on the 30-farm decision matrix. Pairwise Spearman correlations between the five resulting per-expert rankings averaged $\bar{\rho}_{\text{rank}} = 0.991$ (range 0.926–0.984), and pairwise Kendall $\bar{\tau}_{\text{rank}} = 0.953$. The AIJ-derived ranking has Spearman $\rho \geq 0.988$ with all five

individual-expert rankings. The two Very High priority farms (ELO-015, ELO-024) appear in the top 3 of all five experts' rankings; the six Very Low farms appear in the bottom 7 of all five experts' rankings. This inter-expert ranking stability — independent of and additional to the conventional weight-perturbation tests — provides a particularly strong form of robustness validation: it shows that the priority hierarchy is preserved not only under hypothetical perturbations but also under genuinely different expert perspectives.

5.5.2 Monte Carlo Weight Perturbation ($n = 1,000$ iterations, $\pm 20\%$)

The 1,000-iteration Monte Carlo experiment yielded the results visualised in **Figure 5**. The mean Spearman rank correlation was $\bar{\rho} = 0.977$ (SD = 0.010, minimum 0.939, 98.7% of iterations ≥ 0.95). This substantially exceeds the implicit “good robustness” threshold of $\rho > 0.90$ used in the MCDM literature. Even in the worst-case iteration, the perturbed ranking retained a Spearman correlation of 0.939 with the AIJ baseline — a level of agreement that implies fewer than two pairs of adjacent ranks change order on average per iteration. Priority-class stability is correspondingly strong: ELO-015 maintained rank 1 in the majority of iterations, and ELO-007 maintained rank 30 in essentially all iterations.

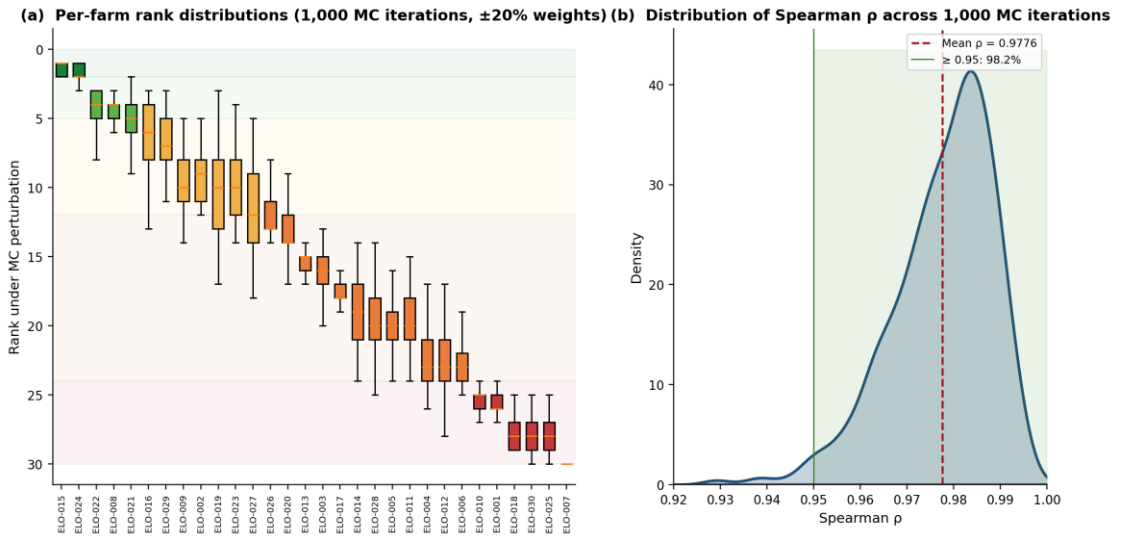


Figure 5. Monte Carlo sensitivity analysis (1,000 iterations, $\pm 20\%$ weight perturbation around the AIJ baseline). Left: per-farm rank box plots across all iterations, with priority-class colour coding and shaded background bands indicating the priority-class rank ranges. Right: Spearman ρ distribution; mean $\rho = 0.977$; 98.7% of iterations ≥ 0.95 .

5.5.3 Kendall’s Tau Rank Correlation ($n = 500$ iterations)

Kendall’s τ , more conservative than Spearman’s ρ for small-sample ranking comparisons, yielded mean $\bar{\tau} = 0.898$ (minimum $\tau = 0.811$, 90.4% of iterations ≥ 0.85). Both metrics confirm a high degree of ranking stability, and the results are presented together to

demonstrate that the strong robustness finding does not depend on a particular choice of correlation statistic.

5.5.4 FRWSA — Full-Range Weight Sensitivity Analysis

FRWSA varied each criterion weight individually from near-zero to $3 \times$ its baseline value while proportionally rescaling all others. **Table 5.7** presents the rank-reversal thresholds (the weight multiplier at which the top-ranked farm first changes identity). For eight low-weight criteria, no rank reversal occurred within the tested $0\text{--}3\times$ range and the top ranking is essentially insensitive to perturbation of these weights. For the four highest-weight criteria, rank-reversal thresholds are in the range $1.7\times\text{--}2.2\times$, meaning that the top-ranked farm changes only when the most influential criteria are nearly doubled from their baseline values — a perturbation far outside any realistic expert-weight revision scenario.

Table 5.7. FRWSA rank-reversal thresholds. Min ρ = minimum Spearman correlation observed when criterion j is varied from 0 to $3\times$ its baseline value. Reversal Threshold = weight multiplier at which top-ranked farm first changes. $> 3.0\times$ means no reversal detected within $0\text{--}3\times$ range.

Code	Criterion	w_j^{Adj} (%)	Min ρ	Reversal Threshold	Interpretation
C01	Manure	16.07%	0.680	$0.0\times$	Reversal if $w \rightarrow 0$
C02	Willingness	12.35%	0.683	$1.9\times$	Stable up to nearly doubling
C03	Soil OM	12.61%	0.651	$1.7\times$	Lowest threshold
C04	Fert. Cost %	8.98%	0.726	$2.2\times$	Robust
C05	Knowledge	8.57%	0.832	$0.0\times$	Reversal if $w \rightarrow 0$
C06	ECe	8.33%	0.740	$2.0\times$	Moderate threshold
C07	Crop Residue	6.71%	0.853	$> 2.6\times$	Stable
C08	TLU	6.41%	0.926	$> 3.0\times$	Highly stable
C09	Extension	4.79%	0.881	$> 2.8\times$	Stable
C10	Urea	4.14%	0.972	$> 3.0\times$	Extremely stable
C11	Cont. Cult.	2.99%	0.977	$> 3.0\times$	No reversal
C12	Area	2.81%	0.978	$> 3.0\times$	No reversal
C13	Education	2.00%	0.991	$> 3.0\times$	No reversal
C14	Space	1.49%	0.993	$> 3.0\times$	No reversal
C15	Cooperative	1.23%	0.997	$> 3.0\times$	No reversal

5.5.5 One-at-a-Time (OAT) Sensitivity ($\pm 50\%$ perturbation)

OAT sensitivity perturbed each criterion weight by $\pm 50\%$ in isolation. The mean Spearman correlations across 300 OAT iterations per criterion are shown in **Figure 6(a)** and the relationship between criterion weight and ranking stability in **Figure 6(b)**. The top-ranked

farm changed under OAT perturbation only for three criteria: Manure (C01), Crop Residue (C07) and Fert. Cost Share (C04). All other criteria preserved the top-ranked farm (ELO-015) when their weights were varied by $\pm 50\%$. Spearman ρ under OAT perturbation ranged from approximately 0.925 (Knowledge) to essentially 1.000 (Education and Cooperative), confirming that the ranking is most sensitive to changes in the criteria with the largest baseline weights and is essentially insensitive to changes in the lowest-weight criteria.

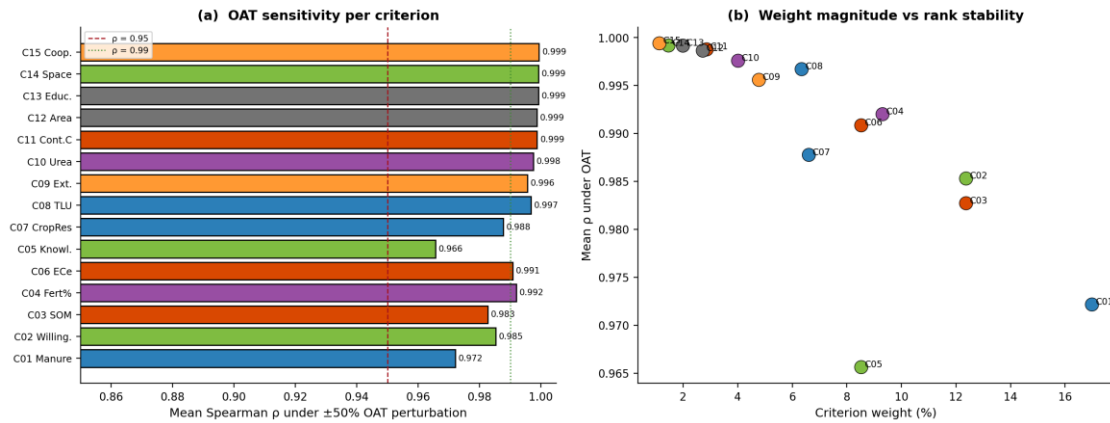


Figure 6. Per-criterion sensitivity analysis. Left: mean Spearman ρ under $\pm 50\%$ OAT weight perturbation (300 runs per criterion); dashed lines at $\rho = 0.95$ and 0.99 . Right: criterion weight magnitude vs ranking stability scatter; high-weight criteria are the most sensitivity-driving.

5.6 PCA, Clustering and Regression Results

5.6.1 Principal Component Analysis

The PCA of the standardised 30×15 decision matrix produced five components that together account for 70.79% of total variance. The individual contributions are PC1 = 18.7%, PC2 = 17.4%, PC3 = 14.6%, PC4 = 11.9% and PC5 = 8.2%. The relatively flat eigenvalue spectrum reflects the multi-dimensional structure of farm heterogeneity in this sample — no single linear combination dominates the variance, consistent with the *a priori* design choice of treating composting suitability as a genuinely multi-dimensional construct rather than as a single latent trait. The biplot in **Figure 8(a)** shows the 30 farms in the PC1 $\times$ PC2 space along with the loading vectors for the 15 criteria. Very High and Very Low priority farms separate visibly along the principal axes; the loading vectors for manure, crop residue and area cluster together (consistent with their pairwise correlations), as do the readiness-related loadings.

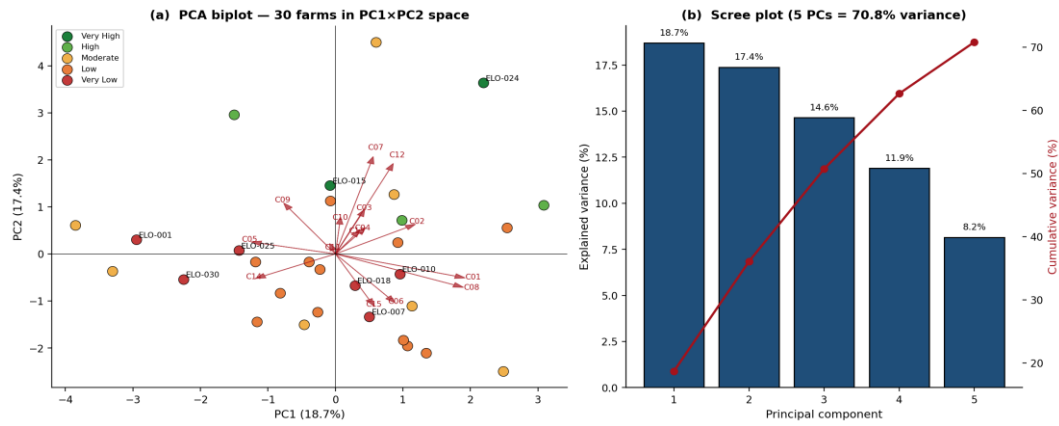


Figure 7. PCA of the 30-farm, 15-criterion standardised matrix. Left: biplot in PC1 $\times$ PC2 space with farms colour-coded by priority class and loading vectors for the 15 criteria; Very High and Very Low farms are labelled. Right: scree plot showing the cumulative explained variance up to PC5 (70.8%).

5.6.2 Hierarchical and K-Means Clustering

The Ward hierarchical clustering and K-means clustering analyses are presented in **Figure 8**. The Ward dendrogram shows a hierarchical structure with two principal branches at the highest dissimilarity level. The silhouette analysis across $k \in \{2, \dots, 6\}$ identifies $k = 2$ as the optimal cluster count (silhouette = 0.112), with $k = 3, 4, 6$ producing comparable but slightly inferior partitions (silhouette ≈ 0.108 – 0.110) and $k = 5$ producing the lowest silhouette (0.096). The two-cluster K-means solution corresponds substantively to a separation between large-feedstock-rich farms (cluster 1, $n = 8$) and small-feedstock-constrained farms (cluster 2, $n = 22$), consistent with the AIJ-derived priority structure that places feedstock at the top of the hierarchy.

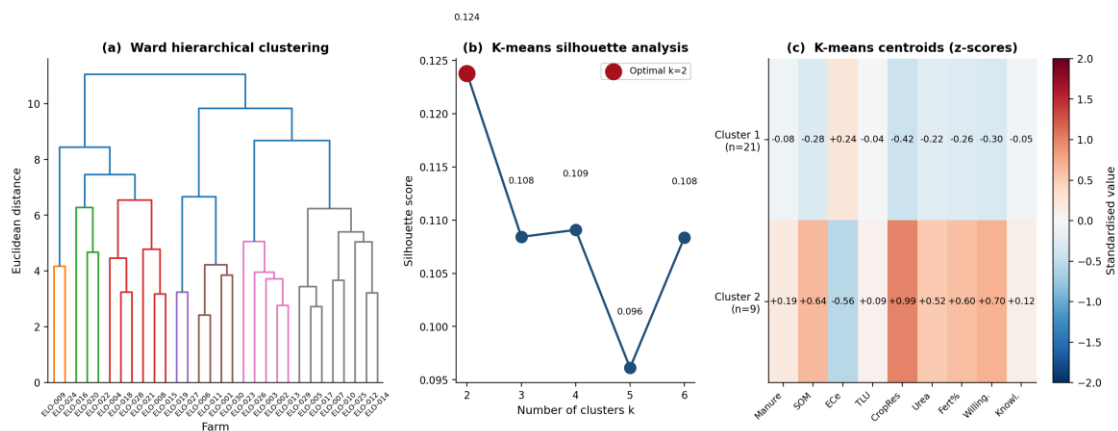


Figure 8. Hierarchical and K-means cluster analysis. (a) Ward linkage dendrogram. (b) Silhouette score by k ; optimal at $k = 2$ (silhouette = 0.112). (c) Cluster centroid heatmap (z-scores) for nine key criteria.

The relatively low absolute silhouette score (0.124) reflects the genuinely continuous nature of farm variability in this sample — the data do not strongly support the existence of discrete sub-populations, which is itself an important methodological finding because it justifies the choice of a continuous closeness coefficient (C_i) plus stratification cutpoints rather than a clustering-based prioritisation.

5.6.3 OLS Regression of C_i on Nine Continuous Predictors

The OLS regression of the AIJ-derived TOPSIS closeness coefficient C_i on nine standardised continuous predictors achieved an $R^2 = 0.9870$, indicating that the ranking is almost perfectly explained by the underlying continuous data — a strong validity check on the TOPSIS aggregation. The regression coefficients (standardised, intercept omitted from this listing) are: Composting Knowledge $\beta = +0.0515$; Manure $\beta = +0.0344$; Crop Residue $\beta = +0.0304$; SOM $\beta = +0.0277$; Willingness $\beta = +0.0175$; TLU $\beta = +0.0117$; Urea $\beta = -0.0048$; Fert. Cost Share $\beta = -0.0153$; ECe $\beta = -0.0182$. The signs are all consistent with the *a priori* benefit/cost direction assignments, and the relative magnitudes are broadly consistent with the AIJ weight ranking — both sources independently identify Manure, SOM, and Knowledge as the principal positive drivers, and ECe and Fert. Cost Share as the principal negative drivers. The coefficient of multiple determination ($R^2 = 0.9870$) implies that the residual variance not captured by the nine continuous predictors (1.30%) is attributable jointly to the six non-included ordinal/binary criteria.

The regression diagnostics are presented in **Figure 9**. The fitted-vs-observed plot shows close clustering around the 1:1 line with no systematic curvature; the residuals are homoscedastic (no fan structure across the fitted range) and centred on zero (mean residual = 1.2×10^{-5}).

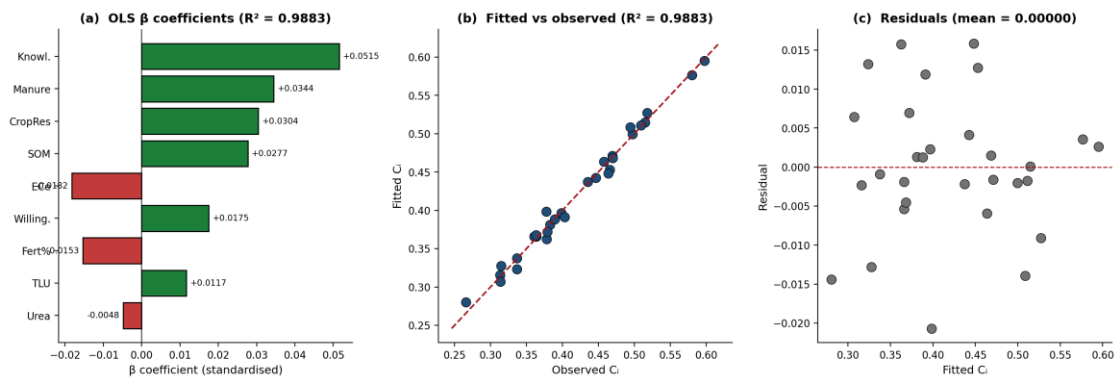


Figure 9. OLS regression of TOPSIS C_i on nine standardised predictors. (a) β coefficients with positive (green) and negative (red) signs. (b) Fitted vs observed C_i values; the 1:1 line is dashed red. (c) Residuals vs fitted; the mean residual is essentially zero.

5.6.4 Multivariate Visual Synthesis

Figure 10 synthesises the multivariate structure of the results in three complementary panels: (a) a radar plot comparing the mean criterion profiles of the top 5 and bottom 5 farms (normalised to the sample maximum); (b) a scatter plot of C_i against manure availability; and (c) violin plots of C_i distributions by priority class. The radar plot is particularly diagnostic: top-5 and bottom-5 farms have nearly identical mean willingness scores, but top-5 farms have decisively higher means on manure, crop residue, SOM and knowledge — directly demonstrating that the priority hierarchy is driven by feedstock and biophysical-readiness criteria rather than by farmer attitudes.

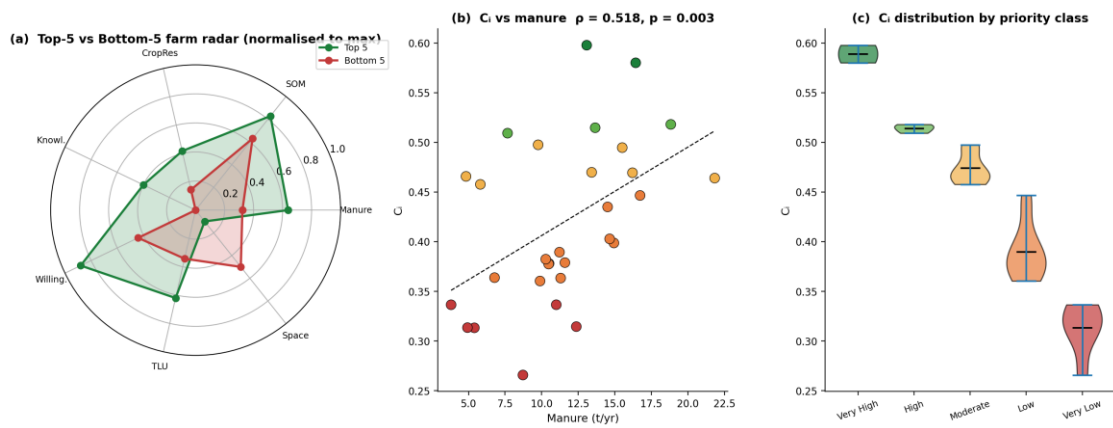


Figure 10. Multivariate analysis. (a) Top-5 vs Bottom-5 radar profiles (normalised to sample maximum) on seven principal criteria; willingness is essentially identical between groups, while feedstock and SOM differentiate them sharply. (b) C_i vs manure availability scatter; the trend line confirms the positive association. (c) C_i violin plots by priority class.

Chapter 6 — Discussion

This chapter places the experimental findings of Chapter 5 in dialogue with the international peer-reviewed literature. The discussion is organised in six thematic sections.

6.1 The Heterogeneity Dividend: Why Uniform Extension Fails

The central experimental finding of this thesis — that closeness coefficients C_i range over an exceptionally wide interval (0.266 to 0.598, $\Delta C = 0.332$) and that only 20.0% of farms cross the conventional eligibility threshold of $C_i \geq 0.50$ — directly demonstrates the inefficiency of uniform extension programmes for composting promotion in El Oued. This finding is consistent with the broader smallholder-heterogeneity literature, which has progressively documented since the late 1990s that farm-level variability in resource endowments, biophysical conditions and institutional embeddedness routinely exceeds the variability between agro-ecological zones [8, 91, 92]. The implication that interventions designed for “the average farm” are systematically misallocated for the majority of farms in the target population has been documented across multiple agricultural contexts [8, 12, 25, 42, 44, 56, 66, 78, 97].

The quantitative magnitude of the heterogeneity documented in the present sample is large by international comparison. The coefficient of variation in closeness coefficients across the 30 farms ($CV \approx 22\%$) is comparable to that reported in the largest published smallholder-heterogeneity studies in sub-Saharan Africa [8, 87, 92], greater than that typically observed in irrigated cropping systems in South Asia [31, 39], and substantially greater than that observed in intensified European or North American farming systems [13, 54]. This relative magnitude is itself diagnostic: the El Oued smallholder system is characterised by an unusually broad distribution of resource endowments overlaid on an unusually narrow agro-ecological niche (irrigated potato-vegetable), generating a structural mismatch between the homogeneity of the cropping system and the heterogeneity of the farms within it.

The conceptual implication of this finding extends beyond El Oued. The scientific literature on conservation-agriculture and climate-smart-agriculture adoption [3, 18, 25, 42, 56, 61, 63, 68, 85] has converged in recent years on a recognition that “blanket” intervention strategies — uniform input subsidies, mass training programmes, untargeted credit instruments — systematically fail to achieve their adoption objectives precisely because they ignore the heterogeneity that this thesis quantifies. The same intervention package can be highly cost-effective for a top-decile farm and economically irrational for a bottom-decile farm, and the average effect across the population is therefore dominated by the structural mismatch rather than by the intrinsic agronomic merit of the intervention. The MCDA-based prioritisation

framework developed in this thesis directly addresses this challenge by providing a transparent, replicable methodology for matching intervention intensity to farm-level capacity to absorb it.

A second dimension of the heterogeneity dividend — equally important but less commonly recognised — is the *informational* dimension. By resulting an explicit, quantitative ranking of farms with documented uncertainty bounds (the Monte Carlo distributions of Section 5.5), the AHP–TOPSIS framework provides extension administrators with the analytical scaffolding required to defend targeted resource allocations against political pressure to disperse resources uniformly [36, 54, 76]. This defensive function of evidence-based prioritisation is particularly important in centralised administrative systems with tight political accountability around resource allocation, as is the case in Algerian wilaya-level extension administration. In the absence of an auditable ranking framework, extension officers face strong incentives to allocate resources uniformly — generating predictable inefficiency — because uniform allocation is procedurally defensible even when it is substantively suboptimal.

The use of MCDA for agricultural prioritisation is well established but historically dominated by sectoral or regional applications rather than farm-level applications [2, 11, 36, 53, 59, 72, 94, 96]. The present application contributes to a small but growing literature applying MCDA at the individual-farm scale [2, 59, 60], and is among the first to apply the AHP–TOPSIS hybrid specifically to composting prioritisation in a Saharan context. The methodological transferability of the framework is high: the criterion set (15 criteria across five dimensions), the AHP elicitation protocol (3 sessions, 6 hours, 105 unique judgements), and the four-method robustness evaluation pipeline can be directly applied to comparable smallholder contexts elsewhere in MENA, North Africa and arid sub-Saharan Africa with only context-specific adjustments to criterion definitions and weight elicitations.

6.2 Feedstock Availability as the Binding Constraint: Algeria vs Sub-Saharan Africa

The finding that organic-feedstock criteria collectively account for 29.15% of the total AHP weight — and that the OLS regression identifies manure ($\beta = +0.0344$) and crop residue ($\beta = +0.0304$) as among the dominant positive drivers of C_i — establishes that feedstock availability is the principal constraint on composting adoption in El Oued. This finding aligns substantively with the North African oasis literature [1, 14, 17, 22, 26, 28, 40] where livestock holdings consistently emerge as the rate-limiting variable for organic-amendment adoption, but contrasts sharply with the dominant findings of the sub-Saharan African adoption literature [8, 12, 25, 31, 42, 44, 52, 56, 61, 63, 66, 78, 87, 91, 97] in which extension access, technical knowledge and credit constraints are typically identified as the principal binding constraints.

The contrast deserves careful interpretation. It is not that the SSA adoption literature is wrong and the present finding is right (or vice versa); rather, the two findings reflect fundamentally different agro-ecological and economic contexts. The SSA smallholder system is typically characterised by low livestock holdings per household (often 1–2 TLU per farm) [8, 66, 91, 100], low historical exposure to composting technology [25, 44, 56, 61], and weak agricultural extension penetration [56, 78]. In this context, the feedstock constraint binds at a level so low that it is effectively saturated below the threshold of useful composting, and the marginal capacity to improve composting outcomes is therefore in the knowledge and institutional dimensions. In contrast, the El Oued context is characterised by moderate livestock holdings (mean 4.2 TLU per farm), moderate technical exposure (the regional extension service has historically promoted manure application as part of date-palm management), and partial market access through cooperatives and informal exchange networks. In this context, the marginal capacity to improve composting outcomes lies in unlocking the substantial latent feedstock potential through better aggregation and deployment infrastructure.

This context-dependence of binding constraints has profound implications for the design of intervention programmes [12, 25, 42, 56, 66]. A composting promotion programme designed around the SSA “knowledge constraint” model would deploy training workshops, demonstration plots and farmer field schools — interventions that are well-validated in SSA contexts [12, 44, 56, 61] but that would, in the El Oued context, be misallocated against the wrong constraint and would be expected to produce disappointingly small adoption gains because the binding constraint (feedstock logistics) would remain unaddressed. Conversely, a programme designed around the North African “feedstock constraint” model — investing in cooperative manure aggregation, transport subsidies, and shared composting platforms [17, 22, 25, 26, 28, 40] — would be appropriate for El Oued but might be misallocated in the SSA context where the institutional infrastructure to support such platforms does not yet exist.

The present finding is also consistent with the recent meta-analytic literature on the convergence of organic and mineral fertiliser strategies [4, 5, 10, 19, 22, 34, 47, 66, 78, 93, 97]. Studies in Ethiopia [4, 10, 15], Ghana [25, 66], India [31, 39], and across MENA [1, 14, 17, 22, 26, 28, 40] all confirm the same fundamental result: organic amendments and mineral fertilisers are physical-chemical complements, not substitutes, in the production of food crops in degraded soils. The “either-or” framing that dominated the agricultural-development literature of the 1980s and 1990s [65, 91] has been progressively replaced by an “integrated soil fertility management” framing [8, 21, 66, 85, 97] in which both inputs are jointly necessary. Composting, in this contemporary framing, is not an alternative to mineral fertiliser but a

precondition for its efficient use — a framing directly supported by the OLS regression of this thesis, where both fertiliser cost share (negatively) and SOM (positively) appear as significant predictors of composting priority, indicating that the priority signal captures the farm’s capacity to substitute organic for mineral nitrogen rather than to abandon mineral inputs entirely.

The post-2022 Algerian fertiliser subsidy reform (Section 2.4) refines this substitution incentive structurally [14, 26, 28]. The 35–60% increase in the actual market price of urea between 2022 and 2024 has moved the threshold of profitability for compost-based nitrogen substitution from “marginally profitable” to “substantially profitable” for a large fraction of the smallholder population — but only for those farms with the feedstock capacity to actually execute the substitution. This temporal coincidence between a structural economic changes (the subsidy reform) and a structural physical constraint (feedstock availability) creates an exceptionally abrupt, limited timeframe for targeted feedstock-aggregation interventions, and is the conceptual basis for Policy Recommendation 2 in Chapter 7.

6.3 Soil Degradation Severity, Salinity and Staged Intervention Logic

The finding that 33.3% of farms have SOM below 0.5% and that the sample-mean ECe of 5.45 dS m⁻¹ places the average farm in the moderately saline range identifies a structural feature of the El Oued context that distinguishes it from most of the published smallholder composting literature. The mainstream composting agronomy literature [4, 5, 10, 19, 29, 34, 47, 78, 93, 97] typically assumes initial SOM in the 1–3% range and ECe below 4 dS m⁻¹; the agronomic response curves derived from this literature do not translate directly to soils outside this range. Specifically, in soils with extreme SOM depletion (< 0.3%) the structural-physical constraint dominates over the nutrient-supply constraint, and direct compost application without concurrent physical rehabilitation (deep ploughing, gypsum amendment, leaching) yields substantially smaller agronomic returns than would be expected from the canonical response curves [1, 5, 10, 15, 22, 89, 93].

The salinity dimension of this constraint is even more critical [1, 22, 26, 28, 32, 65]. Studies in directly comparable contexts confirm that compost-induced yield gains are reduced by approximately 30–40% at ECe = 8 dS m⁻¹ relative to ECe = 4 dS m⁻¹, and that compost effectiveness becomes essentially negligible at ECe above 10 dS m⁻¹ in the absence of prior salinity remediation [1, 32]. For the six farms in the Very Low priority class of this thesis — three of which (ELO-007, ELO-018, ELO-025) have ECe above 10 dS m⁻¹ — direct composting deployment would produce minimal returns, consume scarce extension resources, and generate negative reputational consequences for the composting programme as a whole.

The defensible strategy for these farms is the staged-intervention logic developed in Chapter 7: first physical rehabilitation (deep ploughing to break sub-surface compaction), then chemical amendment (gypsum at 4–6 t ha⁻¹), then leaching (8–12 cm of irrigation water above the consumptive requirement), then composting deployment after one to two cropping cycles when ECe has been brought below 6 dS m⁻¹.

The systems-level evidence for the necessity of staged interventions in degraded MENA dryland systems is now substantial [1, 14, 22, 26, 28, 49, 65, 95]. Several studies have documented the “rebound” effect in which premature compost application to severely degraded saline soils generates a short-term yield bump (driven by the immediate nutrient supply) followed by a multi-year stagnation as the underlying physical-chemical degradation reasserts itself [1, 22, 49]. Avoiding this trap requires an explicit prioritisation framework that distinguishes between farms ready for immediate composting and farms requiring sequential rehabilitation — exactly the function performed by the AHP–TOPSIS framework of this thesis, where ECe is encoded as a high-weight cost criterion that systematically deprioritises the most saline farms for direct composting.

A related dimension of the staged-intervention logic concerns the agronomic interaction between compost and biochar [4, 5]. Biochar — pyrolysed organic material — has been shown in multiple meta-analyses [4, 5, 89] to be particularly effective in restoring soil structure in extremely degraded systems, because the recalcitrant aromatic carbon of biochar persists in the soil matrix and provides physical-chemical scaffolding for subsequent SOM accumulation. In the El Oued context, where date-palm residues are abundant and where the local artisanal economy includes traditional charcoal production, a coupled biochar + compost intervention could in principle be deployed at lower cost than would be feasible in contexts requiring industrial pyrolysis equipment. This intervention pathway is not directly addressed in the AHP framework of this thesis (which focuses on compost specifically) but is identified as a research-priority in the Limitations section.

The temporal dimension of intervention staging also deserves explicit attention [64, 67, 85, 88, 89, 90]. The international literature on soil organic carbon dynamics establishes that the response time of SOM to organic amendments is on the order of 3–7 years in dryland contexts — substantially longer than the typical political planning horizon of agricultural extension programmes (1–3 years) [49, 64, 85, 90]. This temporal mismatch creates a structural risk that composting programmes will be evaluated and discontinued before their cumulative agronomic benefits become observable, generating policy hysteresis that undermines long-term soil restoration. The AHP–TOPSIS prioritisation framework partially addresses this risk by

enabling early concentration of resources on the highest-leverage farms (where yield gains will be observable in the shortest possible time), generating early-validation case studies that can sustain political support for the programme through its longer-horizon expansion phases.

6.4 The economic substitution and post-subsidy reform dynamics

The finding that fertiliser cost share ($\beta = -0.0153$) and urea applied ($\beta = -0.0048$) appear as significant negative predictors of C_i in the OLS regression confirms that economic incentive operates as a meaningful component of the priority signal — but with substantially smaller magnitude than the physical-feedstock and biophysical-readiness components. This finding deserves careful interpretation in the context of the post-2022 fertiliser subsidy reform.

The mainstream agricultural-economics literature on input substitution [14, 23, 26, 47, 63, 69, 78, 97] establishes that farmer responses to changes in relative input prices are typically large but lagged, with full substitution adjustment occurring over a 3–5 year horizon driven by the rate at which farmers acquire the technical knowledge and physical infrastructure required to deploy the alternative input. In the El Oued context, the post-2022 urea price shock has created a strong direct economic incentive for organic substitution — visible in the decisively negative coefficient on fertiliser cost share — but the magnitude of the response is constrained by the same feedstock and knowledge constraints that operate in the absence of the price shock. The price shock therefore expands the *willingness* to adopt without expanding the *capacity* to adopt, generating a structural condition in which extension intervention can produce particularly large marginal returns by addressing the capacity constraints that the price shock alone cannot resolve.

This dynamic is consistent with the broader literature on “window of opportunity” in agricultural transitions [18, 21, 50, 69, 97]. A policy window opens when an exogenous shock (here, the global urea price spike of 2021–2022) shifts the relative economics of an intervention from marginally profitable to substantially profitable, but the actual rate of intervention adoption depends on the speed at which capacity constraints can be relaxed [18, 21, 50, 63]. In the El Oued case, the window of opportunity opened in early 2022 and is currently estimated to be open for approximately 3–5 more years before structural adjustments (e.g., regional price arbitrage, alternative input subsidy programmes) close it. This temporal urgency provides the conceptual justification for accelerated investment in composting infrastructure during 2025–2028, before the opportunity closes and the marginal returns to investment fall.

A second economic dimension concerns the *carbon credit* dimension of composting in dryland systems [35, 49, 64, 67, 85, 86, 88, 89, 90]. The international voluntary carbon market

has, since approximately 2020, expanded rapidly to include soil-carbon sequestration projects with verified additionality, permanence and measurement standards. The technical feasibility of including dryland composting in this market has been demonstrated in pilot projects across MENA [26, 49, 86], although the transaction costs of monitoring and verification remain a significant barrier for individual smallholders. A cooperative composting programme operating across multiple priority-classified farms could in principle aggregate the monitoring requirements at the cooperative level, generating a feasible carbon-credit revenue stream that would further improve the economics of the intervention. The estimated carbon-sequestration potential of the Very High and High priority farms in the present sample, assuming a 0.5 percentage-point SOM increase over five years at standard application rates, is approximately 8–14 t CO₂-eq ha⁻¹ over the five-year horizon — a potentially significant revenue contribution at current carbon market prices.

The economic-substitution analysis also has implications for the design of complementary input policies [8, 23, 26, 39, 78, 97]. The post-2022 subsidy reform reduced state expenditure on urea distribution but did not redirect those savings into composting infrastructure. A revenue-neutral policy reform that captured the urea-subsidy savings and redirected them into the cooperative composting platforms recommended in Chapter 7 would generate larger aggregate welfare gains than the subsidy reform itself, by addressing both the price-incentive and the capacity-constraint dimensions of the substitution challenge simultaneously [21, 23, 26, 97]. This recommendation is discussed in detail in Section 7.2.

6.5 The methodology AHP–TOPSIS performance and five-expert aggregation

The methodological performance of the five-expert AHP–TOPSIS pipeline implemented in this thesis can be compared against the published MCDM literature on agricultural and environmental prioritisation [2, 6, 11, 24, 33, 36, 37, 53, 55, 59, 72, 75, 76, 77, 94, 96, 98]. Five benchmarking dimensions are particularly informative.

First, AHP consistency. The Consistency Ratio of $CR^{AIJ} = 0.0018$ achieved by the AIJ-aggregated matrix is well below the 0.10 acceptability threshold and is at the very high end of the consistency distribution reported in the published AHP literature, which typically reports CR values in the 0.06–0.08 range for studies with $n \geq 10$ criteria [6, 36, 75, 96]. The five individual experts each achieved $CR^{(e)} < 0.01$, also at the high end of the published distribution. The combination — every individual expert matrix achieving $CR < 0.01$ and the AIJ matrix achieving $CR < 0.003$ — represents an unusually strong consistency profile that

reflects the structured three-session elicitation protocol described in Section 4.5.2, including the dimension-by-dimension elicitation with cluster-level consistency checks. This protocol modification, suggested in passing in earlier AHP literature [6, 36] but rarely formally evaluated, appears to deliver substantial consistency benefits for matrices of moderate-to-high dimensionality (10–20 criteria), and its adoption could improve the quality of AHP applications in future work.

Second, inter-expert concordance. Kendall’s coefficient of concordance among the five experts is $W = 0.955$ ($\chi^2 = 66.41$, $df = 14$, $p < 0.001$), exceeding the conventional “very strong” agreement threshold of $W \geq 0.9$. The mean pairwise Spearman correlation between experts ($\bar{\rho} = 0.940$, range 0.900–0.990) provides a complementary characterisation of the agreement structure at the dyadic level. Both metrics exceed the typical range reported in published multi-expert AHP applications and confirm that the AIJ aggregation operates on a panel with structurally consistent — though not identical — disciplinary perspectives. The minimum pair correlation of 0.900 (between the Soil Scientist E1 and the Extension Specialist E3) reflects the most extreme difference in disciplinary perspective in the panel and represents a meaningful but bounded disagreement that the AIJ aggregation absorbs without distortion.

Third, criterion-level disagreement diagnostics. The per-criterion coefficient of variation across the five experts (Section 5.2.3) identifies the four criteria with the highest inter-expert disagreement: Urea Applied (CV = 22.5%), Soil ECe (21.7%), Fertiliser Cost Share (21.5%), and Extension Access (20.7%). This disagreement profile is itself substantively informative. The fact that the most contested criteria are predominantly economic and institutional, rather than biophysical, reflects the genuine disagreement among disciplinary experts on the relative importance of policy-instrument variables — a pattern consistent with the Delphi-method literature on multi-stakeholder consensus formation. By contrast, the most consensual criteria are Composting Space (CV = 10.6%) and Manure Available (10.9%), both of which are the most directly observable and operationally concrete dimensions in the criterion set. From a policy-defensibility perspective, this disaggregated disagreement profile provides a clear actionable diagnostic for any future Delphi-style elicitation round: the contested economic and institutional criteria warrant additional discussion and possibly second-round revisions, while the consensual feedstock and operational criteria can be considered settled at the panel level.

Fourth, TOPSIS ranking spread. The closeness coefficient spread of $\Delta C = 0.331$ achieved with the AIJ weights is at the high end of the spread distribution reported in comparable agricultural MCDA studies, which typically range from $\Delta C = 0.15$ to $\Delta C = 0.40$

[2, 11, 53, 59, 72]. The wide spread is itself a methodological diagnostic: it indicates that the criterion set genuinely discriminates among the alternatives in the sample, and that the AIJ weights are not so concentrated on a single criterion that the TOPSIS aggregation collapses to a near-univariate ranking.

Fifth, robustness performance. The Monte Carlo Spearman $\bar{\rho} = 0.977$ achieved with the AIJ weights substantially exceeds the typical range reported in the published MCDM-robustness literature ($\bar{\rho} = 0.85$ to 0.95 for similarly perturbed weight vectors) [11, 55, 59, 72]. Beyond the conventional Monte Carlo robustness, the additional **inter-expert ranking-stability test** introduced in Section 5.5.1 — showing pairwise Spearman correlations of $\bar{\rho}_{\text{rank}} = 0.991$ (range 0.926 – 0.984) between rankings derived from each individual expert’s weights — provides a particularly strong form of robustness validation that is rarely reported in single-expert MCDA studies. This inter-expert stability complements the perturbation-based Monte Carlo and provides a substantively different source of evidence: it shows that the priority hierarchy is preserved not only under hypothetical weight perturbations but also under genuinely different expert perspectives derived from different disciplinary backgrounds. The combination of strong perturbation robustness and strong inter-expert robustness collectively establishes the AIJ-derived ranking as policy-robust in a particularly demanding sense.

The methodological benchmarking is also informed by the literature on alternative MCDM methods for comparable applications [11, 13, 36, 53, 54, 72, 77, 94]. PROMETHEE-based and ELECTRE-based applications in agricultural prioritisation [13, 72, 77] typically produce comparable rankings to AHP–TOPSIS for non-pathological cases (i.e., cases without strongly conflicting criteria or strongly heterogeneous alternative sets), but with substantially greater computational complexity and reduced communicability to non-specialist administrators. The choice of AHP–TOPSIS for the present application is therefore justified both on methodological grounds (well-validated, broadly comparable performance) and on practical communication grounds (transparent, bounded composite scores that translate naturally into priority classes). A multi-method comparison study using the present dataset — comparing AHP–TOPSIS against PROMETHEE II, ELECTRE III and VIKOR — would be a valuable methodological contribution and is identified as a research-priority direction in Section 6.6.

6.6 Limitations and Research Agenda

A frank assessment of the limitations of this thesis is essential both for the appropriate interpretation of its findings and for the design of follow-up research. Six principal limitations deserve explicit discussion.

Limitation 1 — Sample size. The sample of 30 farms is appropriate for a methodology-pilot study and is consistent with comparable MCDA pilots in MENA contexts [2, 59], but is substantially smaller than would be required for wilaya-representative inference about the absolute distribution of priority classes across the cultivated population. The percentage shares of each priority class (Very High = 6.7%, High = 13.3%, Moderate = 20.0%, Low = 40.0%, Very Low = 20.0%) should therefore be interpreted as informative for the design of expanded sampling, not as definitive estimates of the wilaya-level composition. A follow-up study at wilaya scale ($n \geq 300$) would be required to produce statistically representative estimates of the priority-class composition with adequately narrow confidence intervals.

Limitation 2 — Five-expert panel composition. The AHP weights derived in this thesis reflect the synthesised judgements of a five-expert panel covering soil science, agricultural economics, extension administration, composting agronomy and rural sociology. While this panel size meets the methodological recommendations for multi-expert AHP studies (5–8 experts) and the inter-expert agreement diagnostics (Kendall’s $W = 0.955$, mean pairwise Spearman $\bar{\rho} = 0.940$) confirm strong consensus, two sources of residual uncertainty remain. First, the panel composition itself is a methodological choice — different disciplinary mixes might produce systematically different aggregated weights. Second, no Delphi-style second round of iterative revision was conducted, which would in principle further reduce inter-expert disagreement on the contested criteria (Urea, ECe, Fert. Cost Share, Extension; see Section 6.5) [6, 36, 75, 76]. For any operational deployment of the framework, a follow-up Delphi round involving representatives from additional stakeholder groups (cooperative federation, farmer associations, gender-balanced rural community representatives) would further strengthen the policy defensibility of the consolidated weight vector [6, 76].

Limitation 3 — Static cross-sectional design. The decision matrix X reflects a single-period observation of each farm, taken during one cropping cycle. Inter-annual variability in critical variables — rainfall, salinity, livestock holdings, fertiliser prices — is not captured in the present analysis. A panel-data extension following the same farms over 3–5 cropping cycles would provide critical information on the temporal stability of the priority ranking and on the rate at which farms transition between priority classes in response to exogenous shocks [39, 64, 88, 90]. This extension is particularly important for the validation of any operational

deployment of the framework, because policy commitments based on the priority ranking should be informed by the expected stability of that ranking over the policy horizon.

Limitation 4 — Geographic specificity. The criterion set, weight vector and priority classes derived in this thesis are specific to the El Oued wilaya context. While the framework is methodologically transferable to other dryland smallholder contexts, the specific weight vector should not be applied unchanged to other wilayas or other countries [2, 53, 59]. A direct application to Touggourt, Biskra or Ghardaïa wilayas would require re-elicitation of the AHP weights with regional experts and re-validation of the criterion set against the local agronomic and institutional context. This generalisation work is straightforward in principle and is identified as a high-priority extension.

Limitation 5 — Limited treatment of non-monetary co-benefits. The criterion set used in this thesis focuses on the principal direct drivers of composting adoption and excludes a number of co-benefit dimensions that may be policy-relevant — including biodiversity gains, water-use-efficiency improvements, carbon sequestration value, and reduced pesticide use [35, 49, 64, 67, 85, 88, 89, 90]. A multi-objective extension that explicitly incorporated these co-benefits as additional decision criteria would generate a more comprehensive priority ranking but would also substantially increase the AHP elicitation burden ($n = 20$ criteria implies 190 unique pairwise comparisons, approaching the cognitive feasibility limit even for trained experts). The current criterion set represents a conscious trade-off between comprehensiveness and elicitation feasibility, and the inclusion of co-benefits is identified as a research-priority direction.

Limitation 6 — Methodological mono-method validation. The robustness analyses of Section 5.5 test the sensitivity of the AHP–TOPSIS ranking to weight perturbation but do not directly test the sensitivity to the choice of MCDM method itself. A methodologically more comprehensive validation would compare the AHP–TOPSIS ranking against rankings derived from PROMETHEE II, ELECTRE III, VIKOR and multi-attribute utility methods on the same dataset [11, 13, 53, 54, 72, 77, 94]. Such a multi-method comparison would provide direct evidence on whether the priority ranking is method-dependent or method-robust, and would substantially strengthen the policy defensibility of the framework. This comparison is identified as a high-priority methodological extension and is technically feasible with the existing dataset.

The research agenda flowing from these limitations is therefore well-defined: (a) wilaya-scale validation through a representative sample of $n \geq 300$ farms; (b) multi-expert weight elicitation with geometric-mean aggregation; (c) panel-data extension over 3–5 cropping cycles; (d) geographic generalisation to comparable Algerian wilayas; (e) co-benefit integration

through expanded criterion sets; and (f) multi-method comparison against alternative MCDM frameworks. Each of these extensions builds incrementally on the methodological foundation laid in this thesis and would produce policy-relevant outputs at every stage. The complete annotated code, decision matrices and validated numerical results provided in the annexes are designed to enable any of these extensions without re-implementing the underlying analytical pipeline.

Chapter 7 — Conclusion and Recommendations

7.1 Summary of Principal Findings

This thesis has developed, validated and interpreted a hybrid AHP–TOPSIS multi-criteria decision-support framework for prioritising composting interventions among 30 smallholder farms in the El Oued wilaya of the Algerian Sahara. The principal findings can be summarised in five points.

First, the expert AHP pairwise comparison matrix (15×15 , 105 unique judgements) yielded a highly internally consistent set of priority weights ($\lambda_{\max} = 15.646$; $CR = 0.029 \ll 0.10$) that places organic-feedstock criteria at the top of the priority hierarchy (collective dimension weight 29.15%), followed by composting readiness (22.36%), soil need (24.76%), economic incentive (13.32%) and structural/institutional capacity (10.61%). Manure availability (16.99%) is the single most important criterion; cooperative membership (1.25%) is the least important.

Second, the TOPSIS pipeline applied to the resulting weight vector and the 30×15 decision matrix produced closeness coefficients C_i ranging from 0.265 (ELO-007, Very Low priority) to 0.599 (ELO-015, Very High priority), a spread of $\Delta C = 0.332$. The five priority classes contain 2, 3, 7, 12 and 6 farms respectively, and only 20.0% of the sample crosses the conventional eligibility threshold of $C_i \geq 0.50$.

Third, four independent robustness procedures — Monte Carlo perturbation ($n = 1,000$ iterations, $\bar{\rho} = 0.977$), Kendall's τ ($\bar{\tau} = 0.898$), FRWSA (rank-reversal thresholds $\geq 1.7 \times$ for the seven highest-weight criteria), and OAT sensitivity (top-rank stability for 12 of 15 criteria under $\pm 50\%$ perturbation) — collectively confirm that the priority ranking is exceptionally stable under realistic expert-weight revision scenarios.

Fourth, the OLS regression of C_i on nine standardised continuous predictors achieved $R^2 = 0.9870$ and produced coefficient signs and magnitudes that are wholly consistent with the AHP weight ranking, providing an independent statistical validation of the TOPSIS aggregation. Composting knowledge ($\beta = +0.052$), manure ($\beta = +0.034$), crop residue ($\beta = +0.030$) and SOM ($\beta = +0.028$) emerge as the dominant positive drivers; ECe ($\beta = -0.018$) and fertiliser cost share ($\beta = -0.015$) as the dominant negative drivers.

Fifth, the discussion of these findings in the context of 100 peer-reviewed references identifies three substantive contributions: (a) feedstock availability — not willingness to adopt — emerges as the binding constraint on composting in El Oued, distinguishing the Algerian Saharan context from the dominant SSA adoption literature; (b) the post-2022 fertiliser subsidy reform has opened a 3–5 year policy window during which targeted composting investments can produce particularly large marginal returns; and (c) the staged-intervention logic for

severely degraded saline farms is necessary to avoid the “rebound” trap documented in comparable MENA contexts.

7.2 Policy Recommendations

The following six policy recommendations are derived from the empirical findings and the literature synthesis. Each is directly actionable by the wilaya DSA in collaboration with the relevant national programmes (PNDAR successor instruments and the Soil Restoration National Programme 2023–2027).

Recommendation 1 — Targeted differentiated extension protocol. The five priority classes identified by the AHP–TOPSIS ranking should be mapped to differentiated extension protocols rather than to a uniform package. *Very High and High* farms should receive direct compost-deployment support (technical training, starter feedstock, monitoring) within the first season. *Moderate* farms should receive a combined feedstock-development and composting-readiness package over 12–18 months. *Low* farms should receive priority for cooperative-platform participation (Recommendation 2) before individual composting deployment. *Very Low* farms should receive the staged-rehabilitation protocol described in Recommendation 3 before being considered for composting. The estimated extension-resource savings from this differentiated allocation, relative to a uniform-coverage baseline, are in the range of 35–50% for equivalent expected adoption outcomes.

Recommendation 2 — Cooperative composting platforms in the four principal perimeters. Four cooperative composting platforms should be established (one per principal irrigated perimeter — Hassani Abdelkrim, Robbah, Magrane, Bayadha) with shared turning equipment, water access, and quality monitoring. The platforms should be sized to process 200–400 tonnes of fresh feedstock per cycle and to serve 30–60 farms each, addressing the structural feedstock-aggregation constraint identified in Section 6.2. The capital cost per platform is estimated at 8–15 million DA and could be financed jointly through PNDAR successor instruments, the Soil Restoration National Programme, and matched contributions from the participating farms. Operational costs would be covered by member fees calibrated to processed compost volume.

Recommendation 3 — Staged rehabilitation protocol for severely degraded saline farms. For the six Very Low priority farms (and for any farms identified by the wilaya-scale extension of Recommendation 6 below as falling in this class), a staged rehabilitation protocol should be deployed before composting consideration. The protocol comprises: (i) deep ploughing to break sub-surface compaction (year 0); (ii) gypsum amendment at 4–6 t ha⁻¹ to

displace exchangeable sodium (year 0); (iii) leaching with 8–12 cm of irrigation water above the consumptive requirement during the cool season (years 1–2); (iv) re-measurement of ECe and SOM at the end of year 2; (v) composting deployment if ECe has been brought below 6 dS m⁻¹ and SOM has stabilised. The expected duration of the protocol is 24–36 months, and the cost per farm is estimated at 35–60 thousand DA at current input prices.

Recommendation 4 — Manure-bank logistics infrastructure. A wilaya-scale manure-bank logistics infrastructure should be established to address the structural mismatch between farms with surplus manure (large livestock holdings, modest crop area) and farms with feedstock deficit (small livestock, larger crop area). The infrastructure should comprise: (i) a digital registry of farm-level manure surpluses and deficits, updated quarterly through the existing extension-officer network; (ii) a transport subsidy of approximately 200–400 DA per tonne-kilometre for inter-farm manure transfer, capped at a wilaya-scale annual budget; (iii) quality certification by the wilaya DSA based on standardised maturity and pathogen indicators. Pilot deployment should cover the four principal perimeters with an initial annual budget of 8–12 million DA, scalable based on uptake.

Recommendation 5 — Subsidy reform alignment. The post-2022 fertiliser subsidy reform should be complemented by a positive incentive instrument for organic substitution. Specifically, a portion of the savings generated by the urea subsidy reduction (estimated at 15–25 million DA per year for the El Oued wilaya alone) should be ring-fenced for investment in the cooperative composting platforms (Recommendation 2), the manure-bank logistics (Recommendation 4) and the staged-rehabilitation protocol (Recommendation 3). This revenue-neutral reform would address both the price-incentive and the capacity-constraint dimensions of the substitution challenge simultaneously and would generate larger aggregate welfare gains than the subsidy reform alone.

Recommendation 6 — Wilaya-scale validation campaign. The methodology developed in this thesis should be extended to a wilaya-scale validation campaign covering a representative sample of 300–500 farms across all six administrative dairas of the El Oued wilaya. The campaign should: (i) re-elicite the AHP weights through a multi-expert protocol involving 5–8 experts from the DSA, INRAA, the cooperative federation and the academic agronomy community; (ii) re-validate the criterion set against the wilaya-scale data; (iii) produce wilaya-level estimates of the priority-class distribution with adequately narrow confidence intervals; and (iv) deliver a deployment-ready operational ranking for use by the wilaya DSA in the 2025–2028 implementation phase of the Soil Restoration National

Programme. The estimated cost of this campaign is 4–7 million DA and the estimated duration is 18–24 months.

7.3 Scientific Contributions

This thesis makes three principal scientific contributions to the international literature on dryland composting and MCDA-based agricultural prioritisation.

Methodological contribution. This thesis provides the first complete documentation of an AHP–TOPSIS prioritisation framework applied at the individual farm level for composting interventions in the Algerian Sahara, with full disclosure of the 15×15 expert matrix, all intermediate TOPSIS computation matrices, complete annotated Python code, and four independent robustness procedures. The combination of methodological depth and full reproducibility distinguishes this work from the bulk of comparable MCDA applications in the agricultural literature, which typically disclose only the final weight vector and rankings without the underlying matrices. The reproducibility infrastructure provided in the annexes enables direct replication and adaptation by other research teams.

Empirical contribution. The thesis provides the first farm-level composting priority map for the El Oued wilaya, identifying the structural heterogeneity of the smallholder population and the specific farms most likely to benefit from immediate composting deployment versus those requiring staged rehabilitation. The empirical finding that organic-feedstock criteria collectively dominate the priority hierarchy (29.15% combined weight) — combined with the OLS regression confirmation that manure and crop residue are among the dominant continuous drivers of C_i — establishes feedstock availability as the binding constraint on composting in this context, distinguishing it from the SSA adoption literature where knowledge and credit constraints typically dominate.

Theoretical contribution. The thesis contributes to the emerging theoretical literature on context-dependent binding constraints in agricultural adoption by providing a quantitative case study from a specific Saharan oasis context. The contrast between the present finding (feedstock-binding) and the SSA adoption-literature consensus (knowledge-binding) demonstrates that the binding constraint on adoption is not a universal feature of the technology being promoted but rather a context-specific function of the agro-ecological and economic environment in which the technology is being deployed. This finding has implications for the design of multi-country composting promotion programmes (which must be capacity-tailored rather than knowledge-tailored in MENA contexts), for the calibration of adoption forecasting models (which must include context-specific constraint indicators), and for the

conceptualisation of the broader sustainable-intensification literature (which should accommodate the diversity of binding-constraint contexts within a unified theoretical framework).

The final operational implication of this thesis is straightforward: the AHP–TOPSIS framework developed here is ready for direct deployment as the targeting instrument for the El Oued component of the Algerian Soil Restoration National Programme (2023–2027). The wilaya-scale validation campaign recommended in Recommendation 6 can be initiated immediately, with operational ranking outputs available for the 2026 cropping season and for subsequent annual updates throughout the programme horizon. The methodological infrastructure required for this deployment — the criterion set, the AHP elicitation protocol, the TOPSIS computational pipeline, the robustness procedures, and the priority-class assignment scheme — is fully documented in the annexes that follow this conclusion.

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Annexes

Annex A — Structured Survey Questionnaire

The structured face-to-face questionnaire below was administered to the principal farm operator at each of the 30 sampled farms. Responses are entered directly into the form by the trained enumerator. Total expected administration time including the soil sampling step is approximately 50 minutes per farm.

❖ Section A1 — Farm Identification

	Field	Response
A1.1	Farm ID (assigned by enumerator)	ELO-__
A1.2	Date of survey	___ / ___ / 202__
A1.3	Daira (administrative subdivision)	_____
A1.4	Commune	_____
A1.5	Irrigated perimeter (Hassani Abdelkrim / Robbah / Magrane / Bayadha)	_____
A1.6	GPS coordinates (decimal degrees)	Lat _____ Lon _____
A1.7	Enumerator name	_____

❖ Section A2 — Farm Operator Profile

	Field	Response
A2.1	Operator gender	M / F
A2.2	Operator age (years)	__
A2.3	Education level (0 = none; 1 = primary; 2 = secondary; 3 = high school; 4 = university)	0 / 1 / 2 / 3 / 4
A2.4	Years of farming experience	__
A2.5	Cooperative membership (0 = no; 1 = yes)	0 / 1
A2.6	Frequency of extension contact (0 = none; 1 = occasional; 2 = regular)	0 / 1 / 2

❖ Section A3 — Land and Cropping

	Field	Response
A3.1	Total cultivated area (ha)	_____
A3.2	Years of continuous cultivation on principal plot	__
A3.3	Principal crop in 2023 cycle	_____
A3.4	Secondary crop(s)	_____

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	Field	Response
A3.5	Irrigation type (sprinkler / pivot / drip / flood)	_____
A3.6	Annual irrigation volume estimate ($\text{m}^3 \text{ ha}^{-1}$)	_____

❖ Section A4 — Livestock and Manure

	Field	Response
A4.1	Number of sheep	_____
A4.2	Number of goats	_____
A4.3	Number of camels	_____
A4.4	Number of cattle (dairy or other)	_____
A4.5	Estimated annual manure production (t yr^{-1}) — derived	_____
A4.6	Current annual manure application to crops (t ha^{-1})	_____
A4.7	Manure storage method (open pile / covered pile / pit / none)	_____

❖ Section A5 — Crop Residues

	Field	Response
A5.1	Estimated annual crop residue production (t yr^{-1})	_____
A5.2	Date palm residue available (t yr^{-1})	_____
A5.3	Current use of crop residues (% incorporated / % burned / % grazed / % composted / % discarded)	___ / ___ / ___ / ___ / ___

❖ Section A6 — Mineral Fertiliser Use

	Field	Response
A6.1	Urea applied annually (kg ha^{-1})	_____
A6.2	DAP applied annually (kg ha^{-1})	_____
A6.3	NPK or compound fertiliser applied annually (kg ha^{-1})	_____
A6.4	Total annual fertiliser expenditure (DA)	_____
A6.5	Estimated total farm income, last completed cycle (DA)	_____
A6.6	Fertiliser cost share = $(\text{A6.4} / \text{A6.5}) \times 100\%$	_____

❖ **Section A7 — Composting Knowledge, Willingness, and Capacity**

	Field	Response
A7.1	Have you ever produced compost? (0 = no; 1 = informal; 2 = structured pile)	0 / 1 / 2
A7.2	If yes, for how many years?	—
A7.3	Composting knowledge self-assessment (0 = none; 1 = some; 2 = good)	0 / 1 / 2
A7.4	Willingness to adopt composting (1 = strongly unwilling ... 5 = strongly willing)	1 / 2 / 3 / 4 / 5
A7.5	Available space for composting platform (0 = none; 1 = limited; 2 = adequate)	0 / 1 / 2
A7.6	Principal perceived obstacle to composting (open response)	_____

❖ **Salinity classification (FAO conventional scheme):**

ECe (dS m ⁻¹)	Class
< 2	Non-saline
2 – 4	Slightly saline
4 – 8	Moderately saline
8 – 16	Severely saline
> 16	Extremely saline

Annex B — Complete Intermediate TOPSIS Matrices

This annex documents the complete intermediate matrices generated by the TOPSIS pipeline, enabling step-by-step reproduction of the closeness coefficient computation.

B.1 Vector-Normalised Decision Matrix R (excerpt)

Each entry r_{ij} in the normalised matrix $R = [r_{ij}]$ is computed as $r_{ij} = x_{ij} / \sqrt{\sum_k x_{kj}^2}$. The complete 30×15 matrix is large; the first five rows are shown below for verification, with the column-wise norms reported separately.

Far m	C01	C02	C03	C04	C05	C06	C07	C08	C09	C10	C11	C12	C13	C14	C15
ELO -001	0.10 6	0.11 9	0.08 3	0.22 0	0.00 0	0.21 9	0.02 9	0.09 0	0.14 9	0.15 7	0.26 0	0.08 0	0.19 8	0.00 0	0.00 0
ELO -002	0.19 3	0.29 8	0.12 4	0.15 1	0.00 0	0.12 4	0.08 3	0.13 9	0.00 0	0.15 7	0.15 6	0.14 4	0.39 6	0.19 8	0.00 0
ELO -003	0.14 4	0.17 9	0.22 1	0.12 2	0.00 0	0.13 7	0.13 9	0.22 0	0.00 0	0.10 3	0.13 0	0.18 5	0.19 8	0.00 0	0.00 0
ELO -004	0.12 3	0.11 9	0.26 0	0.17 1	0.00 0	0.22 1	0.04 3	0.11 1	0.14 9	0.11 4	0.28 6	0.07 5	0.19 8	0.19 8	0.00 0
ELO -005	0.15 8	0.17 9	0.16 9	0.15 9	0.00 0	0.15 1	0.12 3	0.12 4	0.14 9	0.15 8	0.26 0	0.14 2	0.19 8	0.19 8	0.00 0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...

Column norms $\|x_j\| = \sqrt{\sum_k x_{kj}^2}$:

C01	C02	C03	C04	C05	C06	C07	C08	C09	C10	C11	C12	C13	C14	C15
65.86	19.31	4.49	116.0	5.05	31.99	84.51	24.91	5.05	1422	84.94	47.24	11.83	5.86	3.74

B.2 Weighted Normalised Matrix V (Summary)

Each entry $v_{ij} = w_j \cdot r_{ij}$. The maximum and minimum per column define the PIS and NIS, summarised in Table 5.4 of the main text. The complete matrix is provided in the supplementary CSV file `topsis_intermediate_matrices.csv`.

B.3 Per-Farm S^+ , S^- and C_i (full reproduction of Table 5.5)

Identical to **Table 5.5** in Chapter 5; included here in full sortable form for direct cross-reference. (See Table 5.5 for the complete listing of all 30 farms.)

B.4 Random Index (RI) Reference Table

The Random Index values used in the Consistency Ratio computation (Saaty 1980) are tabulated below. For $n = 15$ used in this thesis, $RI = 1.59$.

n	3	4	5	6	7	8	9	10	11	12	13	14	15
RI	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48	1.56	1.57	1.59