LatIA. 2024; 2:330
doi: 10.62486/latia2025330
ISSN: 3046-403X

ORIGINAL

AI Application in Climate-Smart Agricultural Technologies: A Synthesis Study

Aplicación de la Inteligencia Artificial en Tecnologías Agrícolas Climáticamente Inteligentes: Un Estudio de Síntesis

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Cite as: Chavula P, Kayusi F, Lungu G, Mambwe H, Uwimbabazi A. AI Application in Climate-Smart Agricultural Technologies: A Synthesis Study. LatIA. 2024; 2:330. https://doi.org/10.62486/latia2025330

Submitted: 27-05-2024 **Revised:** 17-08-2024 **Accepted:** 27-11-2024 **Published:** 28-11-2024

Editor: Dr. Rubén González Vallejo

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ABSTRACT

Climate change poses significant challenges to global agriculture, necessitating innovative solutions to enhance sustainability and productivity. Artificial intelligence (AI) has emerged as a key enabler in climate-smart agricultural technologies (CSAT), offering data-driven approaches to optimize resource use, mitigate climate risks, and improve decision-making. This study aims to evaluate AI's integration into CSAT, focusing on its applications, benefits, and adoption challenges, particularly in climate-vulnerable regions. A bibliographic review employing machine learning (ML) and natural language processing (NLP) techniques was conducted to analyze over 40 000 scientific articles from global academic databases. Topic modeling and classification algorithms were applied to identify key trends, adoption barriers, and implementation pathways for AI-driven CSAT. The study also incorporated expert validation through the Delphi method to refine AI-generated insights and ensure their alignment with real-world agricultural challenges. Findings indicate that AI enhances decision-making in conservation agriculture, precision farming, water management, and market intelligence. AI-powered tools facilitate early pest detection, optimize irrigation schedules, and provide real-time climate advisory services, significantly improving agricultural resilience and food security. However, major barriers to AI adoption include high implementation costs, limited digital literacy, and inadequate infrastructure, particularly in low-income regions. Despite these challenges, AI-driven CSAT presents significant potential to transform agriculture, especially in climate-affected areas. Strategic investments in digital literacy, infrastructure development, and supportive policy frameworks are essential to facilitate AI adoption. Strengthening interdisciplinary collaboration among researchers, policymakers, and farmers will be crucial in advancing sustainable agricultural practices and ensuring long-term food security.

Keywords: Climate-Smart Agriculture; Artificial Intelligence; Machine Learning; Precision Farming; Greenhouse Gas Emissions; Sustainability; Climate Resilience; Digital Agriculture; Food Security.

RESUMEN

El cambio climático plantea desafíos significativos para la agricultura global, lo que hace necesarias soluciones innovadoras para mejorar la sostenibilidad y la productividad. La inteligencia artificial (IA) ha surgido como un elemento clave en las tecnologías agrícolas climáticamente inteligentes (CSAT), ofreciendo enfoques basados en datos para optimizar el uso de recursos, mitigar los riesgos climáticos y mejorar la toma de decisiones. Este estudio tiene como objetivo evaluar la integración de la IA en las CSAT, centrándose en sus aplicaciones, beneficios y desafíos de adopción, particularmente en regiones vulnerables al clima. Se realizó una revisión bibliográfica utilizando técnicas de aprendizaje automático (ML) y procesamiento de lenguaje natural (NLP) para analizar más de 40 000 artículos científicos de bases de datos académicas globales. Se aplicaron modelos de temas y algoritmos de clasificación para identificar tendencias clave, barreras de adopción y vías de implementación para las CSAT impulsadas por IA. Además, el estudio incorporó la validación de expertos a través del método Delphi para refinar los conocimientos generados por IA y garantizar su alineación con los desafíos agrícolas del mundo real. Los resultados indican que la IA mejora la toma de decisiones en la agricultura de conservación, la agricultura de precisión, la gestión del agua y la inteligencia de mercado. Las herramientas basadas en IA facilitan la detección temprana de plagas, optimizan los horarios de riego y proporcionan servicios de asesoramiento climático en tiempo real, mejorando significativamente la resiliencia agrícola y la seguridad alimentaria. Sin embargo, las principales barreras para la adopción de la IA incluyen los altos costos de implementación, la baja alfabetización digital y la infraestructura inadecuada, particularmente en regiones de bajos ingresos. A pesar de estos desafíos, las CSAT impulsadas por IA tienen un gran potencial para transformar la agricultura, especialmente en áreas afectadas por el clima. Es fundamental realizar inversiones estratégicas en alfabetización digital, desarrollo de infraestructura y marcos normativos de apoyo para facilitar la adopción de la IA. El fortalecimiento de la colaboración interdisciplinaria entre investigadores, formuladores de políticas y agricultores será crucial para avanzar en prácticas agrícolas sostenibles y garantizar la seguridad alimentaria a largo plazo.

Palabras clave: Agricultura Climáticamente Inteligente; Inteligencia Artificial; Aprendizaje Automático; Agricultura de Precisión; Emisiones de Gases de Efecto Invernadero; Sostenibilidad; Resiliencia Climática; Agricultura Digital; Seguridad Alimentaria

INTRODUCTION

The escalating challenge of climate change demands immediate and innovative solutions. Greenhouse gases (GHGs), particularly nitrous oxide (N_2O), play a central role in global warming by trapping heat in the atmosphere. N_2O is 300 times more effective at trapping heat than carbon dioxide on a per-molecule basis and is predominantly emitted through agricultural activities, mainly due to nitrogen-based fertilizer use. With agriculture accounting for approximately 60 % of anthropogenic GHG emissions, the sector faces mounting pressure to balance food production with environmental sustainability.(1,2,3)

Climate variability further exacerbates this challenge, disrupting weather patterns and increasing the frequency of extreme climate events.(1) These fluctuations threaten agricultural productivity and food security, particularly in regions already vulnerable to economic and environmental stressors.(1,2,3) As the global population grows, traditional agricultural systems must adapt to sustain yields under shifting climatic conditions.(4,5,6) The Green Revolution (GR) has historically enhanced food production through synthetic fertilizers and high-yield crop varieties, but these approaches have led to severe environmental and public health concerns.(7) Given the urgency of mitigating climate change, a paradigm shift in agricultural management is essential—one that integrates sustainability with technological innovation.

Climate-smart agricultural technologies (CSAT) offer a promising pathway to enhance crop resilience, optimize nitrogen use efficiency, and reduce N_2O emissions.(8,9,10,11,12) These technologies encompass intercropping systems, ecological compensation measures, and data-driven decision-making tools. However, widespread adoption requires robust evidence and tailored strategies to optimize their performance under different agro-ecological conditions. Addressing climate variability and improving agricultural sustainability necessitates interdisciplinary research that bridges agronomy, environmental science, and artificial intelligence (AI).

This study leverages AI methodologies—specifically, machine learning and natural language processing—to analyze a corpus of over 40 000 scientific articles, mapping the global landscape of climate-smart technology applications at the district level. By synthesizing expert knowledge with AI-driven insights, this research aims to identify, adoption barriers, and potential pathways for optimizing agricultural practices. (2) In the face of increasing global food, water, and energy demands, implementing CSAT requires a multi-scale approach, from local farm-level innovations to national and global policy frameworks. This study provides a methodological framework for assessing the current state of climate-smart technology adoption and informing evidence-based agricultural and land-use strategies.

METHOD

Bibliographic Review Approach

This study employs a bibliographic review approach, leveraging artificial intelligence (AI) methodologies—specifically, machine learning (ML) and natural language processing (NLP)—to analyze a corpus of over 40 000 scientific articles related to climate-smart agricultural technologies (CSAT). The review critically examines the integration of AI in CSAT by comparing multiple perspectives, identifying trends, and discussing adoption challenges and opportunities. By incorporating discussion and debate among different viewpoints, this study ensures a comprehensive understanding of AI's role in sustainable agriculture.

Data Collection and Preprocessing

The dataset includes peer-reviewed journal articles, conference proceedings, government reports, and institutional research documents sourced from global academic databases such as Web of Science, Scopus, PubMed, and Google Scholar. To ensure comprehensive coverage and reduce bias, sources were selected based on predefined keywords, including "climate-smart agriculture," "artificial intelligence in agriculture," "GHG mitigation," and "precision farming." Preprocessing steps were undertaken to enhance data reliability. These included filtering and selecting relevant documents, cleaning the text by removing duplicates and stopwords, extracting bibliographic metadata, and structuring the documents into thematic sections such as abstracts, methodologies, results, and discussions for systematic comparison.

Thematic Analysis and Comparative Approach

To extract key insights and identify dominant themes, topic modeling was applied using Latent Dirichlet Allocation (LDA) and BERT-based models. This enabled the classification of studies into thematic clusters, including sustainable soil and nutrient management, AI-driven precision agriculture, drought-resistant crop technologies, and greenhouse gas (GHG) emission reduction strategies. A comparative analysis was conducted to contrast findings across different geographical regions, agricultural practices, and levels of AI implementation.

The review categorized studies based on their stance on AI's effectiveness in CSAT. Some sources presented positive perspectives, showcasing AI-driven decision-making in conservation agriculture, irrigation management, and pest detection. Others provided critical perspectives, highlighting barriers such as high costs, digital illiteracy, and infrastructure deficits that limit AI adoption, particularly in developing regions. Finally, some studies presented neutral or mixed perspectives, acknowledging both AI's potential benefits and its limitations, advocating for context-specific applications rather than universal solutions.

Machine Learning for Trend Analysis

To identify emerging patterns in CSAT research, ML techniques were employed for trend analysis. Supervised learning models such as Random Forest and XGBoost were used to classify studies based on CSAT adoption rates, effectiveness, and scalability. Meanwhile, unsupervised clustering techniques such as K-means and hierarchical clustering grouped regions with similar CSAT adoption trends, enabling cross-country comparisons. Temporal analysis was also applied to track the evolution of AI applications in agriculture over time, revealing shifts in research priorities and technological advancements.

Expert Validation and Theoretical Debates

To validate AI-generated insights and ensure their applicability, a Delphi method was employed, engaging experts from agricultural research institutions, policymakers, and industry stakeholders. The validation process involved three phases. In the initial review phase, AI-driven insights were presented to domain experts for assessment. The feedback incorporation phase integrated expert opinions to refine ML models and improve classification accuracy. Finally, the consensus-building phase ensured that findings aligned with real-world agricultural challenges.

This expert validation provided a balanced synthesis of theoretical debates, juxtaposing different analytical frameworks, including techno-optimism, which views AI as a game-changer in climate adaptation, critical realism, which acknowledges AI's benefits while scrutinizing socioeconomic and ethical concerns, and the sustainability paradigm, which evaluates AI's long-term viability in CSAT based on ecological and economic sustainability indicators.

https://doi.org/10.62486/latia2025330 ISSN: 3046-403X

Multi-Scale Analysis for Policy and Land-Use Strategies

This study adopts a multi-scale approach to assess AI adoption in CSAT, analyzing its implications at local, national, and global levels. At the local level, the review examines farm-specific practices and the barriers to AI adoption among smallholder farmers. At the national level, the study evaluates policy interventions and the economic feasibility of AI-driven agricultural solutions. At the global level, cross-country comparisons are conducted to understand how different regions implement AI to mitigate climate change in agriculture. The findings are synthesized to provide evidence-based recommendations for policymakers, guiding investment priorities and technology dissemination strategies tailored to diverse agricultural contexts.

DISCUSSION

AI in Climate-Smart Agriculture - A Multi-Perspective Analysis

The integration of artificial intelligence (AI) into climate-smart agricultural technologies (CSAT) has generated a broad spectrum of perspectives within the academic and scientific communities. While some researchers highlight AI's potential to revolutionize agriculture by optimizing resource use, mitigating climate risks, and enhancing productivity, others caution against its challenges, including high implementation costs, digital illiteracy, and infrastructural deficits.(8,9,10) This discussion synthesizes these viewpoints by analyzing the key themes identified in the bibliographic review, drawing from machine learning-based trend analysis and expert validation processes.(11,12,13)

AI's Transformative Potential in CSAT

Studies advocating for AI's role in CSAT emphasize its ability to improve precision farming, conservation agriculture, and water management.(11,12,13,14) AI-powered models enhance decision-making by providing real-time insights into soil health, crop needs, and climate conditions. For example, AI-driven pest detection systems, such as the PlantVillage Nuru app, enable early identification of crop diseases, reducing agricultural losses and improving food security.(15,16,17) Similarly, AI-based climate advisory services help farmers adjust their practices in response to extreme weather events. (15-27) These applications align with the techno-optimistic perspective, which views AI as a transformative tool capable of addressing global food security challenges through data-driven interventions.

Challenges and Criticisms of AI in Agriculture

Despite AI's promise, critical perspectives highlight several adoption barriers. High implementation costs make AI-based solutions inaccessible to many smallholder farmers, particularly in developing regions. Furthermore, the digital divide—characterized by limited internet access and low digital literacy—hinders widespread AI adoption.(15) Studies also point to infrastructural deficiencies, such as unreliable electricity supplies and inadequate data collection frameworks, which limit AI's effectiveness.(15,16,17,18) From a critical realism standpoint, scholars argue that while AI-driven solutions are beneficial, they must be accompanied by significant investments in infrastructure, training, and regulatory frameworks to ensure equitable adoption and long-term sustainability.(6-27)

Comparing Regional Adoption and Implementation Strategies

AI adoption in agriculture varies significantly across regions. In high-income countries, precision farming technologies have been widely implemented due to strong digital infrastructure and financial incentives.(19) In contrast, in lower-income regions like Zambia, AI integration remains limited, primarily due to economic constraints and technological gaps.(20) Some researchers propose context-specific AI applications, where low-cost AI tools, such as mobile-based weather prediction services, can be prioritized over high-cost technologies like drone-based monitoring systems. This nuanced approach reflects the sustainability paradigm, which suggests that AI should be tailored to local agricultural and socio-economic conditions to maximize impact.(20)

Towards a Balanced AI Implementation Strategy

The bibliographic review underscores the need for a multi-scale approach that integrates AI with policy interventions, farmer training, and infrastructure development.(21,22,23,24) Governments and agricultural institutions must collaborate to create supportive policies, provide financial incentives, and develop accessible digital literacy programs. Bridging the gap between AI's potential and its real-world application requires interdisciplinary collaboration among technologists, agronomists, and policymakers to ensure that AI-driven CSAT solutions are scalable, inclusive, and sustainable (table 1).(21,22,23,24,25,26,27)

https://doi.org/10.62486/latia2025330 ISSN: 3046-403X

Table 1. Summarizing the studies included in this bibliographic review, highlighting their focus areas, methodologies, and key findings

Study	Author(s) & Year	Focus Area	Methodology	Key Findings
Climate-Smart Agriculture and Potato Production in Kenya	Waaswa et al. [1]	Climate-smart agriculture (CSA) practices in Kenya	Literature review & field surveys	Identifies determinants of CSA adoption and highlights AI's role in optimizing farming decisions
AI-Powered Satellite Imagery Processing for Global Air Traffic Surveillance	Kayusi et al.[5]	AI-driven remote sensing in agriculture	Machine learning & satellite data analysis	Demonstrates AI's potential for real-time monitoring of agricultural activities
Climate-Smart Agriculture in India: A Meta-Analysis	Tyagi & Haritash[2]	AI applications in climate adaptation strategies	Meta-analysis of climate-smart agricultural technologies	AI-driven predictive models enhance precision agriculture and resource efficiency
Effects of Climate-Smart Agricultural Practices in Ethiopia	Adimassu et al.[3]	Impact assessment of CSA interventions	Meta-analysis & field data evaluation	CSA improves adaptation and mitigation indicators; AI integration enhances decision-making
Smart and Climate-Smart Agricultural Trends in Africa	Adesipo et al.[9]	Smart farming and AI applications in agriculture	Systematic review	AI-based decision support systems improve resource management and climate resilience
Sustainable Farming Practices and Soil Health	Sharma et al.[6]	AI-driven soil fertility management	Experimental research & data analytics	AI models optimize soil nutrient management, reducing fertilizer waste and emissions
Institutional Perspectives on Climate-Smart Agriculture	Totin et al.[12]	Policy and governance in CSA adoption	Systematic literature review	Institutional support and digital literacy programs are essential for AI adoption in CSA
Climate-Smart Agriculture: Global Research Agenda	Steenwerth et al.[13]	AI's role in global CSA strategies	Research synthesis & expert consultation	AI contributes to climate risk mitigation and enhances data-driven agricultural strategies
Meta-Analysis of Innovation Attributes in Climate-Smart Agriculture	Lee et al.[15]	AI-driven innovations in CSA	Global meta-analysis	AI adoption is influenced by economic, social, and policy factors
AI and Participatory Approaches in Modern Agricultural Extension	Prajapati et al.[21]	AI in knowledge dissemination and farmer decision-making	Participatory research & case studies	AI enhances agricultural extension services but requires localized adaptation

CONCLUSION

The integration of AI in Climate-Smart Agricultural Technologies holds immense potential for transforming Zambian agriculture. By addressing current challenges such as climate variability, pest infestations, and inefficient resource use, AI can enhance food security and economic stability. While challenges like high costs and infrastructure constraints exist, strategic investments and policy support can drive AI adoption, ensuring long-term sustainability in Zambia's agricultural sector.

REFERENCES

1. Waaswa A, Oywaya Nkurumwa A, Mwangi Kibe A, Ngeno Kipkemoi J. Climate-Smart agriculture and potato production in Kenya: review of the determinants of practice. Clim Dev. 2022;14(1):75–90. https://doi.org/10.1080/17565529.2021.1885336

2. Tyagi A, Haritash AK. Climate-smart agriculture, enhanced agroproduction, and carbon sequestration potential of agroecosystems in India: A meta-analysis. J Environ Stud Sci. 2024;1–19. https://doi.org/10.1007/s13412-024-00917-1

3. Adimassu Z, Tibebe D, Tamene L, Abera W. Evaluating the Effects of Climate Smart Agricultural (CSA) Practices on Productivity, Adaptation, and Mitigation Indicators in Ethiopia: A Meta-analysis Approach. Heliyon. https://doi.org/10.1016/j.heliyon.2025.e42796

4. Chavula P, Lungu G, Turyasingura B, Abdi E, Mwewa T, Abrahim A. Promoting a Human-Rights-Centered Just Energy Transition for Communities in Zambia ' s Mineral Resource Areas : A Critical Review of Policies , Challenges , and Pathways. 2025;7(1):169–83. https://doi.org/10.56557/abaarj/2025/v7i1164

5. Kayusi F. AI-Powered Satellite Imagery Processing for Global Air Traffic Surveillance Procesamiento de Imágenes Satelitales Impulsado por IA para la Vigilancia Global del Tráfico Aéreo. 2025;(Ml). https://doi.org/10.62486/latia202580

6. Sharma P, Sharma P, Thakur N. Sustainable farming practices and soil health: A pathway to achieving SDGs and future prospects. Discov Sustain. 2024;5(1):250. https://doi.org/10.1007/s43621-024-00447-4

7. Gupta D, Gujre N, Singha S, Mitra S. Role of existing and emerging technologies in advancing climate-smart agriculture through modeling: A review. Ecol Inform. 2022;71:101805. https://doi.org/10.1016/j.ecoinf.2022.101805

8. Jariwala H, Santos RM, Lauzon JD, Dutta A, Wai Chiang Y. Controlled release fertilizers (CRFs) for climate-smart agriculture practices: a comprehensive review on release mechanism, materials, methods of preparation, and effect on environmental parameters. Environ Sci Pollut Res. 2022;29(36):53967–95. https://doi.org/10.1007/s11356-022-20890-y

9. Adesipo A, Fadeyi O, Kuca K, Krejcar O, Maresova P, Selamat A, et al. Smart and climate-smart agricultural trends as core aspects of smart village functions. Sensors. 2020;20(21):5977. https://doi.org/10.3390/s20215977

10. Hu C, Wang X, Li J, Luo L, Liu F, Wu W, et al. Climate Smart Agriculture. https://doi.org/10.1016/j.csag.2024.100026

11. Wally D. Exploring the application of ICTs and big data analytics on climate data in climate-smart agriculture to increase productivity for small-scale farmers: The case of Ghana. Publ master thesis Fac Cult Soc Sci Paris, Lodron Univ Salzbg Tech Fac IT Des Aalborg Univ Copenhagen. 2021. https://doi.org/10.56669/zvps3203

12. Totin E, Segnon AC, Schut M, Affognon H, Zougmoré RB, Rosenstock T, et al. Institutional perspectives of climate-smart agriculture: A systematic literature review. Sustainability. 2018;10(6):1990. https://doi.org/10.3390/su10061990

13. Steenwerth KL, Hodson AK, Bloom AJ, Carter MR, Cattaneo A, Chartres CJ, et al. Climate-smart agriculture global research agenda: scientific basis for action. Agric Food Secur. 2014;3:1–39. https://doi.org/10.1186/2048-7010-3-11

14. Gemtou M, Kakkavou K, Anastasiou E, Fountas S, Pedersen SM, Isakhanyan G, et al. Farmers' transition to climate-smart agriculture: A systematic review of the decision-making factors affecting adoption. Sustainability. 2024;16(7):2828. https://doi.org/10.3390/su16072828

15. Lee C-L, Orton G, Lu P. Global Meta-Analysis of Innovation Attributes Influencing Climate-Smart Agriculture Adoption for Sustainable Development. Climate. 2024;12(11):192. https://doi.org/10.3390/cli12110192

16. Barasa PM, Botai CM, Botai JO, Mabhaudhi T. A review of climate-smart agriculture research and applications in Africa. Agronomy. 2021;11(6):1255. https://doi.org/10.3390/agronomy11061255

17. Erekalo KT, Pedersen SM, Christensen T, Denver S, Gemtou M, Fountas S, et al. Review on the contribution of farming practices and technologies towards climate-smart agricultural outcomes in a European context. Smart Agric Technol. 2024;7:100413. https://doi.org/10.1016/j.atech.2024.100413

18. Rosenstock TS, Lamanna C, Chesterman S, Bell P, Arslan A, Richards M, et al. The scientific basis of climate-smart agriculture: a systematic review protocol. 2016. https://doi.org/10.1007/978-3-319-92798-5_12

19. Branca G, McCarthy N, Lipper L, Jolejole MC. Climate-smart agriculture: a synthesis of empirical evidence of food security and mitigation benefits from improved cropland management. 2011. https://doi.org/10.1201/9781003246237-12

20. Sathianarayanan M, Kirdemir U, Gianoli A. Urban intelligence: Navigating climate challenges with ai. In: Nexus of AI, Climatology, and Urbanism for Smart Cities. IGI Global Scientific Publishing; 2025. p. 59-90. https://doi.org/10.4018/979-8-3693-5918-1.ch003

21. Prajapati CS, Priya NK, Bishnoi S, Vishwakarma SK, Buvaneswari K, Shastri S, et al. The Role of Participatory Approaches in Modern Agricultural Extension: Bridging Knowledge Gaps for Sustainable Farming Practices. https://doi.org/10.9734/jeai/2025/v47i23281

22. Jillahi KB, Iorliam A. A Scoping Literature Review of Artificial Intelligence in Epidemiology: Uses, Applications, Challenges and Future Trends. J Comput Theor Appl. 2024;2(2):204-28. https://doi.org/10.62411/jcta.10350

23. Rana P, Ahmad M, Stephen T, Chemingui H. Agricultural Intelligence (AI)'s Impact on Society 5.0 Farming. In: Open AI and Computational Intelligence for Society 50. IGI Global Scientific Publishing; 2025. p. 109-28. https://doi.org/10.61915/pes.009224

24. Clarke De La Cerda J, Bejaui R, Bonyo L. AI innovation in Africa: An overview of opportunities, risks and the legal context. Commun Technol développement. 2024;(16). https://doi.org/10.4000/12nfk

25. Manikandan S, Kaviya RS, Shreeharan DH, Subbaiya R, Vickram S, Karmegam N, et al. Artificial intelligence-driven sustainability: Enhancing carbon capture for sustainable development goals-A review. Sustain Dev. 2024. https://doi.org/10.1002/sd.3222

26. Hlatshwako Z, Tsabedze V. Unlocking the future: exploring librarian's perspectives and readiness for artificial intelligence integration in eswatini libraries. J Web Librariansh. 2024;18(3):149-68. https://doi.org/10.1080/19322909.2024.2364324

27. CLN CC, Austin PC. Promoting Quality Education in Nigeria through the Adoption of Artificial Intelligence and Machine Learning Systems. Contemp ISSUES Educ. 2024;2(1):38-47. https://doi.org/10.48009/2_iis_2024_104

FINANCING
The authors did not receive financing for the development of this research.

CONFLICT OF INTEREST
The authors declare that there is no conflict of interest.

AUTHORSHIP CONTRIBUTION
Conceptualization: Fredrick Kayusi, Petros Chavula.
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