06,2025
Volume 3
Issue 2

Agricultural & Rural Studies

EDITOR-IN-CHIEF:JUNBIAO ZHANG

ISSN 2959-9784
9 772959 978259 02 >

SCC PRESS

https://sccpress.com/ars

OPEN ACCESS

ISSN 2959-9784

Cover Story

Xinyu Village, located in Linping District, Hangzhou City, Zhejiang Province, spans 2.2 square kilometers and borders the Beijing-Hangzhou Grand Canal.

Renowned for Northern Snakehead (Channa argus) aquaculture in its ponds, the village once faced environmental challenges due to the distinctive aquatic aroma permeating the air. While Northern Snakehead farming generated substantial income, its ecological impact prompted a transformation. Since 2015, the village has pioneered ecological aquaculture innovation by introducing lotus cultivation in ponds, evolving from "high-pollution, high-yield" practices to high-efficiency ecological agriculture through the "lotus root-softshell turtle co-culture" model. This shift achieves dual benefits: water resource optimization (one water body, two uses), dual harvests (lotus and aquaculture), stable yields, and enhanced profitability.

Building upon lotus root cultivation, the village has developed a series of value-added lotus-themed products, including lotus seeds, roots, hearts, root starch, lotus leaf tea, and edible fresh lotus fruits, complemented by unique "Lotus Banquet" cuisine. By attracting visitors with picturesque lotus landscapes and distinctive culinary experiences, the village aims to create a viral social media hotspot, driving the development of beautiful rural villages and comprehensive tourism along the Canal. This initiative fosters an integrated lotus industry chain spanning farming, processing, and ecotourism.

The village has established six pillars of high-efficiency ecological agriculture—governance innovation, technology R&D, cultural preservation, industrial upgrading, policy support, and service optimization—to drive agriculture toward ecological resilience, economic vitality, smart efficiency, and shared prosperity, establishing itself as the Xinyu Model for revitalizing suburban rural areas.

(Professor Xiaohui Ma, Dean, Continuing Education College of Zhejiang A&F University, Zhejiang, China.)

Agricultural & Rural Studies

Vol. 3, No. 2 June, 2025

Contents

0007 Growing Opportunities: Considering a Thriving Agroforestry Industry in Appalachia, USA
Jason A. Hubbart, Fabricio Comacho, Kathryn Gazal, Larissa Martins, Kirsten Stephan and Kristi Wood-Turner

0008 Knowledge Domain and Emerging Trends in Monitoring of Forest Fires Using Remote Sensing: A Scientometric Review Based on CiteSpace Analysis
Juan Zhang, Yawen Dong, Yan Liu, Yuelin Kang, Shaofeng Xie and Haizhou Xu

0009 Bayesian Data Fusion Framework for Soil Moisture Interpolation in Entre Ríos, Argentina: Analysis of Topographic Indices
César Augusto Aguirre, Guillermo Antonio Rondán, Carlos Germán Sedano, Macarena Cardozo and Tatiana Rut

0010 The Impact of Non-Agricultural Management Experience on Eco-Friendly Practices in Chinese Family Farms
Jia Yue, Siyao Chen, Qiang Liu and Zhixiong Weng

0011 Investigating the Influence Mechanism of Douyin Live on the Sale of Traditional Handicrafts in China—Based on a Dual Perspective of Youth Participation
Linlin Li, Jiayan Chen, Dubin Dong, Jialu Chen and Luhu Shuai

0012 Spatial Modeling of Child Malnutrition and Farming Methods in Rural Sub-Sahara Africa
Brent Lloyd

About the Journal

Agricultural & Rural Studies (**A&R**, **ISSN 2959-9784**) is an exclusively digital, open-access journal dedicated to advancing interdisciplinary scholarship at the critical nexus of agricultural sustainability, rural revitalization, and farmer well-being. Published quarterly, **A&R** features a range of content types—including original research, reviews, perspectives, and commentaries—serving as a professional and innovative platform for rigorous academic dialogue and global knowledge dissemination.

Core Features:

(1) **Interdisciplinary Scope:** A&R centers on interdisciplinary and multidisciplinary inquiry, integrating insights from economics, sociology, human geography, and cognate disciplines to address pressing contemporary issues in agriculture, rural development, and farmer-related policies—bridging theoretical frameworks to advance holistic understandings of these dynamic systems.

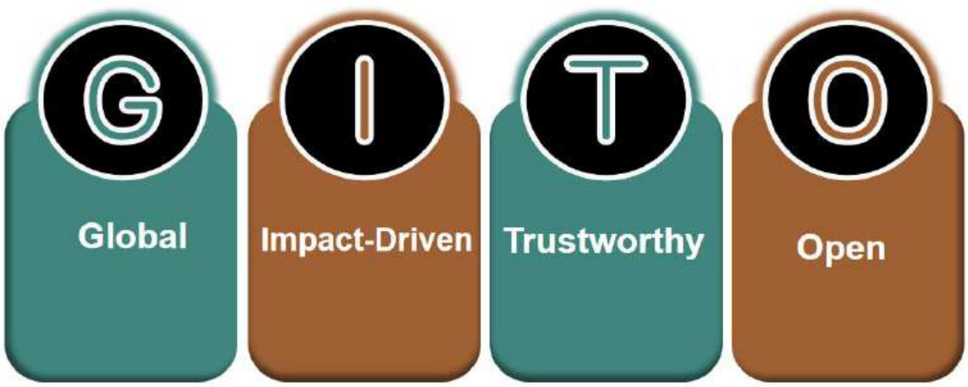
(2) **Global Editorial Excellence:** The journal is guided by a distinguished, highly specialized, and globally diverse editorial board, ensuring rigorous peer review, cultural sensitivity, and alignment with international scholarly standards.

(3) **Culture-Driven Operations:** Rooted in our mission, vision, and values, cultural stewardship lies at the core of A&R's identity. Our unwavering commitment to ethical principles, community engagement, and purposeful impact permeates every facet of the journal's operations.

(4) **Sustainable Non-Profit Model:** No Article Publishing Charges (APC) for the first four years. Beyond this, it will maintain a reasonable level of APC for authors worldwide in the future.

(5) **Fully Independent OA Platform:** As an independent OA publication (https://sccpress.com/ars), A&R prioritizes equitable global access to scholarship while actively promoting your work to a worldwide audience, maximizing its reach and impact.

(6) **Tailored Publication Support:** Committed to fostering a seamless research journey, A&R offers comprehensive, efficient, and professional editorial services. Recognizing the unique demands of each study, our dedicated team provides structured guidance—from refining article frameworks to managing references—simplifying the publication process and empowering authors to focus on their core scholarship.



Agricultural & Rural Studies

Review

Growing Opportunities: Considering a Thriving Agroforestry Industry in Appalachia, USA

Jason A. Hubbart [1,2,*], Fabricio Comacho [3], Kathryn Gazal [4], Larissa Martins [4], Kirsten Stephan [4] and Kristi Wood-Turner [5]

1 Division for Land-Grant Engagement, Davis College of Agriculture and Natural Resources, School of Natural Resources and the Environment, West Virginia University, Morgantown, WV 26506, USA
2 West Virginia Agriculture and Forestry Experiment Station, West Virginia University, Morgantown, WV 26506, USA
3 The Tropical Agroforestry Institute, Monteverde 60109, Costa Rica; fcamachocr@agroforestryengineering.org
4 School of Natural Resources and the Environment, Davis College of Agriculture and Natural Resources, West Virginia University, Morgantown, WV 26506, USA; kathryn.arano@mail.wvu.edu (K.G.); larissa.martins@mail.wvu.edu (L.M.); Kirsten.Stephan@mail.wvu.edu (K.S.)
5 The Center for Community Engagement, West Virginia University, Morgantown, WV 26506, USA; kwood@wvu.edu
* Correspondence: jason.hubbart@mail.wvu.edu

Abstract: The Appalachian region of the United States of America, known for its extensive forests and rich cultural heritage, faces significant socioeconomic and environmental challenges, including high poverty rates, food insecurity, and the decline of traditional industries. Agroforestry, a sustainable land-use system that combines trees, crops, and livestock, offers a practical solution by boosting biodiversity, improving soil quality, sequestering carbon, and generating diverse income streams. This article explores how agroforestry can help address economic vulnerabilities and mitigate environmental degradation in Appalachia, while also building resilience to unpredictable climate conditions. Key practices, such as silvopasture, forest farming, riparian buffer restoration, and alley cropping, offer both ecological and economic benefits, aligning with the region's traditional land-use systems. Although agroforestry offers great potential, several challenges hinder its widespread adoption, including insufficient awareness, limited technical expertise, and inadequate access to resources. Overcoming these obstacles requires targeted research, education, policy support, and community engagement. Demonstration sites and extension programs can provide landowners with practical knowledge and confidence to adopt agroforestry practices, while financial incentives, such as tax credits and payments for ecosystem services, can help reduce economic barriers. Additionally, the integration of agrivoltaics, which combines solar energy production with agroforestry, offers an innovative pathway to economic resilience by maximizing land productivity and diversifying income streams. This article emphasizes the importance of strategic investment in research, education, and policy to promote agroforestry in Appalachia, with a focus on market-driven strategies and community engagement for sustainable development.

Keywords: agroforestry; sustainability; Appalachia; biodiversity; economic resilience; forest industry; non-timber forest products; silvopasture; climate resilience; community engagement

Check for updates

Citation: Hubbart, J. A., Comacho, F., Gazal, K., Martins, L., Stephan, K., & Wood-Turner, K. (2025). Growing Opportunities: Considering a Thriving Agroforestry Industry in Appalachia, USA. *Agricultural & Rural Studies*, *3*(2), 12.
https://doi.org/10.59978/ar03020007

Received: 24 February 2025
Revised: 14 May 2025
Accepted: 19 May 2025
Published: 23 May 2025

1. Introduction

The Appalachian region, renowned for its rich cultural heritage and extensive forest landscapes, may hold untapped potential for sustainable development through agroforestry (Castle et al., 2021). Stretching across portions of 13 states, from southern New York to northern Mississippi, Appalachia is home to diverse ecosystems and communities that rely heavily on natural resources for their survival and livelihoods. Forests cover nearly 40% of the land area, making Appalachia one of the most biodiverse temperate forest ecosystems in the world (Udawatta et al., 2019). However, despite great wealth in natural resources, environmental and socioeconomic challenges persist, including high poverty rates, food insecurity, and economic dependency on industries in decline, such as coal mining and traditional timber production (Elagib & Al-Saidi, 2020). These issues have left many communities struggling to sustain their way of life, highlighting the need for innovative approaches to regional development (Bettles et al., 2021). Agroforestry practices that traditionally integrate trees and crops to create sustainable systems have been recognized globally for their ability to conserve biodiversity, sequester carbon, and enhance ecosystem services (Abbas et al., 2017; Cialdella et al., 2023; Dobhal et al., 2024; Kaushal et al., 2021; Nair et al., 2021; Pantera et al., 2021; Singh et al., 2021), offering a promising solution to Appalachia's challenges (Kuyah et al., 2019). By blending the ecological advantages of forest ecosystems with the productivity of agricultural practices, agroforestry may enhance biodiversity, sequester carbon, and improve soil health, and therefore, facilitate new economic opportunities for rural Appalachian communities (Fahad et al., 2022). Practices such as silvopasture, forest farming, and riparian buffer restoration have shown the potential to generate diverse income streams while promoting sustainable land use (Castle et al., 2021). Furthermore, agroforestry practices have shown the potential to play a critical role in mitigating the impacts of climate change by boosting carbon storage and enhancing the resilience of ecosystems (Abbas et al., 2017; Dobhal et al., 2024; Ghale et al., 2022; Kaushal et al., 2021; Nair et al., 2021; Pantera et al., 2021; Zomer et al., 2022). Given the region's reliance on forests and agriculture, scaling up agroforestry could provide long-term economic and environmental benefits.

A significant and persistent challenge in Appalachia is the prevalence of food deserts, areas with limited access to affordable and nutritious food that can disproportionately affect rural and underserved populations. Food deserts exacerbate health disparities and deepen the region's economic difficulties, particularly in areas already challenged with poverty and unemployment (K. E. Smith et al., 2020). Agroforestry may present a viable and innovative solution by integrating perennial crops such as fruit and nut trees into agricultural systems, including ungulate agricultural systems, thereby offering locally grown, nutritious food options to underserved populations. The practice also facilitates the cultivation of high-value non-timber forest products (NTFPs), including ginseng, mushrooms, and medicinal herbs, which hold significant economic promise while preserving the integrity of forest ecosystems (Bentrup et al., 2019). By finding a balance between agricultural productivity and ecological conservation, agroforestry can help address critical issues such as food insecurity while simultaneously creating economic pathways for communities in need (Munsell et al., 2021; Zawarus & Ortega, 2022). Additionally, the integration of agroforestry practices into existing land-use frameworks may help alleviate environmental degradation, restore biodiversity, and contribute to a healthier and more resilient regional food system. The dual ability of agroforestry to provide both ecological and economic benefits underscores its potential as a transformative tool for improving the quality of life in Appalachia.

Despite its immense promise, agroforestry remains significantly underutilized across the Appalachian region. Barriers to its adoption include a lack of awareness, technical expertise, and access to necessary resources, all of which hinder its widespread implementation. Overcoming these challenges requires a multifaceted approach that incorporates research, education, and community engagement. Research initiatives can provide the scientific basis for agroforestry practices explicitly tailored to the unique ecosystems of Appalachia, offering evidence-based strategies to maximize their effectiveness (Pattanayak et al., 2012). Meanwhile, education and extension programs can equip landowners, farmers, and practitioners with the skills and knowledge needed to adopt and sustain agroforestry practices (Hemmelgarn & Gold, 2021; Salve et al., 2022). Community engagement is equally essential, ensuring that agroforestry initiatives are aligned with local needs, priorities, and values while fostering trust and collaboration among stakeholders (Zinkhan & Mercer, 1996). The purpose of this article is to explore the transformative potential of agroforestry as a sustainable land-use strategy to address the unique environmental, economic, and social challenges facing Appalachia. It highlights the benefits of agroforestry, including enhancing biodiversity, improving food security, and fostering economic resilience, while underscoring the importance of research, education, policy support, and community engagement in achieving these outcomes. The article aims to inspire policymakers, researchers, landowners, and community members to act by adopting agroforestry practices to promote sustainable development. While drawing from a broad body of global agroforestry literature, this review critically integrates findings within the Appalachian context by examining their specific applicability, limitations, and potential adaptation needs. Rather than presenting literature descriptively, the article synthesizes evidence to highlight patterns, contrasts, and research gaps relevant to the region's unique ecological, economic, and socio-cultural conditions.

2. The Appalachian Forest Industry: A Snapshot

Appalachia's forest industry has long been a cornerstone of the region's economy, providing essential employment, raw materials, and ecosystem services that sustain local livelihoods and contribute to national markets. Renowned for its biodiversity, the region's forests support both timber production and a variety of non-timber forest products (NTFPs), forming a vital component of Appalachia's economy (Zipper et al., 2013). According to the Appalachian Regional Commission (ARC), the forest industry generates approximately $18 billion annually, with high-demand timber products such as oak, hickory, and maple forming the bulk of this revenue (Boettner et al., 2014; Kiernan, 2024). However, despite its economic importance, the Appalachian Forest industry faces mounting challenges that threaten its sustainability and long-term viability. Deforestation, coupled with market pressures and the far-reaching impacts of climate change, continues to strain the industry, resulting in diminished forest health and economic instability (Martin et al., 2020). Historically centered around timber harvesting for construction, furniture, and paper production, the industry has struggled to adapt to shifts in global trade dynamics and rising competition from international markets (Buehlmann et al., 2007). These challenges have led to the closure of numerous small and medium-sized sawmills, resulting in job losses and economic stagnation across many rural communities (Leakey, 1999; Schwartzman, 2023). The need to mitigate these challenges and revitalize the Appalachian Forest economy has never been more urgent. Agroforestry, which combines forestry and agriculture to create integrated, sustainable systems, may offer a promising solution by providing alternative revenue streams and promoting ecological balance alongside traditional timber production (Cialdella et al., 2023; Lasco et al., 2014; Pantera et al., 2021).

Agroforestry systems, such as forest farming and alley cropping, enable landowners to cultivate high-value non-timber forest products (NTFPs) while maintaining the benefits of forest cover and enhancing ecosystem services. Practices like forest farming allow for the production of economically lucrative crops such as ginseng, mushrooms, and medicinal herbs under the forest canopy, ensuring income generation without compromising the ecological health of the forests. Research indicates that forest farming can yield economic returns of up to $50,000 per acre annually, depending on market conditions and the products cultivated (Salve et al., 2022). Beyond economic benefits, these practices contribute to biodiversity conservation by preserving multi-layered forest structures that support diverse wildlife populations (Santos et al., 2019; Udawatta, Rankoth, et al., 2021). Additionally, Appalachia's forests serve an indispensable role in watershed protection, as the region includes the headwaters of major rivers, including the Ohio, Tennessee, and Potomac. Riparian buffer systems, which include vegetated strips along waterways, are an agroforestry practice that provides vital ecosystem services such as pollutant filtration, soil erosion control, and streambank stabilization (Abesh et al., 2022; Kaushal et al., 2021; Udawatta, Garrett, et al., 2021; Udawatta et al., 2019). Bentrup et al. (2019) highlighted how integrating edible species like fruit and nut trees into riparian buffers not only enhances ecological functionality but also creates economic opportunities for landowners. Other Agroforestry practices such as silvopasture, which integrates trees, forage, and livestock, facilitates additional climate-resilient strategies by diversifying land use, mitigating heat stress for livestock, enhancing carbon sequestration, and improving soil health (Fahad et al., 2022; Ntawuruhunga et al., 2023; M. M. Smith et al., 2022). These practices underscore the potential for agroforestry to bolster ecological resilience and economic sustainability, providing Appalachia with a transformative approach to forest and agricultural management.

3. Innovation in Forestry and Agriculture

Traditional (historical) forestry and agricultural practices in Appalachia have operated as unilateral endeavors, often overlooking opportunities for collaboration and mutual benefit. Agroforestry may facilitate a transformative solution by integrating these practices into synergistic systems that enhance productivity, biodiversity, and resilience. Examples of agroforestry systems well-suited to the Appalachian landscape include, but are not limited to, silvopasture, alley cropping, forest farming, riparian buffers, ungulate agriculture (grazing), and agrivoltaics, each offering distinct ecological and economic advantages. These systems provide innovative pathways for landowners and farmers to address persistent challenges while maintaining the region's cultural and ecological heritage.

Silvopasture, which combines trees, forage, and livestock, creates multifunctional landscapes that enhance productivity and sustainability. By providing shade from tree canopies, silvopasture reduces heat stress on livestock and improves forage quality by maintaining soil moisture (Udawatta et al., 2019). Silvopasture systems have also been shown to sequester up to 35% more carbon compared to traditional grazing methods (Castle et al., 2021). The reduced need for external inputs such as supplemental feed and fertilizers makes silvopasture a cost-effective option for landowners. Similarly, alley cropping integrates rows of trees with crops like grains, vegetables, or berries, enhancing land-use efficiency and increasing overall productivity. The roots of nitrogen-fixing trees improve soil fertility while stabilizing the soil and preventing erosion, reducing reliance on synthetic fertilizers (Fahad et al., 2022). The complementary use of light, water, and nutrients in these systems minimizes competition and maximizes yields (Udawatta et al., 2019).

Other agroforestry practices, such as forest farming and riparian buffers, offer additional benefits tailored to Appalachian needs. Forest farming allows landowners to cultivate high-value non-timber forest products (NTFPs), including mushrooms, ginseng, and goldenseal, under the forest canopy, blending sustainable income generation with the preservation of forest ecosystems (Castle et al., 2021). Some NTFPs can yield up to $50,000 per acre annually, depending on market conditions, making forest farming a lucrative option for many (Kaur & Tiwana, 2024; Salve et al., 2022). Notably, while studies from other regions demonstrate significant economic returns from agroforestry, such as forest farming and silvopasture, it is critical to recognize that comparable data for Appalachia are lacking, underscoring the need for localized research to validate these findings under regional conditions. As the Brundtland Report suggests, NTFPs offer a pathway to balance ecological conservation with the economic, social, and cultural needs of forest-dependent communities (Delgado et al., 2016). In a region historically shaped by extractive industries, NTFPs offer a sustainable alternative that aligns with the Appalachian traditions of forest-based subsistence and trade. Riparian buffers, which involve planting trees and shrubs along waterways, address multiple critical environmental challenges by reducing nitrate runoff by up to 90%, stabilizing stream banks, and providing essential habitats for wildlife (Bentrup et al., 2019). Integrating economically valuable species, such as fruit or nut trees, into riparian buffers enhances their utility, creating multifunctional landscapes that benefit both the environment and local communities. These practices offer innovative solutions to soil degradation, water quality decline, and economic vulnerability while fostering climate resilience and ensuring the sustainable development of Appalachian farms and forests (Hubbart, 2021; Hubbart et al., 2022; Hubbart & Skousen, 2021). The examples provided here are admittedly global in scope and provide valuable insights. However, their application in Appalachia requires careful consideration of the region's distinct topography, land-use history, and market dynamics, which may influence both the feasibility and outcomes of such practices.

4. Addressing Food Deserts

Food deserts, defined as areas with limited access to affordable and nutritious food, remain a significant challenge in Appalachia, where rural isolation, economic disparities, and insufficient infrastructure exacerbate food insecurity (Dean-Witt & Hardin-Fanning, 2020). Agroforestry presents a transformative approach to addressing these challenges by integrating sustainable food production into the existing landscape, thereby enhancing ecological and community resilience. Community orchards are one such agroforestry strategy, transforming underutilized spaces into hubs for fruit and nut production. These orchards, which include apples, pear, walnut, and chestnut trees, provide fresh produce, enhancing food availability and broadening local diets. Beyond their nutritional benefits, community orchards foster a sense of ownership and engagement among residents, strengthening social connections and environmental stewardship (Bentrup et al., 2019). Moreover, these orchards require minimal maintenance and provide long-term productivity, making them well-suited for both rural and urban Appalachian settings. Economically, surplus produce from community orchards can be sold at local markets, creating revenue streams for residents. Educational initiatives tied to orchards, such as partnerships with schools and local organizations, may further enhance community impact by teaching sustainable agriculture and promoting healthy eating habits (Koempel et al., 2022). By establishing orchards on public lands or through partnerships with private landowners, Appalachian communities can effectively reduce food deserts and foster greater self-reliance.

An innovative and progressive agroforestry technique involves establishing riparian buffers that incorporate fruit- and nut-bearing plants, such as elderberries, hazelnuts, and pawpaws, in vegetative zones adjacent to watercourses. Traditionally implemented to improve water quality and reduce erosion, riparian buffers offer additional functionality by addressing food insecurity and generating economic opportunities. These buffers filter agricultural runoff, reducing nutrient pollution and protecting aquatic habitats while simultaneously providing locally grown food resources for nearby communities (Castle et al., 2021). Studies have demonstrated that riparian buffers can reduce nitrate runoff by up to 90%, significantly enhancing the health of adjacent streams and rivers (Bentrup et al., 2019). The integration of edible plants into these buffers not only improves biodiversity but also aligns with Appalachian traditions of utilizing native species, ensuring cultural relevance and community acceptance. The sale of harvested products from edible riparian buffers can provide supplementary income for farmers and landowners, enhancing their economic resilience. By adopting community orchards and edible riparian buffers, Appalachian communities can tackle food deserts through solutions that are both locally driven and ecologically sound. Agroforestry's framework combines environmental restoration and human well-being, yielding impactful, culturally relevant, and sustainable long-term practices.

5. The Need for Research: Advancing a Conceptual Framework and Identifying Regional Priorities

Appalachian agroforestry success depends on substantial research that identifies best practices, overcomes obstacles, and optimizes environmental, economic, and social outcomes. One critical area of focus is the economic viability of agroforestry systems. Uncertainty about profitability remains a significant barrier for landowners considering these practices, as they must have compelling evidence of financial returns before transitioning. Existing studies suggest that systems such as silvopasture and forest farming can generate substantial economic benefits, but detailed, region-specific, and physiographic analyses are crucial for validating these claims (Rodrigues Maia, 2023). For example, research could model the costs and benefits of implementing community orchards, riparian buffers, and silvopasture systems, providing precise data on return on investment, scalability, and long-term sustainability. These insights would not only reduce economic uncertainty (financial risk) but also empower landowners to make informed decisions about adopting agroforestry practices.

The literature consistently identifies knowledge gaps, policy barriers, and socio-cultural factors as obstacles to agroforestry adoption; however, few studies directly explore these dimensions within Appalachian communities, revealing a specific research gap that warrants urgent attention. Equally important is understanding the ecological impacts of agroforestry, particularly under Appalachian conditions. Agroforestry systems are known to enhance ecosystem services such as carbon sequestration, soil conservation, and biodiversity (Castle et al., 2022). However, more localized studies are needed to quantify these benefits in the complex topography, diverse microclimates, and distinct land-use histories of Appalachia. For example, research could investigate how alley cropping with native tree species affects soil nutrient dynamics and microbial communities, or how agroforestry systems contribute to watershed health and forest restoration. Additionally, the resilience of these systems to climate stressors like droughts, pests, and shifting weather patterns requires further investigation to ensure their sustainability over time (Pancholi et al., 2023). Such studies would provide the scientific basis for tailoring agroforestry practices to Appalachian landscapes, maximizing their environmental and economic potential while addressing the region's unique ecological challenges. Together, these studies suggest that agroforestry systems enhance ecosystem services globally; yet their performance in Appalachia's complex, mountainous ecosystems remain largely untested, necessitating regionally focused ecological studies. Tailored practices may enhance the viability of agroforestry as a sustainable land-use strategy for both landowners and policymakers in the region.

The socio-cultural factors influencing the adoption of agroforestry also require significant research attention. Understanding the traditions, perceptions, and values of Appalachian landowners and farmers is essential for developing strategies that align with community needs and priorities. Participatory research methods, which engage stakeholders directly, can inform decision-making processes and identify barriers to adoption (Mercer, 2004). Understanding the potential drivers of agroforestry adoption is essential for identifying the social and environmental factors that hinder or facilitate its implementation, providing a foundation for designing and implementing effective policies (Zabala et al., 2025). Notably, while this review integrates diverse disciplinary perspectives, it does not attempt to construct a formalized theoretical model. Advancing the field would benefit from the development of regionally grounded theoretical or decision-support frameworks that can more systematically guide agroforestry adoption, assess ecosystem service trade-offs, and inform policy design in the Appalachian context. Additionally, technological innovations such as remote sensing, GIS mapping, and precision agriculture hold promise for revolutionizing agroforestry practices by enabling efficient monitoring of tree health, soil conditions, and crop yields. Furthermore, research into policy and institutional support is crucial for creating an enabling environment for the adoption of agroforestry. This evaluation includes existing incentive programs like cost-sharing initiatives and tax credits, identifying gaps, and drawing lessons from successful policies in other regions (Gonçalves et al., 2021). By addressing these interconnected research priorities, Appalachian policymakers may be able to facilitate agroforestry's transformative potential, fostering collaboration among academic institutions, government agencies, nonprofits, and local stakeholders to drive innovation and achieve sustainable, community-driven outcomes.

It is worthwhile restating that currently there is no consolidated or comprehensive database documenting integrated agroforestry practices, outcomes, or adoption rates, case studies, and even pictorial representations of agroforestry specific to the Appalachian region. This significant gap in empirical data underscores the need for foundational research, including site-specific field trials, economic modeling, ecological assessments, and socio-cultural studies. The absence of such datasets has limited the ability to conduct statistical analyses or present regionally tailored empirical data within this review. Therefore, a core purpose of this article is to synthesize the broader body of agroforestry literature, identify its potential applicability to Appalachia, and, critically, highlight the urgent need for systematic research efforts to build the datasets necessary for evidence-based policy, practice, and investment. The development of these datasets and corresponding analyses represents a critical next step beyond the scope of the current work.

6. The Integration of Agrivoltaics into Agroforestry Systems

Combining solar energy production with agriculture, known as agrivoltaics, enables landowners to boost productivity by generating energy and crops simultaneously. The integration of agrivoltaics into agroforestry systems offers a contemporaneous and timely approach to addressing economic and environmental challenges while promoting diversified income and sustainable land use. When combined with agroforestry practices, this integration creates synergistic systems that enhance land-use efficiency and resilience. For example, shade-tolerant crops or medicinal herbs may thrive beneath solar panels, while silvopasture systems can incorporate livestock grazing alongside tree growth and renewable energy production. Research has shown that agrivoltaic systems can increase land-use efficiency by up to 70%, demonstrating their potential to meet both energy and agricultural needs simultaneously (Dupraz et al., 2011). Agrivoltaics can increase annual net revenues for landowners by 300–5,000% compared to farming alone. This approach also enhances financial resilience, particularly for crops vulnerable to weather and market fluctuations, by diversifying income streams and boosting worst-case net revenues by 48–53% (Cuppari et al., 2021). Given the economic challenges in Appalachia, agrivoltaics may provide a sustainable approach to enhance farm profitability while maintaining agricultural productivity. By carefully designing these systems to optimize light distribution and resource utilization, landowners can achieve both economic and ecological benefits, ensuring long-term sustainability and resilience.

Beyond its economic potential, the integration of agrivoltaics into agroforestry systems addresses critical socioeconomic challenges, particularly in rural regions such as Appalachia. By combining renewable energy with agriculture and forestry, these systems generate multiple income streams and create new job opportunities. For example, solar energy projects often spur local employment in installation, maintenance, and technical support, offering high-paying jobs that can revitalize rural economies (Proctor et al., 2020). Additionally, the energy produced can reduce on-farm electricity costs, freeing up resources for further investment in agricultural operations. These systems also contribute to energy equity by providing access to renewable energy in underserved areas. Furthermore, agrivoltaic agroforestry systems align with traditional land-use practices and cultural values, fostering local acceptance and encouraging broader adoption. The socioeconomic benefits, coupled with its ecological advantages, make this approach a compelling strategy for addressing poverty and economic instability while promoting environmental stewardship.

From an environmental perspective, agrivoltaic agroforestry systems enhance ecosystem services, mitigate climate change, and improve resource efficiency. Solar panels provide shade, creating a microclimate that reduces soil temperature and evapotranspiration, thereby conserving water and improving soil health. Studies indicate that such systems can reduce irrigation needs by up to 30%, a significant benefit in water-scarce regions and during drought conditions (Barron-Gafford et al., 2019). However, realizing the full potential of integrated agroforestry and agrivoltaics systems requires robust research and supportive policies. Studies must focus on optimizing designs to balance energy generation with agricultural and forestry outputs. At the same time, policies should provide financial incentives, such as grants, tax credits, and subsidies, to lower the barriers to adoption. With concerted efforts from researchers, policymakers, and communities, agrivoltaics in agroforestry can serve as a transformative tool for diversified income, socioeconomic upliftment, and environmental resilience.

7. The Role of Education, Extension, and Community Engagement

Education serves as the cornerstone for advancing the adoption of agroforestry practices in Appalachia, addressing critical knowledge gaps that often hinder the transition to sustainable land use. Comprehensive education initiatives empower farmers, foresters, community leaders, policymakers, and consumers with the technical expertise, economic rationale, and ecological benefits needed to implement agroforestry systems effectively. Integrating agroforestry into formal education and extension services not only builds the capacity of current practitioners but also inspires future generations of researchers and innovators, ensuring the long-term sustainability of agroforestry practices. University academic programs, community organizations, and cooperative extension can lead this effort by providing tailored educational programs that align with the region's unique environmental and socioeconomic conditions.

Extension programs represent one of the most impactful approaches to agroforestry education. These programs bridge the gap between scientific research and practical application, offering hands-on training, demonstration plots, and workshops to landowners and agricultural professionals (Pattanayak et al., 2012). For example, demonstration projects on silvopasture and riparian buffer systems, which incorporate edible species, can guide farmers with the knowledge of how to align agricultural productivity with ecological goals. Additionally, collaborative workshops offer opportunities for peer-to-peer learning, enabling local farmers to apply practical agroforestry techniques and exchange best practices. Incorporating agroforestry into school and university curricula is another critical strategy for fostering innovation and expertise. Programs in environmental science, agriculture, and forestry can incorporate agroforestry principles, equipping students with the interdisciplinary knowledge required to address complex sustainability challenges. Experiential learning opportunities, such as internships and fieldwork, enhance students' ability to apply theoretical concepts in real-world contexts, preparing a new generation of practitioners to advance sustainable development (Denham et al., 2004).

Community engagement is foundational to the success of agroforestry initiatives, as it ensures that strategies and practices align with the unique needs, priorities, and values of local stakeholders (Hubbart, 2023a, 2023b, 2024a, 2024b). Actively involving stakeholders in the planning, implementation, and management of agroforestry systems fosters trust, collaboration, and shared responsibility, enabling communities to take ownership of sustainable land-use practices. This participatory approach is particularly critical in Appalachia, where diverse cultural traditions, historical contexts, and socioeconomic challenges significantly influence land management decisions (Carlson, 2019). By tailoring engagement efforts to the specific characteristics of the region, agroforestry practitioners can build stronger connections with communities and encourage broader adoption of innovative practices. Cultural relevance is another critical component of successful community engagement. Appalachia's rich heritage and traditions can be leveraged to enhance the acceptance and impact of agroforestry initiatives. Incorporating native species into agroforestry systems not only supports biodiversity but also resonates with the cultural identity of local communities (Castle et al., 2021). Storytelling, an essential Appalachian tradition, offers a powerful tool for sharing success stories, building trust, and inspiring broader adoption of agroforestry practices. Moreover, engaging youth through education-focused initiatives, such as school curricula and student-managed projects like community gardens and orchards, ensures the sustainability of these efforts by cultivating a new generation of informed practitioners (Koempel et al., 2022). Digital tools and online platforms further enhance engagement by overcoming geographic barriers, connecting dispersed communities, and providing accessible resources, expert advice, and peer support (Williams et al., 2010).

8. Policy and Funding Support

The policy recommendations presented here are intended to strike a balance between established, operational mechanisms and forward-looking, innovative approaches tailored to Appalachia's specific challenges. Recognizing the need for both immediate practical actions and longer-term systemic change, the recommendations draw on successful programs while proposing adaptive strategies that leverage emerging markets, technologies, and cooperative models. This dual approach may provide landowners, communities, and policymakers with actionable pathways that are both feasible within existing frameworks and capable of driving transformative outcomes. Policy and funding support play a crucial role in scaling up agroforestry initiatives across Appalachia, addressing the region's socioeconomic and environmental challenges. A well-structured policy framework coupled with robust funding mechanisms should lower barriers to adoption, create diversified income opportunities, and enhance environmental resilience. Financial incentives remain crucial in promoting the adoption of agroforestry. Cost-sharing programs for agroforestry establishment, such as tree planting, silvopasture development, and riparian buffer restoration, may alleviate the initial financial burden on landowners (Bettles et al., 2021). Tax credits for ecosystem services, including carbon sequestration and biodiversity conservation, may provide another avenue for demonstrating the economic value of ecological stewardship (Castle et al., 2021). Additionally, payments for ecosystem services (PES) schemes may incentivize sustainable practices by rewarding landowners for contributing to water quality improvement, soil health, and carbon storage (Mukhlis et al., 2022). For example, agroforestry presents significant opportunities for landowners to participate in the emerging forest carbon market. By adopting agroforestry, landowners can generate income from carbon credits while continuing to earn revenue from timber, non-timber forest products (NTFPs) like ginseng and mushrooms, and agricultural yields. This diversification reduces financial risk and increases long-term economic stability. Recent developments in carbon offset programs are making participation increasingly viable, allowing landowners to generate revenue while promoting sustainable land management (Gazal et al., 2024).

Investments in research and education are cornerstones to the successful broad-scale adoption of agroforestry practices. Research grants and other funding mechanisms should be developed that support region-specific studies on the economic viability and ecological benefits of agroforestry systems, providing landowners with data-driven insights (Brown et al., 2018). For example, pilot projects and demonstration sites funded by grants can showcase best practices, while education-focused funding could expand extension services, training workshops, and technical support programs for practitioners (Pattanayak et al., 2012). Agroforestry also holds significant potential for addressing socioeconomic disparities in Appalachia. By diversifying income streams through the cultivation of high-value non-timber forest products (NTFPs) like ginseng, mushrooms, and medicinal herbs, agroforestry provides alternative revenue opportunities for communities affected by declining industries (Kaur & Tiwana, 2024).

Collaborations between public and private entities could mobilize resources and expertise, driving large-scale adoption of agroforestry. Partnerships with private forestry companies, agricultural cooperatives, and renewable energy firms can pool funding and technical knowledge, while nonprofits can facilitate community engagement and capacity building. For example, agroforestry cooperatives focused on NTFPs can help aggregate production, secure fair market access, and enhance economic returns for small-scale farmers (Koempel et al., 2022). Integrating agroforestry into broader environmental and economic policies can amplify its impact. Policies aligning with the USDA's Conservation Reserve Program (CRP) or international initiatives like the United Nations Sustainable Development Goals (SDGs) may provide additional funding opportunities and elevate the visibility of Appalachian agroforestry efforts (Santiago-Freijanes et al., 2021). By prioritizing these strategies and others not presented here, the potential for agroforestry to foster resilient communities and sustainable landscapes may be realized in Appalachia.

9. Synthesis: Advancing Agroforestry in Appalachia

The practical significance of advancing agroforestry in Appalachia can be understood at three critical levels. First, the importance of this work lies in agroforestry's potential to address the region's interrelated environmental, economic, and social challenges, including degraded ecosystems, economic stagnation, and food insecurity. Second, the necessity is underscored by the current absence of regionally tailored research, data, and adoption frameworks, which limit informed decision-making and impede policy development. Finally, the feasibility of advancing agroforestry is demonstrated through existing federal programs, emerging market mechanisms, and community engagement strategies that offer practical and scalable pathways for implementation. Together, these dimensions highlight the urgency and opportunity for coordinated action by researchers, policymakers, and practitioners. This review, therefore, integrates global evidence with Appalachian realities, critically identifying both the promise and the pronounced research gaps that must be addressed to translate the potential of agroforestry into practice in the region.

The adoption of agroforestry practices in Appalachia presents a transformative opportunity to address the region's environmental, economic, and social challenges by integrating sustainable land-use practices with community-driven approaches. Some of the most critical needs for advancing agroforestry in the region include (1) the establishment of agroforestry demonstration sites with community-engaged field days, (2) robust policy and funding support, (3) enhanced educational initiatives, and (4) strategic marketing.

(1) *Establishing Agroforestry Demonstration Sites with Community-Engaged Field Days:* Demonstration of agroforestry sites represents a vital tool for showcasing the practical applications of agroforestry practices and fostering adoption. Research shows that participatory workshops and practical demonstrations are among the most effective ways to bridge the gap between theoretical knowledge and actionable practice (Kruger et al., 2012). Community-engaged field days at these sites provide hands-on learning opportunities, allowing participants to observe the benefits of silvopasture, agrivoltaics, riparian buffers, and forest farming in real-world contexts. Effective community engagement ensures that agroforestry initiatives align with local traditions, values, and priorities. Participatory approaches that involve stakeholders in the planning, implementation, and management of agroforestry systems foster trust, collaboration, and ownership (Mukhlis et al., 2022). Digital tools, including online platforms and mobile applications, provide accessible resources and peer support, overcoming geographic barriers and connecting dispersed communities (Williams et al., 2010). Demonstration sites also act as platforms for piloting innovative practices, such as the integration of agroforestry with agrivoltaic systems, which have been shown to enhance land-use efficiency and diversify income streams (Barron-Gafford et al., 2019).

(2) *Robust Policy and Funding Support:* Scaling agroforestry requires a well-structured policy framework and financial incentives to reduce barriers to adoption. Cost-sharing programs, tax credits for ecosystem services, and payments for ecosystem services (PES) are critical mechanisms to support landowners in transitioning to agroforestry systems (Bettles et al., 2021). Policies aligning with national and international initiatives, such as the USDA's Conservation Reserve Program and the United Nations Sustainable Development Goals, can elevate agroforestry's visibility and unlock additional funding opportunities (Castle et al., 2021). Collaborations between public and private entities, including forestry companies, agricultural cooperatives, and renewable energy firms, can further mobilize resources and expertise. Nonprofits play a crucial role in advocating for policy reforms and facilitating grassroots engagement, ensuring equitable access to funding and technical support (Santiago-Freijanes et al., 2021).

(3) *Enhanced Educational Initiatives:* Education is foundational for agroforestry's success, equipping stakeholders with the knowledge and skills needed to innovate and implement sustainable practices. Extension programs offering hands-on training, workshops, and technical support are essential for bridging knowledge gaps and building practitioner capacity (Pattanayak et al., 2012). In addition to technical training, increasing landowners' awareness

of financial incentives and support programs, such as cost-share programs, tax incentives, and grants, can help reduce economic barriers to agroforestry adoption. Many landowners remain unaware of available assistance programs, which limits participation in sustainable practices (Butler et al., 2014). Providing clear, accessible information about these opportunities through extension can facilitate greater adoption of agroforestry. Integrating agroforestry principles into school and university curricula fosters innovation and ensures the sustainability of these efforts by cultivating a new generation of informed practitioners (Koempel et al., 2022). Demonstration sites, in combination with experiential learning opportunities such as internships, provide students with real-world experience, preparing them to address complex sustainability challenges.

(4) *Strategic Marketing:* A well-developed marketing strategy is crucial for creating consumer demand and ensuring the financial viability of agroforestry-based products. Farmers, ranchers, and forest owners are increasingly interested in integrating fruit, nuts, root crops, mushrooms, and other specialty crops into their production systems using agroforestry practices. However, many producers seek information and market connections before committing to these practices (USDA National Agroforestry Center, 2021). Establishing cooperative networks, farm-to-market programs, and branding Appalachian agroforestry products, such as specialty crops, non-timber forest products (e.g., ginseng, mushrooms, nuts) and sustainably raised livestock, can help differentiate them in local and national markets. Additionally, strengthening value chains through regional food hubs, direct-to-consumer marketing, and partnerships with retailers can improve profitability and encourage broader adoption of agroforestry.

By addressing these and other critical needs, the transformative potential of agroforestry may be realized in Appalachia, promoting sustainable land use, economic resilience, and preservation of the rich cultural heritage for a more sustainable future. In addition to established strategies reported here, advancing agroforestry in Appalachia will also benefit from innovative approaches such as integrating agrivoltaics, leveraging carbon markets and payments for ecosystem services, fostering cooperative models for non-timber forest products, and utilizing digital platforms and participatory demonstrations to accelerate adoption. These scalable and regionally tailored strategies complement existing frameworks and can help catalyze transformative outcomes for Appalachian communities.

10. Conclusions

The development of a thriving agroforestry industry in Appalachia may offer a transformative opportunity to address the region's interconnected environmental, economic, and social challenges. By integrating trees, shrubs, ungulate agriculture, specialty crops, agrivoltaics, and many other production systems into agricultural landscapes, agroforestry combines ecological benefits with economic incentives, making it a powerful tool for sustainable development. These systems are particularly well-suited to Appalachia's unique environmental and cultural landscape, where deforestation, soil degradation, and food insecurity remain pressing issues. The cultivation of high-value non-timber forest products (NTFPs), including ginseng, mushrooms, and medicinal herbs, offers a viable alternative to declining industries like coal mining and traditional timber production. These opportunities not only address environmental sustainability but also support economic resilience in rural communities.

While the opportunities presented by agroforestry in Appalachia are compelling, it is essential to recognize that the current knowledge base lacks region-specific empirical data, integrated assessments, and statistical analyses necessary to fully validate these opportunities under Appalachian conditions. This review has been undertaken to address this deficiency by synthesizing global literature, identifying applicable practices, and framing the potential pathways forward. The generation of new research data, including experimental trials, economic feasibility studies, and ecological impact assessments, is urgently needed. By spotlighting these knowledge gaps, the article seeks to catalyze the research community, policymakers, and practitioners to prioritize the development of these critical datasets, which are foundational for informed decision-making and the successful establishment of a thriving agroforestry sector in Appalachia.

Realizing the full potential of agroforestry in Appalachia requires a concerted and collaborative effort among policymakers, researchers, educators, and local communities. Education and community engagement are pivotal to fostering the widespread adoption of agroforestry practices. Tailored extension services, participatory workshops, and experiential learning programs can bridge knowledge gaps and empower stakeholders with the skills necessary to implement agroforestry systems effectively. Policy and funding support are equally essential; cost-sharing programs, tax credits for ecosystem services, and grants for research and education can significantly reduce barriers for landowners. Public-private partnerships and alignment with broader strategies like the USDA Conservation Reserve Program may further strengthen these efforts.

Simultaneously, rigorous research on economic feasibility, ecological impacts, and socio-cultural factors can provide a robust scientific foundation for scaling agroforestry practices. By prioritizing inclusivity and leveraging the region's natural and cultural resources, Appalachia can position itself as a leader in sustainable agroforestry practices, creating a future marked by resilience, innovation, and shared prosperity.

Supplementary Materials: Not applicable.

CRediT Author Statement: Jason A. Hubbart: Conceptualization, Methodology, Data curation, Writing-original draft, Visualization, Investigation, Supervision, and Writing-review & editing; **Fabricio Comacho:** Writing-review & editing; **Kathryn Gazal:** Writing-review & editing; **Larissa Martins:** Writing-review & editing; **Kirsten Stephan:** Writing-review & editing; **Kristi Wood-Turner:** Writing-review & editing.

Data Availability Statement: Not applicable.

Funding: This work was supported by the USDA National Institute of Food and Agriculture McIntire Stennis accession number 7003934 and the West Virginia Agricultural and Forestry Experiment Station. The Agriculture and Food Research Initiative supported a portion of this research, Grant No. 2020-68012-31881, from the USDA National Institute of Food and Agriculture. The results presented may not reflect the sponsors' views, and no official endorsement should be inferred. The funders had no role in study design, data collection and analysis, the decision to publish, or the preparation of the manuscript.

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

Acknowledgments: Not applicable.

References

Abbas, F., Hammad, H. M., Fahad, S., Cerdà, A., Rizwan, M., Farhad, W., Ehsan, S., & Bakhat, H. F. (2017). Agroforestry: A sustainable environmental practice for carbon sequestration under the climate change scenarios—a review. *Environmental Science and Pollution Research*, *24*, 11177–11191. https://doi.org/10.1007/s11356-017-8687-0

Abesh, B. F., Jin, L., & Hubbart, J. A. (2022). Predicting climate change impacts on water balance components of a mountainous watershed in the Northeastern USA. *Water*, *14*(20), 3349. https://doi.org/10.3390/w14203349

Barron-Gafford, G. A., Pavao-Zuckerman, M. A., Minor, R. L., Sutter, L. F., Barnett-Moreno, I., Blackett, D. T., Thompson, M., Dimond, K., Gerlak, A. K., Nabhan, G. P., & Macknick, J. E. (2019). Agrivoltaics provide mutual benefits across the food–energy–water nexus in drylands. *Nature Sustainability*, *2*, 848–855. https://doi.org/10.1038/s41893-019-0364-5

Bentrup, G., Hopwood, J., Adamson, N. L., & Vaughan, M. (2019). Temperate agroforestry systems and insect pollinators: A review. *Forests*, *10*(11), 981. https://doi.org/10.3390/f10110981

Bettles, J., Battisti, D. S., Cook-Patton, S. C., Kroeger, T., Spector, J. T., Wolff, N. H., & Masuda, Y. J. (2021). Agroforestry and non-state actors: A review. *Forest Policy and Economics*, *130*, 102538. https://doi.org/10.1016/j.forpol.2021.102538

Boettner, F., Hansen, E., Clingerman, J., Hereford, A., Zegre, S., Martin, R., Askins, N., Deng, J., Anderson, J., Collins, A., Harris, T., Jackson, R., LaFone, F., Lamont, S., Strager, J., Strager, M., Veselka, W., Zegre, N., Abdalla, C., & Goetz, S. J. (2014). *An assessment of natural assets in the Appalachian region: Water resources*. Appalachian Regional Commission. https://www.arc.gov/wp-content/uploads/2020/06/AssessmentofNaturalAssetsintheAppalachian-Region-WaterResources.pdf

Brown, S. E., Miller, D. C., Ordonez, P. J., & Baylis, K. (2018). Evidence for the impacts of agroforestry on agricultural productivity, ecosystem services, and human well-being in high-income countries: A systematic map protocol. *Environmental Evidence*, *7*, 24. https://doi.org/10.1186/s13750-018-0136-0

Buehlmann, U., Bumgardner, M., Schuler, A., & Barford, M. (2007). Assessing the impacts of global competition on the Appalachian hardwood industry. *Forest Products Journal*, *57*(3), 89–93. https://www.nrs.fs.usda.gov/pubs/jrnl/2007/nrs_2007_buehlmann_001.pdf

Butler, B. J., Markowski-Lindsay, M., Snyder, S., Catanzaro, P., Kittredge, D. B., Andrejczyk, K., Dickinson, B. J., Eryilmaz, D., Hewes, J. H., Randler, P., Tadle, D., & Kilgore, M. A. (2014). Effectiveness of landowner assistance activities: An examination of the USDA Forest Service's Forest Stewardship Program. *Journal of Forestry*, *112*(2), 187–197. https://doi.org/10.5849/jof.13-066

Carlson, E. B. (2019). *"There is wealth in the struggle": Unearthing and embracing community knowledges through organized work in Appalachia.* [Doctor Dissertation, Perdue University]. https://dx.doi.org/10.25394/PGS.8292149.V1

Castle, S. E., Miller, D. C., Merten, N., Ordonez, P. J., & Baylis, K. (2022). Evidence for the impacts of agroforestry on ecosystem services and human well-being in high-income countries: A systematic map. *Environmental Evidence*, *11*, 10. https://doi.org/10.1186/s13750-022-00260-4

Castle, S. E., Miller, D. C., Ordonez, P. J., Baylis, K., & Hughes, K. (2021). The impacts of agroforestry interventions on agricultural productivity, ecosystem services, and human well-being in low- and middle-income countries: A systematic review. *Campbell Systematic Reviews*, *17*(2), e1167. https://doi.org/10.1002/cl2.1167

Cialdella, N., Jacobson, M., & Penot, E. (2023). Economics of agroforestry: Links between nature and society. *Agroforestry Systems*, *97*, 273–277. https://doi.org/10.1007/s10457-023-00829-z

Cuppari, R. I., Higgins, C. W., & Characklis, G. W. (2021). Agrivoltaics and weather risk: A diversification strategy for landowners. *Applied Energy*, *291*, 116809. https://doi.org/10.1016/j.apenergy.2021.116809

Dean-Witt, C., & Hardin-Fanning, F. (2020). P41 Exploring the stigma of childhood food insecurity in Appalachia. *Journal of Nutrition Education and Behavior*, *52*(7), S34–S35. https://doi.org/10.1016/j.jneb.2020.04.086

Delgado, T. S., McCall, M. K., & López-Binqüist, C. (2016). Recognized but not supported: Assessing the incorporation of non-timber forest products into Mexican forest policy. *Forest Policy and Economics*, *71*, 36–42. https://doi.org/10.1016/j.forpol.2016.07.002

Denham, S. A., Meyer, M. G., Toborg, M. A., & Mande, M. J. (2004). Providing health education to Appalachia populations. *Holistic Nursing Practice*, *18*(6), 293–301. https://doi.org/10.1097/00004650-200411000-00005
Dobhal, S., Kumar, R., Bhardwaj, A. K., Chavan, S. B., Uthappa, A. R., Kumar, M., Singh, A., Jinger, D., Rawat, P., Handa, A. K., & Ramawat, N. (2024). Global assessment of production benefits and risk reduction in agroforestry during extreme weather events under climate change scenarios. *Frontiers in Forests and Global Change*, *7*. https://doi.org/10.3389/ffgc.2024.1379741
Dupraz, C., Marrou, H., Talbot, G., Dufour, L., Nogier, A., & Ferard, Y. (2011). Combining solar photovoltaic panels and food crops for optimising land use: Towards new agrivoltaic schemes. *Renewable Energy*, *36*(10), 2725–2732. https://doi.org/10.1016/j.renene.2011.03.005
Elagib, N. A., & Al-Saidi, M. (2020). Balancing the benefits from the water–energy–land–food nexus through agroforestry in the Sahel. *Science of the Total Environment*, *742*, 140509. https://doi.org/10.1016/j.scitotenv.2020.140509
Fahad, S., Chavan, S. B., Chichaghare, A. R., Uthappa, A. R., Kumar, M., Kakade, V., Pradhan, A., Jinger, D., Rawale, G., Yadav, D. K., Kumar, V., Farooq, T. H., Ali, B., Sawant, A. V., Saud, S., Chen, S., & Poczai, P. (2022). Agroforestry systems for soil health improvement and maintenance. *Sustainability*, *14*(22), 14877. https://doi.org/10.3390/su142214877
Gazal, K. A., Hwang, J., & Eastman, B. (2024). West Virginia forest landowners' preferences for forest carbon offset programs. *Trees, Forests and People*, *18*, 100683. https://doi.org/10.1016/j.tfp.2024.100683
Ghale, B., Mitra, E., Sodhi, H. S., Verma, A. K., & Kumar, S. (2022). Carbon sequestration potential of agroforestry systems and its potential in climate change mitigation. *Water, Air, & Soil Pollution*, *233*, 228. https://doi.org/10.1007/s11270-022-05689-4
Gonçalves, C. D. B. Q., Schlindwein, M. M., & Martinelli, G. D. C. (2021). Agroforestry systems: A systematic review focusing on traditional indigenous practices, food and nutrition security, economic viability, and the role of women. *Sustainability*, *13*(20), 11397. https://doi.org/10.3390/su132011397
Hemmelgarn, H. L., & Gold, M. A. (2021). Agroforestry education and training. In H. E. G. Garrett, S. & Jose, M. A. Gold (Eds.), *North American Agroforestry* (3rd ed., pp.543–554). ACSESS. https://doi.org/10.1002/9780891183785.ch19
Hubbart, J. A. (2021). Improving best management practice decisions in mixed land use and/or municipal watersheds: Should approaches be standardized? *Land*, *10*(12), 1402. https://doi.org/10.3390/land10121402
Hubbart, J. A. (2023a). Considering use-inspired design and tangible impacts in the agricultural sector. *Open Access Journal of Agricultural Research*, *8*(4). https://doi.org/10.23880/oajar-16000323
Hubbart, J. A. (2023b). Harmonizing science and society: A change management approach to align scientific endeavors with societal needs. *Sustainability*, *15*(21), 15233. https://doi.org/10.3390/su152115233
Hubbart, J. A. (2024a). The importance of stakeholder engagement across market domains. *Journal of Global Entrepreneurial Management*, *2*(1), 1–7. https://scitechjournals.com/articles/the-importance-of-stakeholder-engagement-across-market-domains.pdf
Hubbart, J. A. (2024b). Maximizing research impact in higher education: An approach to identify essential stakeholders and ensure use-inspired outcomes. *Journal of Humanities and Education Development*, *6*(1), 43–50. https://doi.org/10.22161/jhed.6.1.6
Hubbart, J. A., Kellner, E., & Petersen, F. (2022). A 22-site comparison of land-use practices, *E-coli* and enterococci concentrations. *International Journal of Environmental Research and Public Health*, *19*(21), 13907. https://doi.org/10.3390/ijerph192113907
Hubbart, J. A., & Skousen, J. (2021). *Effects of Legacy Coal Mining in Contemporary Watersheds: A West Virginia Case Study*. In L. McLean (Ed.), *Reclamation Matters, Spring 2021* (pp. 30–35). DEL Communications Inc. https://www.asrs.us/wp-content/uploads/2021/08/Reclamation-Matters-Spring-2021.pdf
Kaur, M., & Tiwana, B. S. (2024). Agroforestry methods as a substitute for sustainability in the economy and environment. *International Journal For Multidisciplinary Research*, *6*(4). https://doi.org/10.36948/ijfmr.2024.v06i04.26040
Kaushal, R., Mandal, D., Panwar, P., Rajkumar, Kumar, P., Tomar, J. M. S., & Mehta, H. (2021). Soil and water conservation benefits of agroforestry. In P. K. Shit, H. R. Pourghasemi, P. P. Adhikary, G. S. Bhunia, & V. P. Sati (Eds.), *Forest resources resilience and conflicts* (pp. 259–275). Elsevier. https://doi.org/10.1016/b978-0-12-822931-6.00020-4
Kiernan, P. (2024, October 29). *Logging is a way of life in Appalachia. It's hanging on by a thread*. The Wall Street Journal. https://www.wsj.com/economy/trade/logging-is-a-way-of-life-in-appalachia-its-hanging-on-by-a-thread-e9a5f0a5?msockid=3bb01356a9ca61db1b6f073aa85860cd
Koempel, A., Brislen, L., Jacobsen, K., Clouser, J., Vundi, N., Li, J., Williams, M. A., & Williams, M. V. (2022). Growing health: Building partnerships in healthcare and food systems for improved food access in Appalachia. *Journal of Agriculture, Food Systems, and Community Development*, *11*(4), 261–271. https://doi.org/10.5304/jafscd.2022.114.022
Kruger, T. M., Swanson, M., Davis, R. E., Wright, S., Dollarhide, K., & Schoenberg, N. E. (2012). Formative research conducted in rural appalachia to inform a community physical activity intervention. *American Journal of Health Promotion*, *26*(3), 143–151. https://doi.org/10.4278/ajhp.091223-qual-399
Kuyah, S., Whitney, C. W., Jonsson, M., Sileshi, G. W., Öborn, I., Muthuri, C. W., & Luedeling, E. (2019). Agroforestry delivers a win-win solution for ecosystem services in sub-Saharan Africa. A meta-analysis. *Agronomy for Sustainable Development*, *39*, 47. https://doi.org/10.1007/s13593-019-0589-8
Lasco, R. D., Delfino, R. J. P., & Espaldon, M. L. O. (2014). Agroforestry systems: Helping smallholders adapt to climate risks while mitigating climate change. *WIREs Climate Change*, *5*(6), 825–833. https://doi.org/10.1002/wcc.301
Leakey, R. R. B. (1999). Potential for novel food products from agroforestry trees: A review. *Food Chemistry*, *66*(1), 1–14. https://doi.org/10.1016/s0308-8146(98)00072-7
USDA National Agroforestry Center. (2021). *Marketing agroforestry products: Lessons from producers*. https://www.fs.usda.gov/nac/assets/documents/morepublications/MarketingAgroforestryProducts-508.pdf
Martin, D. A., Osen, K., Grass, I., Hölscher, D., Tscharntke, T., Wurz, A., & Kreft, H. (2020). Land-use history determines ecosystem services and conservation value in tropical agroforestry. *Conservation Letters*, *13*(5), e12740. https://doi.org/10.1111/conl.12740
Mercer, D. E. (2004). Adoption of agroforestry innovations in the tropics: A review. *Agroforestry Systems*, *61*, 311–328. https://doi.org/10.1023/b:agfo.0000029007.85754.70
Mukhlis, I., Rizaludin, M. S., & Hidayah, I. (2022). Understanding socio-economic and environmental impacts of agroforestry on rural communities. *Forests*, *13*(4), 556. https://doi.org/10.3390/f13040556
Munsell, J. F., Bukowski, C. J., Yanez, M., & Allen, J. A. (2021). Urban food forests and community agroforestry systems. In H. E. G. Garrett, S. Jose, & M. A. Gold (Eds.), *North American Agroforestry* (3rd ed., pp. 315–335). https://doi.org/10.1002/9780891183785.ch10
Nair, P. K. R., Kumar, B. M., & Nair, V. D. (2021). *An introduction to agroforestry: Four decades of scientific developments*. Springer Cham. https://doi.org/10.1007/978-3-030-75358-0

Ntawuruhunga, D., Ngowi, E. E., Mangi, H. O., Salanga, R. J., & Shikuku, K. M. (2023). Climate-smart agroforestry systems and practices: A systematic review of what works, what doesn't work, and why. *Forest Policy and Economics*, *150*, 102937. https://doi.org/10.1016/j.forpol.2023.102937

Pancholi, R., Yadav, R., Gupta, H., Vasure, N., Choudhary, S., Singh, M. N., & Rastogi, M. (2023). The role of agroforestry systems in enhancing climate resilience and sustainability- A review. *International Journal of Environment and Climate Change*, *13*(11), 4342–4353. https://doi.org/10.9734/ijecc/2023/v13i113615

Pantera, A., Mosquera-Losada, M. R., Herzog, F., & den Herder, M. (2021). Agroforestry and the environment. *Agroforestry Systems*, *95*, 767–774. https://doi.org/10.1007/s10457-021-00640-8

Pattanayak, S. K., Mercer, D., Sills, E., & Cassingham, K. (2012). *Adopting agroforestry*. Semantic Scholar. https://consensus.app/papers/adopting-agroforestry-pattanayak-mercer/35c6488294fd5058b8cb9ad5fdf491a9/

Proctor, K. W., Murthy, G. S., & Higgins, C. W. (2020). Agrivoltaics align with Green New Deal goals while supporting investment in the US' rural economy. *Sustainability*, *13*(1), 137. https://doi.org/10.3390/su13010137

Rodrigues Maia, F. (2023). The economic viability of an agroforestry system in relation to monoculture. *Journal of Interdisciplinary Debates*, *4*(04), 341–356. https://doi.org/10.51249/jid.v4i04.1744

Salve, A., Tiwari, C., & Baghele, L. (2022). Impact of agroforestry systems: A review. *Asian Journal of Microbiology, Biotechnology & Environmental Sciences*, *24*(2), 214–223. https://doi.org/10.53550/ajmbes.2022.v24i02.002

Santiago-Freijanes, J. J., Mosquera-Losada, M. R., Rois-Díaz, M., Ferreiro-Domínguez, N., Pantera, A., Aldrey, J. A., & Rigueiro-Rodríguez, A. (2021). Global and European policies to foster agricultural sustainability: Agroforestry. *Agroforestry Systems*, *95*, 775–790. https://doi.org/10.1007/s10457-018-0215-9

Santos, P. Z. F., Crouzeilles, R., & Sansevero, J. B. B. (2019). Can agroforestry systems enhance biodiversity and ecosystem service provision in agricultural landscapes? A meta-analysis for the Brazilian Atlantic Forest. *Forest Ecology and Management*, *433*, 140–145. https://doi.org/10.1016/j.foreco.2018.10.064

Schwartzman, G. (2023). *After coal: Power, development, and post-coal politics in Appalachia* (Publication Number. 30487045) [Doctor Dissertation, University of Minnesota]. ProQuest Dissertations & Theses Global. https://conservancy.umn.edu/items/c256d94c-f7ed-43eb-a231-ad825d2c3cca

Singh, V., Johar, V., Kumar, R., & Chaudhary, M. (2021). Socio-economic and environmental assets sustainability by agroforestry systems: A review. *International Journal of Agriculture, Environment and Biotechnology*, *14*(04), 521–533. https://doi.org/10.30954/0974-1712.04.2021.6

Smith, K. E., Bandola-Gill, J., Meer, N., Stewart, E., & Watermeyer, R. (2020). Telling tales of impact: As seen through the eyes of user assessors. In *The impact agenda: Controversies, consequences and challenges* (pp. 183–194). Bristol University Press. https://doi.org/10.51952/9781447339861.ch009

Smith, M. M., Bentrup, G., Kellerman, T., Macfarland, K., Straight, R., Ameyaw, L., & Stein, S. (2022). Silvopasture in the USA: A systematic review of natural resource professional and producer-reported benefits, challenges, and management activities. *Agriculture, Ecosystems & Environment*, *326*, 107818. https://doi.org/10.1016/j.agee.2021.107818

Udawatta, R. P., Garrett, H. E., Jose, S., & Lovell, S. T. (2021). Water quality and quantity benefits of agroforestry and processes: Long-term case studies from Missouri, USA. In R. P. Udawatta & S. Jose (Eds.), *Agroforestry and ecosystem services* (pp. 113–139). Springer Cham. https://doi.org/10.1007/978-3-030-80060-4_6

Udawatta, R. P., Rankoth, L., & Jose, S. (2019). Agroforestry and biodiversity. *Sustainability*, *11*(10), 2879. https://doi.org/10.3390/su11102879

Udawatta, R. P., Rankoth, L., & Jose, S. (2021). Agroforestry for biodiversity conservation. In R. P. Udawatta & S. Jose (Eds.), *Agroforestry and ecosystem services*, (pp. 245–274). Springer Cham. https://doi.org/10.1007/978-3-030-80060-4_10

Williams, M. R., Leatherwood, L., Byrd, L., Boyd, M. S., & Pennington, K. (2010). Alumni engaging students from Under-Served Groups in Southern Appalachia. *Community College Enterprise*, *16*(1), 23–35. https://digitalcommons.odu.edu/efl_fac_pubs/32/

Zabala, A., Pascual, U., García-Barrios, L. E., & Mukherjee, N. (2025). Drivers to adopt agroforestry and sustainable land-use innovations: A review and framework for policy. *Land Use Policy*, *151*, 107468. https://doi.org/10.1016/j.landusepol.2025.107468

Zawarus, P. W., & Ortega, L. (2022). Food desert to food oasis: An engagement with the community through evidence-based methods. *Creative Collaborations*. https://digitalscholarship.unlv.edu/cfa_collaborate/13/

Zinkhan, F. C., & Mercer, D. E. (1996). An assessment of agroforestry systems in the southern USA. *Agroforestry Systems*, *35*, 303–321. https://doi.org/10.1007/BF00044460

Zipper, C. E., Burger, J. A., Barton, C. D., & Skousen, J. G. (2013). Rebuilding soils on mined land for native forests in Appalachia. *Soil Science Society of America Journal*, *77*(2), 337–349. https://doi.org/10.2136/sssaj2012.0335

Zomer, R. J., Bossio, D. A., Trabucco, A., van Noordwijk, M., & Xu, J. (2022). Global carbon sequestration potential of agroforestry and increased tree cover on agricultural land. *Circular Agricultural Systems*, *2*, 3. https://doi.org/10.48130/CAS-2022-0003

Agricultural & Rural Studies

Review

Knowledge Domain and Emerging Trends in Monitoring of Forest Fires Using Remote Sensing: A Scientometric Review Based on CiteSpace Analysis

Juan Zhang [1,2,3], **Yawen Dong** [4], **Yan Liu** [2,3], **Yuelin Kang** [5], **Shaofeng Xie** [5] **and Haizhou Xu** [5,*]

1 College of Forestry, Central South University of Forestry and Technology, Changsha 410004, China; zj@csuft.edu.cn
2 Hunan Provincial Botanical Garden, Changsha 410000, China; 13548786287@163.com
3 Hunan Changsha-Zhuzhou-Xiangtan City Cluster Ecosystem Observation and Research Station, Changsha 410116, China
4 Central South Inventory and Planning Institute of National Forestry and Grassland Administration, Changsha 410014, Hunan, China; 13548627026@163.com
5 College of Advanced Interdisciplinary Studies, Central South University of Forestry and Technology, Changsha 410004, China; kyl@csuft.edu.cn (Y.K.); xieshaofeng@csuft.edu.cn (S.X.)
* Correspondence: xhz@csuft.edu.cn

Abstract: With global warming, the incidence of forest fires has risen significantly, negatively affecting the ecological balance and the environment. This paper is aimed at summarizing the current state of research and global development trends regarding monitoring of forest fires with remote sensing. In the present study, a total of 8841 documents from 2009 to 2024 were extracted with the goal of gaining insights into the progress and dynamics of forest fire monitoring based on remote sensing and the core library of the Web of Science (WoS) and visualized and analyzed with CiteSpace bibliometric software. Results show that research on remote sensing to monitor forest fires has mainly gained momentum in the last 16 years and has shown a significant increase after 2018. The United States, as a major research center, leads the global scientific community in terms of national and institutional collaborations. Forests, with 382 publications, was ranked first as the leading published journal in the field. Dr. Sun of the University of Northeast Forestry University, China, became the most prolific author, ranking first with 16 citations. The influence of driving factors on forest fires imposed on properties of soil drivers is revealed through the analysis of trends in research areas. Forest fire spread, index, fire trend will be the next focus of research. By combining biblio-metric methods and systematic reviews, these findings provide forest fire managers and researchers with a deeper comprehension of the development of monitoring forest fires using remote sensing.

Keywords: forest fire; remote sensing; monitoring; CiteSpace; bibliometric analysis; Web of Science; co-authorship analysis; co-citation analysis; research trend

Citation: Zhang, J., Dong, Y., Liu, Y., Kang, Y., Xie, S., & Xu, H. (2025). Knowledge Domain and Emerging Trends in Monitoring of Forest Fires Using Remote Sensing: A Scientometric Review Based on CiteSpace Analysis. *Agricultural & Rural Studies*, *3*(2), 29. https://doi.org/10.59978/ar03020008

Received: 30 December 2024
Revised: 28 March 2025
Accepted: 9 April 2025
Published: 3 June 2025

1. Introduction

Forest fires often occur in forested ecosystems worldwide and rank first among the three major natural disasters occurring in forests (Xiang et al., 2023). Global warming has led to a rise in both frequency and area impacted by forest fires, not only damaging the environment and jeopardizing ecological security but also endangering human lives and property (Babu et al., 2023; Jiao et al., 2023). For example, fires in the Amazon rainforest and Australia that occurred in 2019 and 2020 burned large areas of forests and wildlife habitats (de Santana et al., 2023; B. Wang et al., 2022). In 2023, the western provinces of Canada, namely British Columbia and Alberta, were afflicted by severe forest fires. These fires engulfed an area exceeding 121,000 square kilometers, rendering it one of the most catastrophic wildfire events in the country's history (Jain et al., 2024). Subsequently, in 2024, deadly fast-moving fires in Hawaii and Chile, as well as widespread fires in northwestern South America had a significant impact on the global environment (Jones et al., 2024). With an advantageous speed and the ability to monitor large areas and document the forest dynamics of a target at any time, remote sensing serves as a crucial means to detect and monitor forest fires in many countries (Xie et al., 2022b). In the early 1980s, with the development of Geographic Information Systems (GISs), the USA, Canada, and other nations began to carry out monitoring of forest fires through remote sensing, such as the United States used the system, Forest

Fire Advanced Technology, to detect and monitor forest fires. Meanwhile, the USA uses earth observation satellites for monitoring forest fires (Dasgupta et al., 2007; Sulla-Menashe et al., 2014; J. Wang & Zhang, 2020), surface temperatures, and humidity, as well as for forecasting levels of forest fire danger. In 1968, Canada established the Canadian Forest Fire Danger Ranking System (Wotton, 2009), which severs as one of the most well-developed and widely used system in the world at present. Exceptionally, Canada uses satellite tower infrared equipment to monitor forest fires much faster and more efficiently than aerial-based equipment. Poland uses remote sensing combined with GIS tools to monitor forest fires for national forest fire risk zoning and monitoring, fire damage surveys and assessments, and monitoring of trail restoration (Niklasson et al., 2010; Hościło & Turleg, 2014). The present study visualizes and analyzes literature related to monitoring forest fires using remote sensing, which provides a clear picture of the status quo and tendency of the remote sensing usage for forest fire monitoring. Researchers concerning this field have made some progress, and the relevant studies review this theme from different angles, like the early forest fire detection using a radio acoustic detection system (Hefeeda & Bagheri, 2009; Sahin & Ince, 2009; Tsiourlis et al., 2009). In recent years, scholars used deep learning and machine learning (ML) methods to conduct research related to forest fire modeling, mapping (Milanović et al., 2023; Y. Zheng et al., 2023), occurrence assessment, and smoke detection model construction (Qian et al., 2023; Shao et al., 2023), burn area detection, and so on while using multi-source remote sensing imagery (da Silva et al., 2023; Xu et al., 2022). Few researches have used knowledge mapping to quantitatively analyze amounts of previous researches using metrics, as most rely on expert opinion such as analyzing publications, word frequencies, citations, and co-citations. Although many nearly accessible online knowledge bases, books, and articles exist, their overall structure is unknown. To overcome the subjectivity of research, knowledge mapping as a new multidisciplinary research field provides scientific research studies with a visual analysis of the knowledge structure of a relevant field (Minaei-Bidgoli et al., 2004). CiteSpace version 6.2.R6 (64-bit) is a tool that measures the literature and presents the structure and trends of the research in a given subject area visually, providing various analytical approaches, like keyword, co-occurrence, as well as collaborative network types of analysis. Therefore, the present study used CiteSpace to visualize the research literature on monitoring forest fires using remote sensing and explored knowledge structure and future development trends concerning the number of issued papers, research collaboration (individual, institutional, and national collaboration), frequently cited literature, keywords, and research frontiers. In terms of the organization of this paper, (1) Section 2 presents the data sources, methods for analysis, and software parameter design, (2) Section 3 analyzes publication sources, research areas, annual trends, collaborative networks of literature, countries, authors, and institutions to show the knowledge structure of the focal topic. In conjunction with the keyword co-occurrence network, emerging trends in the focus topic are analyzed, the main findings are summarized, and new directions for future research of remote-sensing-based forest fire monitoring are suggested.

2. Materials and Methods

2.1. Data Sources, Search Strategy, and Data Processing

The statistics applied for the bibliometrics analysis came from the Thomson Reuters Web of Science (WoS) Core Collection, which consists primarily of SCI-Expanded databases. All of the searches were carried out within one day to prevent any bias owing to daily updates of the database. The strategy used during the search was Topic search #1 = ("forest fire" OR "forest-fire") AND Topic search #2 = ("Remote sensing") AND Topic search #3 = ("monitoring"), and then the results were refined by [Document Types = (Articles and Review) Timespan: 2009–01–01 to 2024–12–31]. Based on the WoS categorization tags, a total of 8841 articles were selected after eliminating unpublished or incomplete studies, like conference papers and abstracts. Furthermore, the authors, titles, abstracts, keywords, and references were imported into CiteSpace 6.2.R6. CiteSpace, a visualization information software, is often used in academic research and shows a visual type of keyword cluster maps, co-authored networks, dynamic knowledge, distribution maps of time zones, and co-cited networks (Xue et al., 2020). We used CiteSpace to combine cluster and correlation analysis, explore the main content, research hotspots, evolution trends, and research areas, analyze internal links of study hotspots in different phases, and discuss the tendencies of future research.

2.2. Setting of Algorithms and Parameters in Econometric Analysis

After the data was processed, the dataset was imported into CiteSpace. Here are the specific parameters in it. Time Slicing consists of "Year Per Slice" and "Time," which is the time frame for published literature. 1 January 2009 to 31 December 2024 was the set time interval; one year was the set time slice. The map produced by CiteSpace was on the basis of the initial collinear matrix and normalized; the new type of matrix was used to visualize the network. These parameters include Jaccard indices, cosine similarity measures, dice coefficients, and pointwise interaction information. The notion of density portrays the tightness or strength of the associations between nodes, and by dividing the "actual number of relationships," the "theoretical maximum number of relationships" was figured up. The value range of density was 0 to 1. Judging from the clustering clarity and the network structure, two indicators, namely, silhouette (S) and modularity (Q) were provided by CiteSpace to assess the mapping impact. Generally, Q remains within the scope of 0–1. A Q value > 0.3 indicates the structure of clustering is pronounced and clustering with S exceeding 0.5 is usually taken as reasonable. Clustering with S over 0.7 is a high confidence level (C. Chen et al., 2014). Mediation centrality, indicating the importance of a node, is on the basis of the quantity of the shortest paths through a node. This metric is applied by CiteSpace to explore and evaluate the influence of studies on the network, and as a node with intermediary centrality greater than 0.1 is called a critical node, it is usually highlighted with a purple circle (C. Chen et al., 2012). Node size in the authors' collaboration graph means the number of published papers by an author, institution, or country, and connections reflect partnership strength. In the network graph of topics, keywords, and scientific categories, node size represents the occurrence frequency, and the connection represents co-occurrence intensity. In addition, data clustering, another important method, is used to facilitate the analysis of knowledge networks in CiteSpace. More specifically, terms are categorized based on their similarity and scored by a specific algorithm, where the highest-scoring term in each cluster is selected as the label for the cluster (Yuan et al., 2021).

2.3. Other Statistical Analysis Tools

This paper used Microsoft Excel software for data analysis.

3. Results

3.1. Analysis of Publication Sources, Research Area, and Annual Trends

The yearly amounts of publications on the research theme can be divided into three time periods: 2009–2012, 2013–2017, and 2018–2024 as discussed in detail below (Figure 1). *Environmental Sciences* had the most publications regarding the monitoring of forest fires using remote sensing during the study period, followed by *Environmental Sciences*; other fields of research had over three hundred publications in total, including those in *Agricultural and Biological Sciences*, *Remote Sensing*, and *Forestry*.

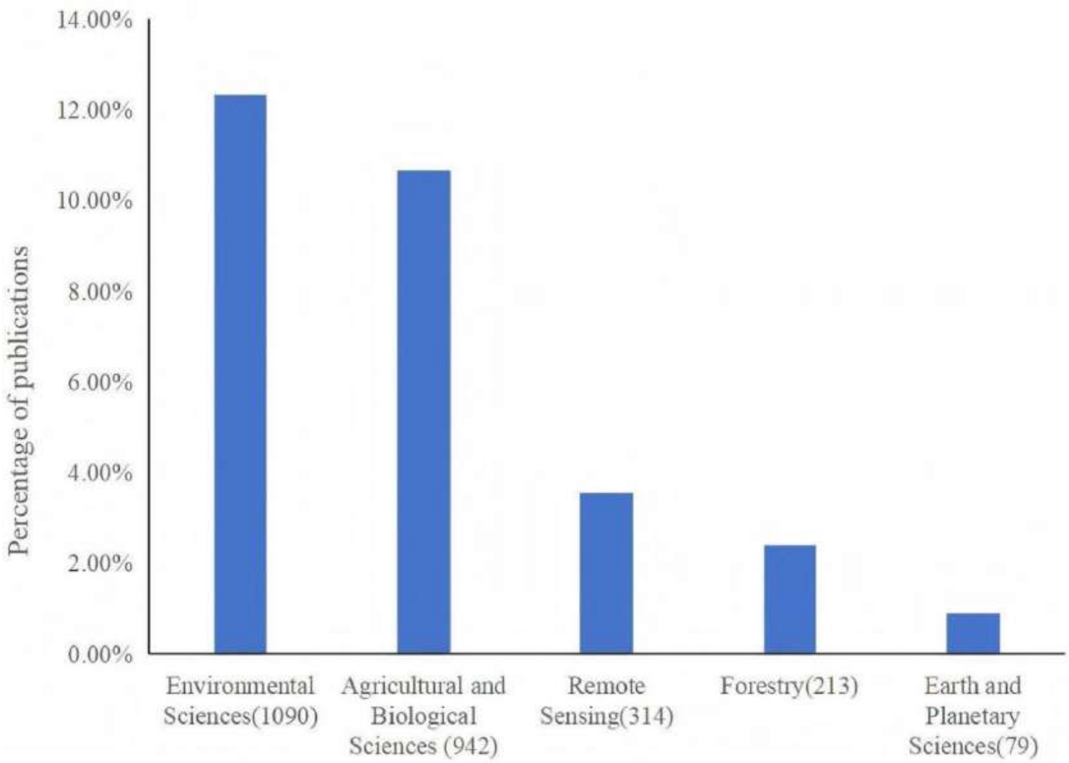


Figure 1. The top five most frequently appearing research areas involving the monitoring of forest fires with remote sensing.

The top seven nations concerning the number of articles in this field are Switzerland, Netherlands, Australia, England, the United States, and Germany. The top 15 journals publishing the largest amount of papers regarding remote-sensing-based forest fire monitoring from 2009 to 2024 are listed in Table 1, with the number two being *Forests* and *Remote Sensing*, followed by *International Journal of Wildland Fire*, *Forest Ecology and Management*, and *Fire Ecology*.

Table 1. The top 15 journals publishing papers on studies using remote sensing to monitor forest fires.

Rank	Research direction	Country	Count	Percentage (%)	IF* 2024	Research Area
1	Forests	Switzerland	382	4.32	2.237	Agricultural and Biological Sciences (Q1)
2	Remote Sensing	Switzerland	314	3.55	3.668	Remote Sensing (Q1)
3	International Journal of Wildland Fire	Australia	313	3.54	2.636	Agricultural and Biological Sciences (Q1)
4	Forest Ecology and Management	Netherlands	247	2.79	3.48	Agricultural and Biological Sciences (Q1)
5	Fire Ecology	United States	232	2.62	3.6	Forestry (Q1)
6	Fire Switzerland	Switzerland	213	2.41	3	Forestry (Q1)
7	Atmospheric Chemistry and Physics	Germany	210	2.37	4.739	Environmental Sciences (Q1)
8	Science of the Total Environment	Netherlands	201	2.27	7.503	Environmental Sciences (Q1)
9	Atmospheric Environment	England	133	1.50	3.301	Environmental Sciences (Q1)
10	Sustainability	Switzerland	112	1.27	2.937	Environmental Sciences (Q2)
11	Journal of Environmental Management	England	92	1.04	7.635	Environmental Sciences (Q2)
12	Natural Hazards	United States	89	1.01	3.359	Environmental Sciences (Q2)
13	Environmental Research Letters	England	87	0.98	5.029	Environmental Sciences (Q1)
14	Remote Sensing of Environment	United States	87	0.98	10.611	Environmental Sciences (Q1)
15	Atmosphere	Switzerland	79	0.89	2.9	Environmental Sciences (Q3)

Note: IF*, impact factor.

The distribution of annual publication outputs related to the topic of this paper from 2009 to 2024 is depicted in Figure 2 and is on the basis of the statistical analysis results of 8841 documents exported from WoS. Obviously, the quantity of publications as a whole shows an upward trend, which implies that research related to remote sensing monitoring forest fires has received a considerable amount of attention; great progress has been made over the past 16 years. Between 2009 and 2012, the number of publications fluctuated sharply. In 2010, the number of documents fell by about 10%, but in 2011 increased by nearly 25% over the numbers in 2010, although the number fell again in 2012 (Figure 2). Several reasons are responsible for this phenomenon; most likely the time required for the design and establishment of a system of forest fire risk rating and a modeling system varied widely in different countries (Laneve et al., 2012), making this type of research exhibit a state of steady growth with some fluctuations (J. H. Zhang et al., 2012). The optimization of methods and systems has resulted in the fast advancement of forest fire monitoring based on remote sensing (Aydin et al., 2019; Freitas et al., 2020; Kotel'nikov et al., 2020; Partheepan et al., 2023; Wang et al., 2018). From 2018 to 2024, the number of publications began to rise steadily, nearly doubling from the average 2009 to 2012 with the average number of documents published annually at this later stage reaching 608.

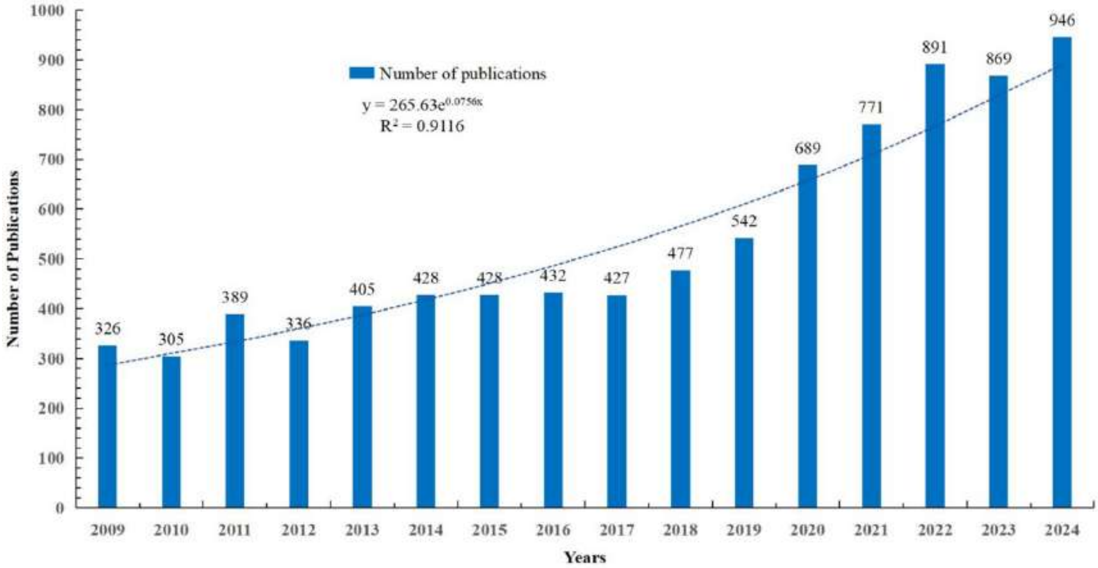


Figure 2. Annual trend chart of publications using remote sensing to monitor forest fires from 2009 to December 31, 2023.

3.2. Document Co-citation Analysis

The relationship between two papers that are cited in the same subsequent work is known as co-citation. A network of document co-citation is made up of co-citation relationships among many documents. A network like this is helpful for analyzing documents, which is more accurate than a straightforward study of citation links and can offer insights into the evolution of literature. As shown in Figure 3, using one year per slice, the top 134 levels of the most frequently cited works from every slice were found with Pathfinder software used to filter the data; then, a document with a co-citation network with clusters was obtained.

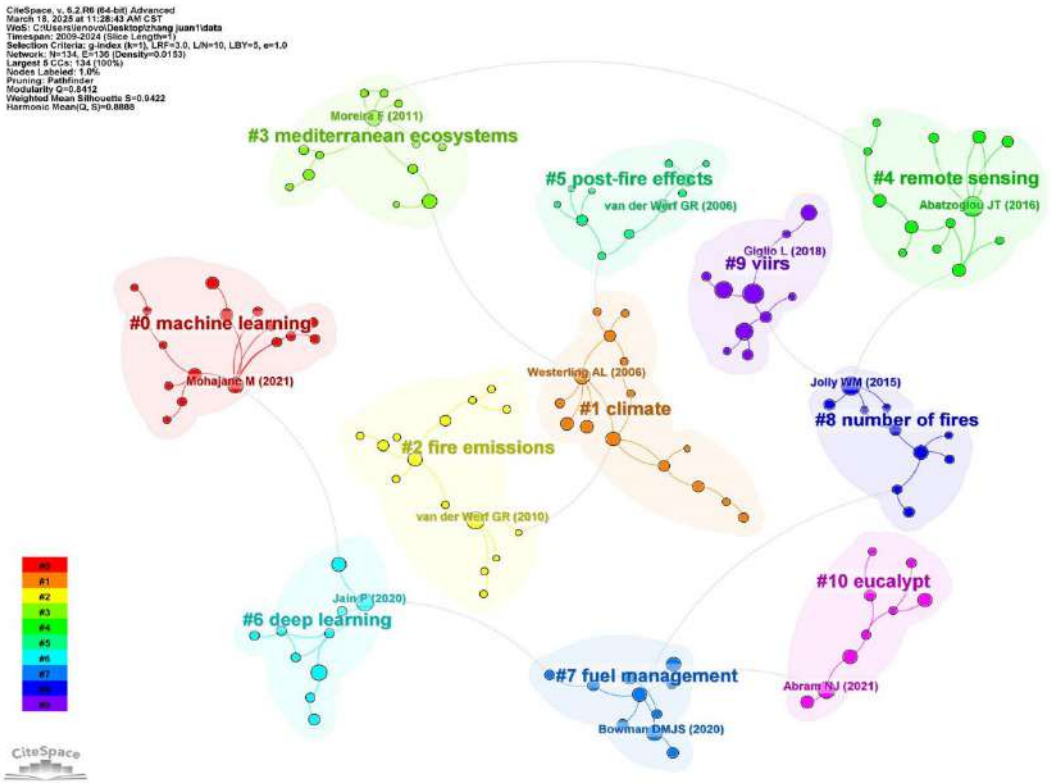


Figure 3. Network of document co-citation with the following clusters: (1) climate, (2) fire emissions, (3) mediterranean, (4) remote sensing, (5) post-fire effects, (6) deep learning, (7) fuel management, (8) number of fires, (9) viirs, (10) eucalypt.

Table 2 presents the top 10 documents, which are the most frequently cited works connected with the major topic. The most commonly used is the publication by Abatzoglou and Williams (2016), which predicts the growing influence of Anthropogenic Climate Change (ACC) on fuel aridity, which is projected to increasingly promote the potential for wildfires across the western USA; fuel aridity is predicted to become important for managing and studying wildfire in the coming decades. Giglio et al. (2016) improved the performance of the active fire detection algorithm known as Collection 6, addressing the false alarms of the previously used Collection 5 product data in small forest fire detection, and the omission of large scales of fires masked by thick smoke. Van der Werf et al. (2010, 2017) quantified global fire emission patterns, providing an international evaluation of the contribution of various sources to the overall international fire emissions. Jain et al. (2020) presented a scoping evaluation of ML methods application in managing and studying wildfire and raised wildfire researchers' awareness of various ML methods. Jolly et al. (2015) created a map of the spatio-temporal tendencies of forest fires from 1979 to 2013 and a basic yearly measure of the duration of the fire weather season using 3 data sets of daily global climate and 3 indices of fire danger. Their study results serve as an indicator for global forest fire management. These papers have been mentioned alongside a wide range of other papers that have established themselves as the foundational works in the area. Chuvieco et al. (2019) summarized and evaluated forest fire burned area mapping methods and burned area products, based on historical trends in satellite sensor-based burned area monitoring, thereby identifying new potential opportunities for enhancing future fire burn area detection techniques. Abram et al. (2021) used climate models to predict the future impact of climate change on bushfires in southeastern Australia, providing optimal fire prevention strategies to limit projected increase in fire risk.

Table 2. Top ten references related to using remote sensing to monitor forest fires based on citation frequency.

References	Citation counts	Betweenness Centrality	Year	Source
Abatzoglou J. T. (Abatzoglou & Williams, 2016)	124	0.09	2016	Proceedings of the National Academy of Sciences
Giglio L. (Giglio et al., 2016)	121	0.12	2016	Remote Sensing of Environment
Jolly W. M. (Jolly et al., 2015)	101	1.14	2015	Nature Communications
van der Werf G. R. (van der Werf et al., 2017)	96	0.06	2017	Earth System Science Data
Jain P. (Jain et al., 2020)	92	0.64	2020	Environmental Reviews
van der Werf G. R. (van der Werf et al., 2010)	87	0.36	2010	Atmospheric Chemistry and Physics
Abram N. J. (Abram et al., 2021)	82	0.23	2021	Communications Earth & Environment
Chuvieco E. (Chuvieco, 2019)	82	0.03	2019	Remote Sensing of Environment
Mohajane M. (Mohajane et al., 2021)	75	0.41	2021	Ecological Indicators
Westerling A. L. (Westerling et al., 2006)	72	0.92	2006	Science

3.3. Country Co-authorship Analysis

Knowledge maps can offer messages concerning nations and productive workteams that contribute significantly to the focus topic highlighting relevant forestry researchers; these maps can contribute to their future collaboration (Liang et al., 2017). Table 3 shows the United States of America (USA) ranked first in the publication to the total number of articles; China ranked second but was closely followed by Canada and Spain leading the top 10. Besides, the overall number of publications in China has been increasing yearly, which tends to place China among the world's top countries studying forest fire. For more information, refer to Figure 4 and Table 3.

Table 3. Top ten countries in the number of published articles related to using remote sensing to monitor forest fires.

Rank	Count	Betweenness Centrality	Country	Mean (Year)
1	2004	0.06	United States	2009
2	1314	0	People's Republic of China	2009
3	866	0	Canada	2009
4	853	0.06	Spain	2009
5	553	0	Australia	2009
6	464	0.24	India	2009
7	462	0.17	Germany	2009
8	438	0	Portugal	2009
9	427	0.55	England	2009
10	407	0	Italy	2009

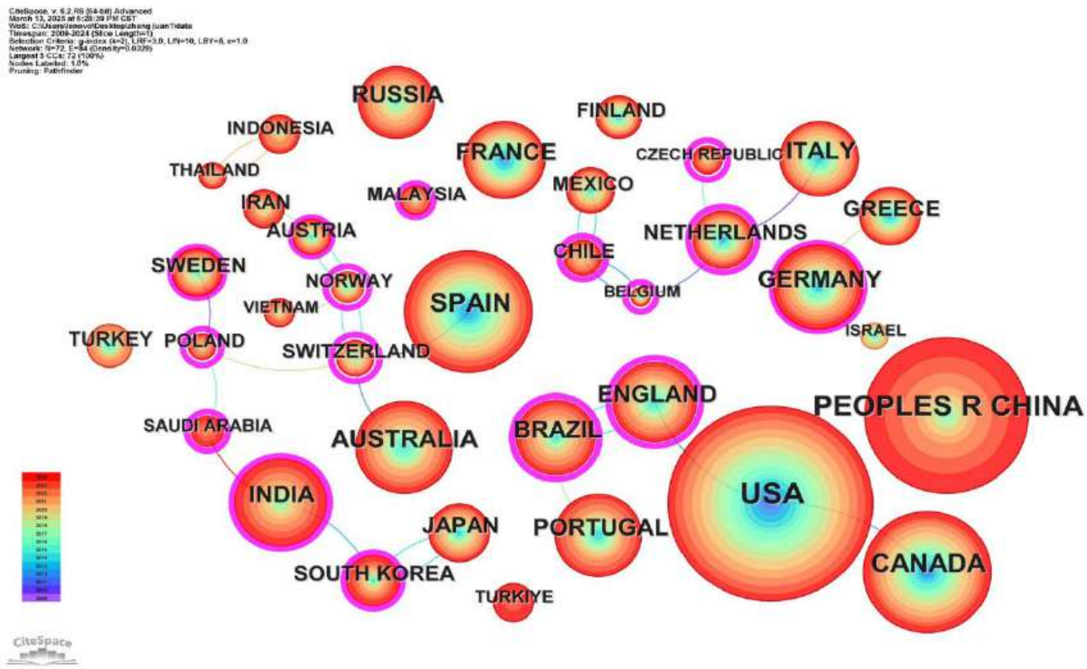


Figure 4. Graphic network of the use of collaborative analysis between countries publishing research related to using remote sensing to monitor forest fires.

Figure 4 presents an analysis of collaboration among countries conducting forest fire monitoring research that is based on remote sensing. Of these, England had the most collaborative efforts and had developed close ties with other countries, such as the USA, Brazil, Portugal, and Canada, with a Betweenness Centrality (BC) of 0.55. India ranks second in terms of cooperation intensity and has established close ties with South Korea, Saudi Arabia, and Japan, with a Betweenness centrality (BC) of 0.24. In addition, Switzerland shows a tendency to cooperate with different countries, including Australia, Spain, Norway, and Poland. The USA, with the largest number of publications, only cooperates closely with Canada and England. China, which has the second-largest number of publications, maintains cooperative relations with several countries, such as Bulgaria, Ethiopia, and Iceland. Although no direct positive connection was found between national partnerships and the number of publications, it looks like firm partnerships appear to facilitate advancements in research, as demonstrated by the top countries' partnerships concerning the number of journal publications. Hence, countries other than England can benefit from strengthening cooperation and exchange.

3.4. Author Co-authorship Analysis

Several researchers have worked with collaborators to publish on the focus topic in several countries as follows (Table 4). For example, Sun Long, a professor at Northeast Forestry University, carried out an investigation on behavior concerning forest fire, forest fire monitoring, and warning systems, along with studying the influences of forest fire imposed on forest ecology (H. Hu et al., 2016; T. Hu et al., 2017a; T. Hu et al., 2017b), which provided an empirical benchmark for exploring the effects of fire disturbance on the carbon balance of soil in boreal forests and estimation of soil carbon flux (Sun et al., 2014). Additionally, Sun and his research team assessed fire risk in temperate forests, analyzed burn severity models in subtropical forests (Guo et al., 2022; Masinda et al., 2022), and conducted satellite-based spatiotemporal wildfire analysis on the Mongolian Plateau (Bao et al., 2023). The results significantly improve the accuracy and efficiency of fire monitoring, prediction, and evaluation. Guo Futao, a professor at Fujian Agriculture and Forestry University, and his team utilized remote sensing, GIS, and machine learning models, they systematically investigated the deposition of nitrogen and other pollutants from wildfire smoke on soil properties, plant physiology, and ecosystem nitrogen cycling (Z. Huang et al., 2024; H. Lin et al., 2023). Additionally, they developed fire risk zoning methods based on fuzzy logic and analytical network processes, and revealed the spatiotemporal dynamics of water-soluble ions and particulate matter emissions from wildfires (Zhan et al., 2023). The research explored the effects of fires on tree ring growth, elemental concentrations, and post-fire forest succession trajectories (Wei et al., 2023; Zhong et al., 2023). Flannigan M., a fire scientist at the University of Alberta, Canada, studies forest fire in North America and Eurasia, including the impact of a shifting climate on wildland fire conditions worldwide (Flannigan et al., 2009), as well as the evolution of fire in Eurasia, and the sensitivity of fuel moisture to changes in precipitation and temperature in relation to wildland fire (Flannigan, 2015). Lin H., a professor at Nanjing Forestry University, developed fuzzy reasoning and big data analysis algorithms used for fire risk assessment and quantification (H. Lin et al., 2018), constructed a small-target model for forest fire detection and a model for forest fire risk for China's national forest parks through computer network technology (J. Lin et al., 2022), drew a fire risk map (P. Zhao et al., 2021), and obtained high precision of forest fire monitoring and prediction results.

Table 4. Data concerning the top twenty authors publishing research related to using remote sensing to monitor forest fires.

Rank	Author	Country	Count	Year of first article
1	Sun, Long	China	16	2022
2	Guo, Futao	China	16	2016
3	Flannigan, Mike D.	Canada	13	2009
4	Pourghasemi, Hamid Reza	Iran	8	2020
5	Zhang, Gui	China	8	2024
6	Yang, Guang	China	7	2023
7	Lin, Haifeng	China	7	2023
8	Feng, Zhongke	China	7	2022
9	Nolan, Rachael H.	Australia	7	2013
10	Palmer, P. I.	UK	6	2022
11	Jin, Huijun	China	6	2022
12	Li, Xiaoying	China	6	2018
13	Parisien, Marc-Andre	Canada	6	2013
14	Camia, Andrea	Italy	6	2014
15	Bergeron, Yves	Canada	6	2020
16	Tiefenbacher, John P.	United States	5	2024
17	Ning, Jibin	China	5	2013
18	Parrington, M.	UK	5	2013
19	San-miguel-ayanz, Jesus	Spain	5	2013
20	Bai, Di	China	5	2023

However, as shown in Figure 5, the connections between the nodes denoting nations tend to be more fragmented than the links between the nodes indicating authors. Forest fire researchers showed less team cohesion, team cooperation among paper authors was less obvious, and academic communication was less obvious, with only four studies showing team cooperation. In 2011, to understand the emission and plume evolution of boreal forest fires, a research team comprising Diskin G. S., Blake D. R., and Fuelberg H. E., utilized a United States National Aeronautics & Space Administration (NASA) DC-8 and other aircraft to monitor the biomass emission factors from northern Canadian forest fires, employing gas chromatography to analyze 79 non-methane volatile organic compounds (Simpson et al., 2011). They also assessed the influence of aerosols from boreal forest fires imposed on the climate of the Arctic (Kondo et al., 2011). Since 2013, a research team, led by Palmer P. I., Parrington M., Oram D. E., and Bauguitte S. J.-B., has used the Aircraft and Satellites experiment (also known as the BORTAS experiment) to assess the effect of boreal forest fires on tropospheric oxidants across the Atlantic, acquiring a complete chemical snapshot of pyrogenic plumes from wildfires (O'Shea et al., 2013) to determine impact extent of the dissemination of volcanic emissions on the atmosphere (Palmer et al., 2013; Parrington et al., 2013). After 2020, Eskandari et al. (2020) used data-mining approaches to construct a fire danger model based on messages about topography, climate, land cover, and other factors influencing fire risk in natural regions of Iran. In subsequent research, the team applied ML models to accurately predict wildfires and map areas susceptible to wildfire (Eskandari et al., 2021; Yousefi et al., 2020). The team consisting of Li X., Jin H., and Sun L. explored the influences of wildfires imposed on Northeast China's permafrost regions, including the effects of wildfire on vegetation succession and on the storage of nitrogen and carbon in soil (X. Li et al., 2023), the characteristics of permafrost after fire and the effects of climate warming (X. Li et al., 2022).

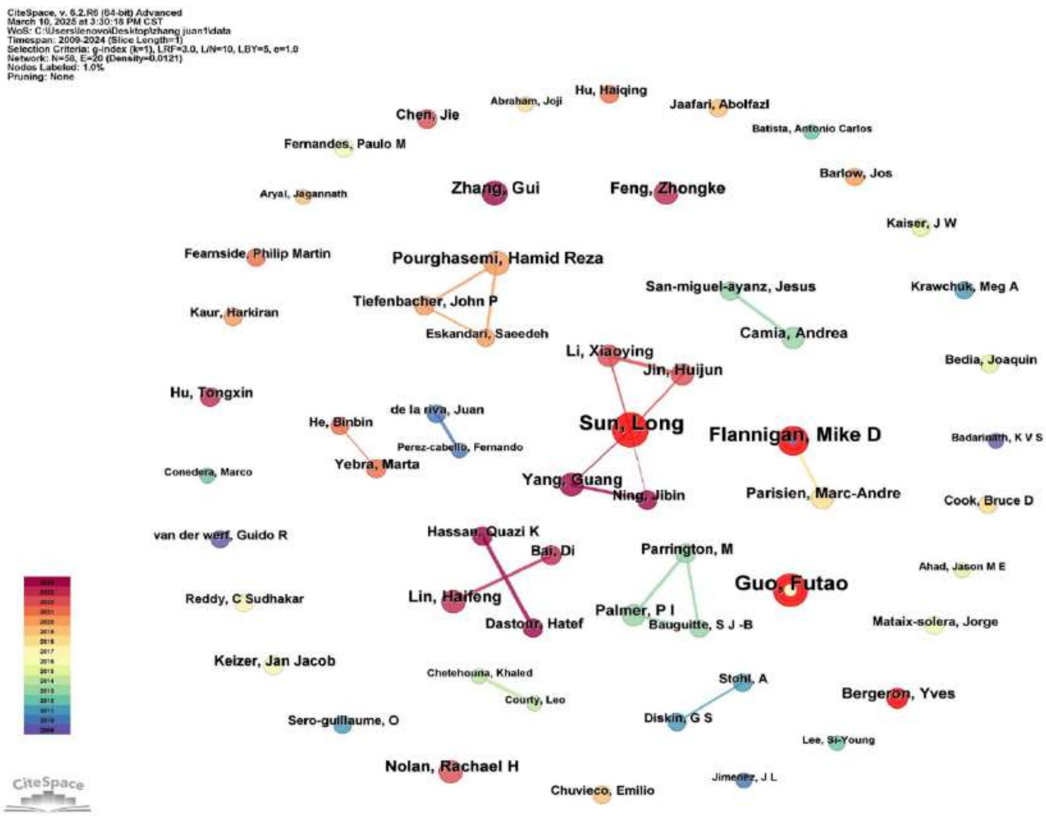


Figure 5. Author collaboration network for published research related to applying remote sensing to forest fire monitoring.

3.5. Analysis of Institution Co-authorship

Figure 6 shows the network of cooperation between institutions related to applying remote sensing to forest fire monitoring. Nodes represent institutions, and the node sizes indicate the number of articles published by each institution. The distance between the nodes indicates the extent to which 2 institutions collaborate. As the distance becomes closer, the cooperation becomes more frequent.

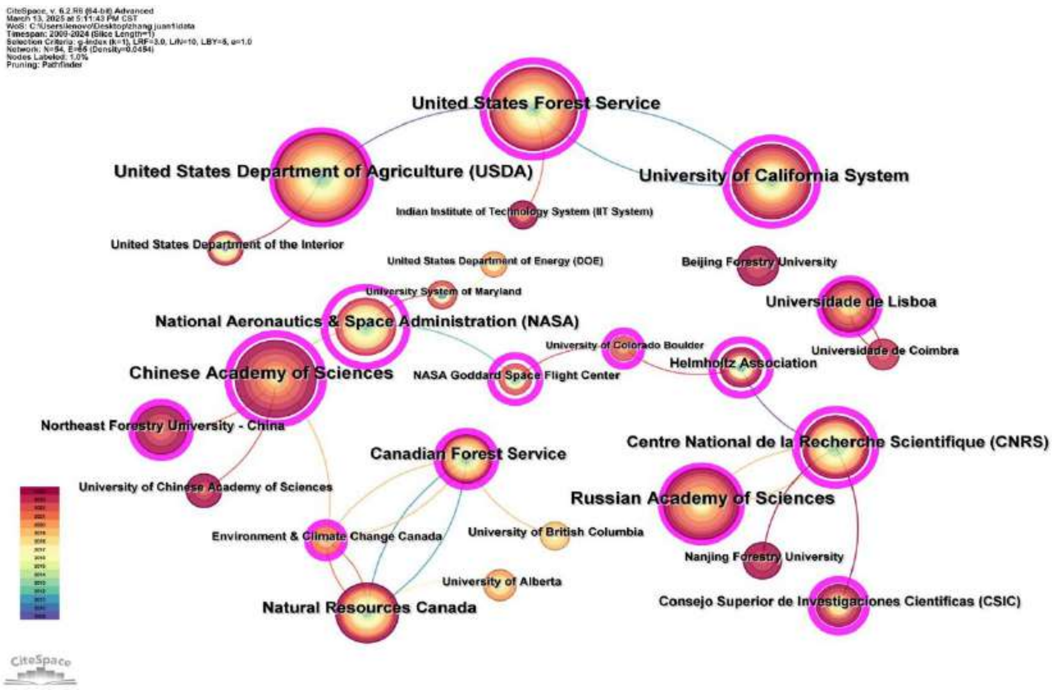


Figure 6. Institutional collaboration network for published research related to applying remote sensing to forest fire monitoring.

The United States Department of Agriculture (USDA) came to first place in the number of articles published, and the next were the United States Forest Service (USFS), the University of California System, and the Chinese Academy of Sciences (Table 5). Almost half of the top twenty institutions came from the USA, accounting for 13.87% of all publications, which shows that United States research dominates this area. In terms of the betweenness centrality, NASA had the largest value, implying that it exerts a greater impact in the area of monitoring forest fires using remote sensing. In addition, China ranks second in the value of betweenness centrality, with the Chinese Academy of Sciences (CAS) as the center in close cooperation with Northeast Forestry University, University of Chinese Academy of Sciences, NASA, and Environment & Climate Change Canada. Institutions all have cooperative relationships with each other, especially the USFS, Canadian Forest Service, Centre National de la Recherche Scientifique (CNRS), and the CAS, which form the key strength of scientific study and actively cooperate closely with many institutions.

Table 5. Statistics of the top 20 authors publishing research related to applying remote sensing to forest fire monitoring.

Rank	Institution	Count	Betweenness Centrality	Year of the first publication
1	United States Department of Agriculture (USDA)	349	0.15	2009
2	United States Forest Service	331	0.61	2009
3	Chinese Academy of Sciences	295	0.64	2010
4	University of California System	284	0.72	2009
5	Russian Academy of Sciences	250	0.15	2011
6	Centre National de la Recherche Scientifique (CNRS)	235	0.79	2009
7	Natural Resources Canada	212	0.07	2009
8	National Aeronautics & Space Administration (NASA)	178	1.22	2009
9	Canadian Forest Service	165	0.22	2009
10	Universidade de Lisboa	121	0.15	2010
11	Consejo Superior de Investigaciones Cientificas (CSIC)	87	0.54	2012
12	Northeast Forestry University - China	86	0.21	2021
13	Helmholtz Association	62	0.88	2009
14	Nanjing Forestry University	54	0	2022
15	Beijing Forestry University	51	0.07	2022
16	University of Chinese Academy of Sciences	45	0	2022
17	United States Department of the Interior	44	0.07	2009
18	NASA Goddard Space Flight Center	41	0.96	2012
19	Environment & Climate Change Canada	39	0.25	2011
20	University of British Columbia	38	0	2016

3.6. Mapping and Analysis of Keywords

3.6.1. High-frequency Keywords

Keywords summarize the content of literature, so evaluating keyword frequency and centrality can help analyze the research frontiers (Luo et al., 2021). This research used CiteSpace to analyze the keywords in the literature that address forest fire monitoring research based on remote sensing. The type of node was set to keyword, with a T = 30 threshold, and the rest were set to the default. A group of similar keywords were combined and invalid ones were eliminated; at last, a knowledge map of the study hotspot was prepared (Figure 7) and the top 20 keywords were obtained (Table 6), which shows the centrality ranking of the top 20 keywords. Nine nodes were found with intermediation centrality greater than 0.1, and the three keywords with the highest intermediation centrality were wildfire, climate, and fire. Other mediation-centric keywords were risk, boreal forest, emissions, management, dynamics, and vegetation, with the highest listed first (Table 6).

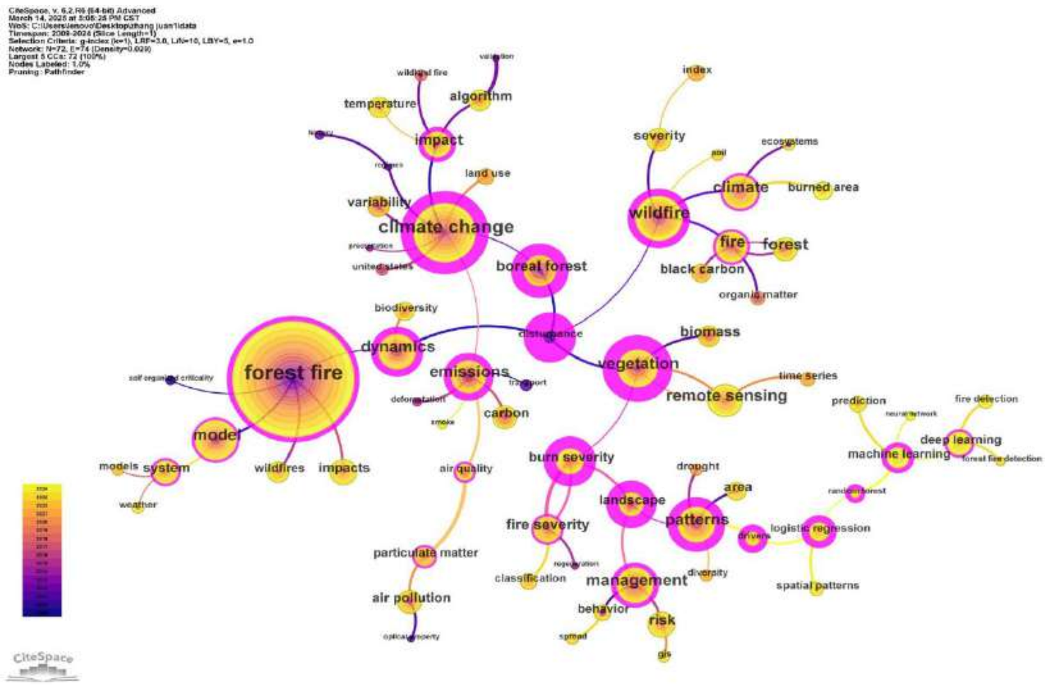


Figure 7. Keyword network for published research related to applying remote sensing to forest fire monitoring.

Table 6. Statistics of the top 20 keywords in published research related to applying remote sensing to forest fire monitoring.

Bank	Keyword	Frequency	Betweenness Centrality	Year of first appearance
1	forest fire	3183	0.37	2009
2	climate change	1149	0.94	2009
3	wildfire	702	0.52	2009
4	model	581	0.16	2009
5	vegetation	568	1.02	2009
6	management	531	0.22	2009
7	climate	531	0.11	2009
8	dynamics	496	0.46	2009
9	fire	495	0.17	2009
10	patterns	460	0.63	2010
11	remote sensing	445	0.06	2010
12	emissions	418	0.42	2009
13	forest	404	0	2009
14	impact	381	0.22	2009
15	boreal forest	351	0.85	2009
16	risk	312	0.06	2014
17	biomass	277	0	2009
18	fire severity	251	0.11	2010
19	landscape	240	0.85	2012
20	carbon	240	0	2009

3.6.2. Keyword Cluster Graph Analysis

Next, the ClusterView module in CiteSpace software was used to carry out cluster investigation on the knowledge map of keywords; this software clustered those keywords into nine clusters (Figure 8). Classes of clusters are represented with the same color nodes and were named subsequent to the key keyword node (Table 7). These included impact of biomass combustion and carbon emissions from forest fires on airborne particulate matter and human health risks (#0 particulate matter, #4 organic matter, #5 Black carbon), forest fire algorithm research using machine learning and deep learning (#2 deep learning, #9 machine learning), effects of forest fires with different severity degrees on vegetation (#fire severity), remote sensing for forest fire risk assessment, biodiversity monitoring and forest management (#3 remote sensing, #6 forest fire), impact of forest fires patterns under climate change across regions (#7 patterns, #8 climate change).

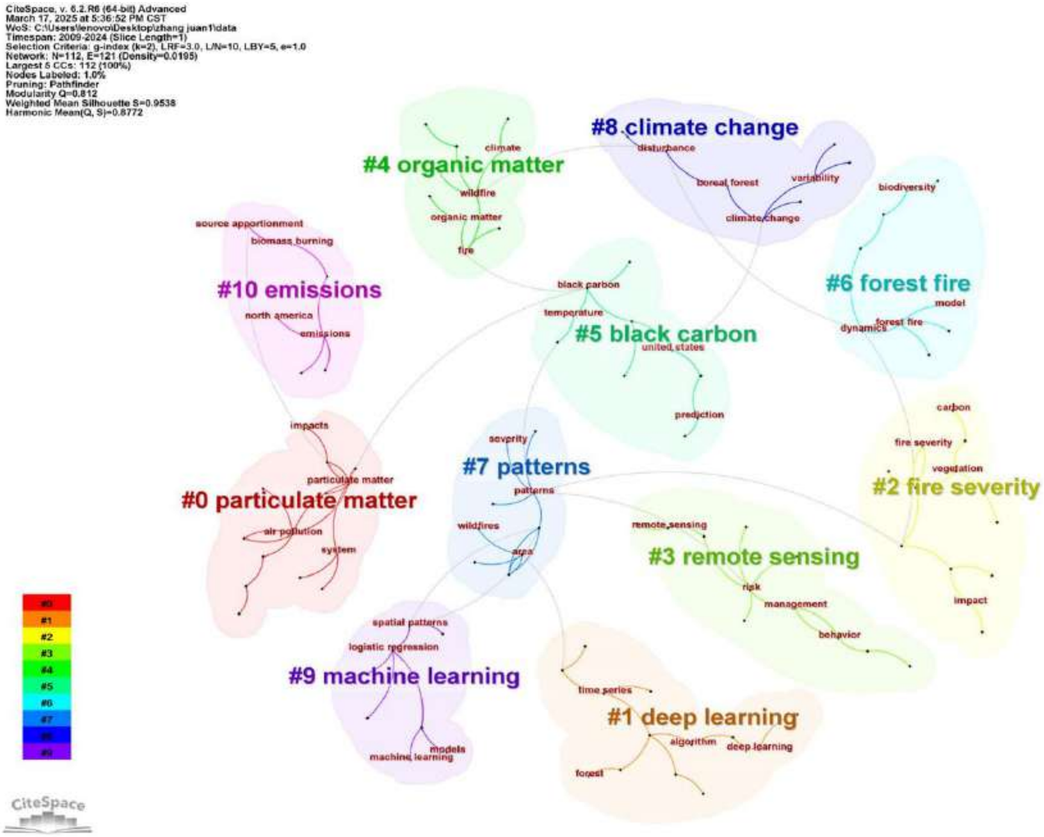


Figure 8. Keyword clustering for research related to using remote sensing to monitor forest fires: (0) particulate matter, (1) deep learning, (2) fire severity, (3) remote sensing, (4) organic matter, (5) black carbon, (6) forest fire, (7) patterns, (8) climate change, (9) machine learning.

Table 7. Statistics of the different clusters of keywords for research related to using remote sensing to monitor forest fires.

Cluster-ID	Cluster	Labels
#0	particulate matter	air pollution; impacts; system; particulate matter; air quality; transport; smoke; fire management; polycyclic aromatic hydrocarbons; exposure; mortality; aerosol; susceptibility; pollution
#1	deep learning	forest; algorithm; deep learning; time series; index; land-use; deforestation; MODIS; fire detection; forest fire detection; validation; Landsat; ndvi
#2	fire severity	vegetation; impact; fire severity; biomass; carbon; landscape; burn severity; regimes; wildland fire; spread; history; California
#3	remote sensing	management; remote sensing; risk; behavior; burned area; gis; self-organized criticality; performance; risk assessment; cover; forest fire model
#4	organic matter	water; fire; soil; forests; organic matter; climate; wildfire; water repellency; prescribed fire; ecosystems
#5	black carbon	black carbon; temperature; prediction; united states; optimization; biomass burning emissions; optical property; probability; Europe; carbon monoxide
#6	forest fire	forest fire; model; dynamics; biodiversity; conservation; diversity; community; ozone; fire history
#7	patterns	patterns; severity; area; wildfires; weather; drought; trends; drivers; regeneration
#8	climate change	climate change; boreal forest; variability; disturbance; classification; growth; precipitation; tree mortality; responses
#9	machine learning	machine learning; logistic regression; spatial patterns; models; random forest; neural network; ignition; regression

The largest cluster was Cluster-ID #0 with the tag particulate matter. The related keywords mainly included air pollution, impacts, system, particulate matter, air quality, transport, smoke, fire management, polycyclic aromatic hydrocarbons, exposure, mortality, aerosol, susceptibility; pollution. During the burning process of forest fires, a large number of inhalable particles will be produced, which will be suspended in the air and form smoke, causing serious impacts on air quality and human health. Remote sensing monitoring of particulate matter after forest fires can provide scientific basis for formulating effective forest management and fire prevention policies (Nurlatifah et al., 2025; Yuchi et al., 2016). The topic, Cluster-ID #0, discusses the use of remote sensing data to monitor and assess the impact of inhalable particulate matter on urban air quality and human health. For example, Sofowote and Dempsey (2015) applied the source term modeling technique of simplified Quantitative Transport Bias Analysis (sQTBA) integrated with meteorological analyses, to determine and identify air quality source locations that influence forest fires in Ontario. Dreessen et al. (2016) employed Surface in situ, balloon-borne, and remote sensing observations to monitor the impact of the Canadian wildfire smoke on air quality across the northern Mid-Atlantic (MA) of the United States. Yao et al. (2018b) utilized the CALIPSO satellite combined with a random forests model to predict and estimate the smoke state of forest fires in Canada. Attiya and Jones (2022) employed MODIS (Moderate Resolution Imaging Spectroradiometer) and CALIPSO satellite data, combined with NAAPS and HYSPLIT models to simulate the forest fires of characteristics of smoke aerosols and air quality levels obtained in Australia. D. Chen et al. (2023) established a methodological framework based on the Wildland Fire Emissions Inventory System (WFEIS), the Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) model, and the Arctic-Boreal Vulnerability Experiment (ABoVE) Wildfire Date of Burning (WDoB) dataset, an Arctic-oriented fire product, and studied changes in Alaska's air quality under the long-term effects of wildfires, providing key data for strategies to improve air quality. Nurlatifah et al. (2025) utilized satellite instruments such as MODIS, VIIRS (Visible Infrared Imaging Radiometer Suite), and the GEMS (Geostationary Environment Monitoring Spectrometer), and employed the WRF-HYSPLIT (Weather Research and Forecasting model coupled with the Hybrid Single Particle Lagrangian Integrated Trajectory model), to identify and analyze the spatial distribution of $PM_{2.5}$ from forest fires in central Kalimantan in October 2023. At present, single satellite data such as MODIS, VIRR, and CALIPSO are insufficient for precise forest fire monitoring, and multi-source data fusion enables long-term fire and smoke monitoring (Yin et al., 2023). Additionally, Sentinel-5P/Tropomi offers high-resolution aerosol, ozone, and nitrogen dioxide data, which supports smoke monitoring (Wang et al., 2020). Combining random forest or deep learning can effectively simulate the impact of forest fire smoke on air quality (L. Li et al., 2020).

The second largest cluster was Cluster-ID #1, with a deep learning tag; the related keywords mainly included forest, algorithm, deep learning, time series, index, land-use, deforestation, MODIS, fire detection, forest fire detection, validation, Landsat, ndvi. This cluster mainly integrates the high spatial resolution of Landsat and the high temporal resolution of MODIS, combined with deep learning models such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM), which has shown significant potential in land-use classification, deforestation monitoring, fire detection, time series analysis, and NDVI calculation. For example, L. Zhao et al. (2022) developed a lightweight Convolutional Neural Network (CNN) model to detect fire smoke from Landsat imagery, significantly improving the accuracy and efficiency of early-stage smoke detection. X. Hu et al. (2024) proposed AF-Net, an active fire detection model based on enhanced Object-Contextual Representations (OCR), addressing the accuracy limitations in UAV image-based fire detection caused by data imbalance, such as insufficient fire samples. Seydi et al. (2022) proposed a deep learning-based fire detection framework capable of capturing multi-scale features of fire regions, significantly enhancing the model's ability to identify complex terrains and fire boundaries. Verbesselt et al. (2010) employed time series analysis and NDVI to monitor post-fire vegetation recovery dynamics mapping. Hansen et al. (2013) integrated Landsat data with machine learning methods to achieve high-accuracy global deforestation mapping, though limitations persisted in data resolution, temporal scale, and classification precision. F. Zhao et al. (2022) introduced a method utilizing dense time-series Sentinel-1 SAR imagery and deep learning, addressing the limitations of optical remote sensing under cloud cover and seasonal variability, and enabling high-precision, high-frequency monthly mapping of forest harvesting. Fodor and Conde (2023) integrated Landsat, Sentinel-2, and MODIS data into a deep multimodal learning framework to rapidly detect deforestation and burned areas in satellite imagery, overcoming the inefficiency and accuracy limitations of traditional methods. The studies provide critical technical support for precise forest fire monitoring and management, and future research could further explore multi-source data fusion and the development of real-time fire early warning systems.

The third largest cluster was Cluster-ID #2, with a fire severity tag; the related keywords mainly included vegetation, impact, fire severity, biomass, carbon, landscape, burn severity, regimes, wildland fire, spread, history, and California. In recent years, remote sensing technology has significantly advanced in forest fire research, particularly in assessing fire severity and its impacts on vegetation, biomass, carbon cycling, and landscape dynamics. Many researchers suggest that fire severity is closely linked to vegetation recovery, carbon emissions, and ecosystem functionality. For example, X. Chen et al. (2011) employed Landsat and MODIS satellite data to derive the Normalized Difference Vegetation Index (NDVI) and the Normalized Burn Ratio (NBR), integrating field-based Composite Burn Index (CBI) measurements to evaluate post-fire burn severity and vegetation recovery in forest ecosystems. Miller et al. (2009) utilized Landsat data to develop the delta Normalized Burn Ratio (dNBR) method for evaluating fire severity and vegetation recovery potential. Liu et al. (2020) utilized ICESat-2 photon-counting data, integrated with Landsat and Sentinel-2 optical remote sensing data, to map burned areas. Compared to traditional optical remote sensing methods such as dNBR, ICESat-2 data demonstrated superior performance in detecting burned areas in complex terrains and low-intensity fire scenarios (Liu et al., 2020). Von Nonn et al. (2024) developed an open-source workflow to spatially align and integrate high-resolution drone imagery with Landsat and Sentinel-2 satellite data, significantly improving the accuracy and spatial resolution of burn severity assessments. Lutz et al. (2010) employed remote sensing data to analyze the effects of high-severity fires on biomass and carbon stocks, highlighting significant carbon release due to wildfires. Herbert (2022) utilized time series analysis and high-resolution remote sensing data to validate forest growth models and quantify tradeoffs between forest growth, carbon storage, and fire risk, offering a scientific foundation for forest management in fire-prone ecosystems. Additionally, Steel et al. (2015) used MODIS and Landsat data to study the relationship between wildfire spread, climate, and topography in California, revealing spatial patterns of fire severity. More recently, Y. Zhao et al. (2023) developed an integrated predictive model combining remote sensing data, climate models, and ecosystem models. Through time series analysis, the model assessed fire frequency, severity, and spatial distribution in California and other global regions, providing an effective tool for evaluating future fire risks (Y. Zhao, 2023). The results provide a scientific foundation for fire management and ecosystem restoration strategies.

The fourth largest cluster was Cluster-ID #3, with a remote sensing tag. The related keywords mainly included management, remote sensing, risk, behavior, burned area, gis, self-organized criticality, performance, risk assessment, cover, and forest fire model. The application of remote sensing technology in forest fire monitoring and management has further advanced, achieving significant progress in fire risk assessment, behavior modeling, and burned area mapping. For example, Adab et al. (2013) employed remote sensing and GIS techniques to model forest fire risk in northeast Iran, achieving high accuracy in identifying fire-prone areas and providing a scientific basis for fire prevention and resource management. Van Le et al. (2021) propose a deep neural computing (DNC) approach combining CNN and LSTM for spatial wildfire danger prediction in tropical climates, achieving 92.5% accuracy and outperforming traditional methods by 20–25%, providing a robust tool for wildfire prevention and ecological management in tropical regions. Maffei et al. (2021) employed multi-spectral and thermal remote sensing data to predict forest fire characteristics, integrating spatial and thermal information for improved fire detection and severity assessment. Ikhsan et al. (2023) used the Information Value Method (IVM) with GIS and remote sensing data to model forest and land fire susceptibility in Kotawaringin Barat Regency, Indonesia, achieving high prediction accuracy for effective fire risk management. Demir and Dursun (2024) utilized the RUSLE model integrated with Google Earth Engine to assess pre- and post-fire erosion in the Manavgat River Basin, providing insights into the impact of forest fires on soil erosion dynamics. González et al. (2024) employed remote sensing and GIS to assess forest fire severity in Vilcabamba, Ecuador, developing a management conceptual model that improved fire severity mapping accuracy in previous studies by integrating multi-source data. Singh and Srivastava (2025) utilized a GIS-based multicriteria technique to identify fire-prone regions in Lamington National Park, validated by field and Sentinel-2 data, achieving high accuracy and providing a reliable tool for fire risk management and conservation planning. The studies provide critical technical support for forest fire management, risk mitigation, and ecosystem restoration.

The fifth largest cluster was Cluster-ID #4, with the organic matter tag. The related keywords mainly included water, fire, soil, forests, organic matter, climate, wildfire, water repellency, prescribed fire, and ecosystems. Remote sensing technology has significantly advanced in monitoring forest fires and their impacts on water, soil, and ecosystems. For example, Van Eck et al. (2016) used physically-based modeling combined with field and remote sensing data to analyze post-fire runoff in a Portuguese forest catchment, improving vegetation recovery estimates by integrating high-resolution spatial and temporal data. Rust et al. (2019) integrated field data, remote sensing, and hydrological modeling to analyze post-fire water quality in western US forests, addressing spatial and temporal monitoring limitations through multi-source data fusion to evaluate fire impacts on watershed dynamics and water quality. Mastrolonardo et al. (2024) employed field measurements and remote sensing to assess post-fire erosion and sediment yield in a Mediterranean forest catchment in Italy, revealing significant increases in sediment transport and providing insights for post-fire land management and erosion control. Ross et al. (2024) utilized LiDAR-derived forest structure data to analyze the impact of fire frequency on forest ecosystems, providing high-resolution 3D insights into post-fire recovery and overcoming limitations of traditional 2D remote sensing methods for fire impact assessment. Busby et al. (2023) employed remote sensing and field inventory to analyze fire effects of wind-driven megafires in the western Cascades, linking fire severity to weather conditions and pre-fire forest structure, providing critical insights for fire management and forest resilience strategies. Beltrán-Marcos et al. (2023) integrated UAV and Sentinel-2 data to estimate post-fire topsoil organic carbon, showing that combining high-resolution and multispectral data enhances soil carbon assessment accuracy and supports ecosystem recovery monitoring. Fernández-García et al. (2023) reviewed wildfire severity impacts on forest soils and outlined post-fire restoration strategies, highlighting soil recovery as critical for climate change mitigation and ecosystem resilience enhancement. These advancements have elucidated fire's role in soil properties, water cycles, and carbon dynamics, aiding climate change mitigation and post-fire restoration. By integrating field data with high-resolution remote sensing, researchers have overcome traditional limitations, providing robust tools for fire management and ecosystem recovery amid rising wildfire risks. The results show the effects of forest fires on soil properties, water cycling, and carbon dynamics, supporting climate change mitigation and post-fire recovery. By integrating field data with high-resolution remote sensing, researchers overcome traditional limitations, offering robust tools for fire management and ecosystem restoration amid increasing wildfire risks.

3.7. Analysis of Research Frontiers and Emerging Trends

In the form of time evolution, the Time Zone View module of CiteSpace was applied to build a Time Zone distribution map of keywords to investigate the thematic shifts in remote sensing monitoring forest fires in the past 16 years. The time slices in CiteSpace were set to one slice per year, the top 50 keywords that were cited with high frequency were extracted from the corresponding slices of each year, and the network was pruned using the pathfinder model to get the network of keyword covariance.

As shown in Figure 9, most of the frequently used keywords are concentrated in the early stage of the study, such as the keywords “forest fire” and “remote sensing” Among them, climate change is the earliest high-frequency word, followed by words related to the research background, how to monitor and manage forest fires including wildfires, and post-disaster vegetation by remote sensing under climate change. In recent years, new keywords have appeared less frequently, with “soil,” “fire detection,” “spread,” and “diversity” being frequently used keywords; their emergence has led to an increasing depth and breadth of research in this field.

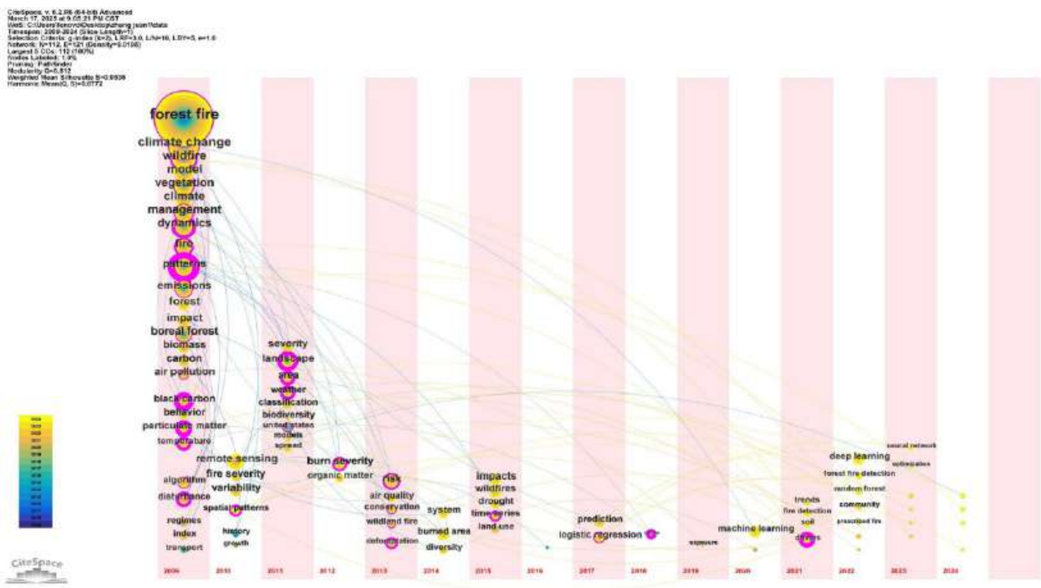


Figure 9. Keyword time zone diagram for published research related to using remote sensing to monitor forest fires.

Subject terms or keywords in the relevant previous studies were explored for emergent terms to decide the ongoing advancement of fire research and new research perspectives. The time-zone function of CiteSpace was used to explore emergent terms and to identify cutting-edge topics in the field. As shown in Figure 10, the top 15 emergent terms over the past 15 years were identified. The first, second, and third were history (from 2010 to 2016), transport (from 2009 to 2012), and the

United States (from 2016 to 2018), respectively. The following less frequently used terms are drivers (from 2021 to 2024), growth (from 2010 to 2014), spread from (2021 to 2024), land use (from 2019 to 2022), and others. Keywords were classified based on the first year of their appearance; the position and length of the red blocks in Figure 10 represent the time interval of keyword highlighting. According to the frequency and time length of the most frequently cited keywords, the research hotspot of monitoring forest fires using remote sensing was divided into three time periods (stages) as discussed below.

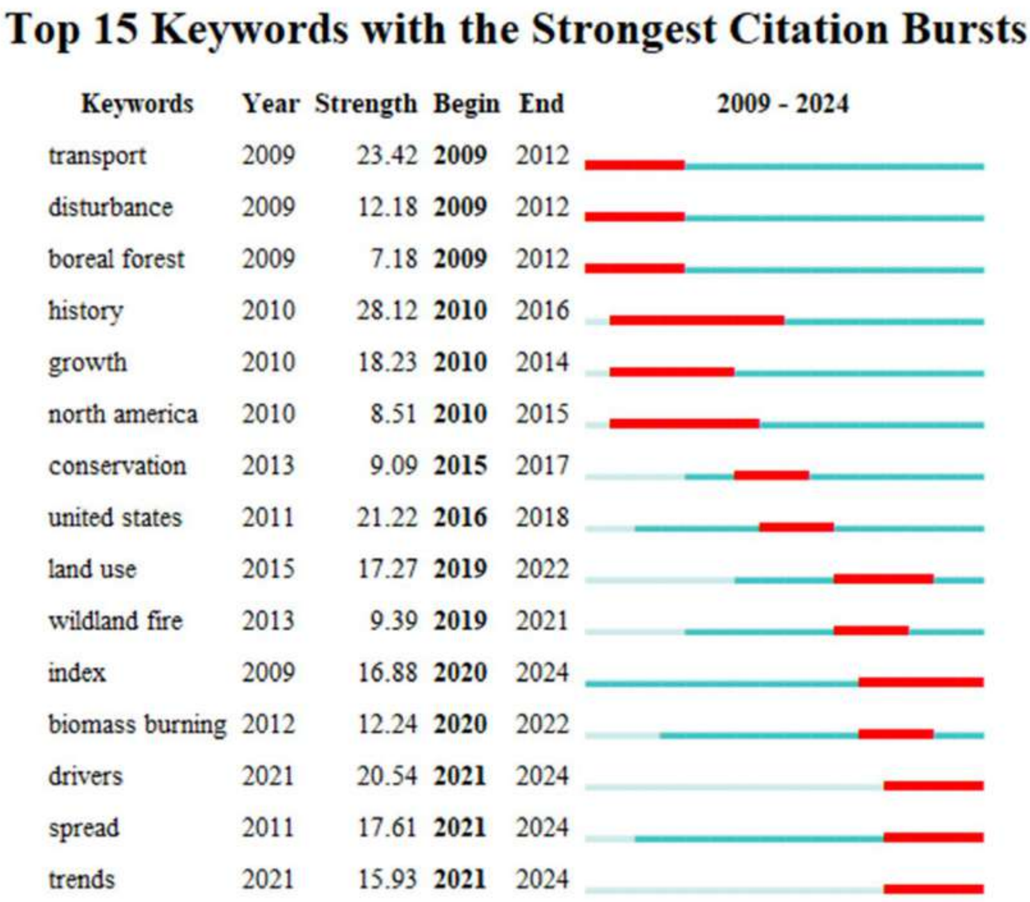


Figure 10. Top fifteen words in emerging frequency in research related to using remote sensing to monitor forest fires.

Stage 1 (2009–2014): Affected by many factors such as global warming, previously rare large-scale forest fires with increasing frequency occurred in the USA, Canada, Spain, and other nations since 2009, causing serious losses and grave consequences. Forest fires discharge air contaminants like PM_{10}, $PM_{2.5}$, black carbon as well as organic aerosols. Specifically, $PM_{2.5}$ is transported over long distances and across administrative borders under the action of weather and weather dynamics, which creates serious influences on the environment and damages the health of human beings. During Stage 1, many researchers began to pay attention to the evaluation and forecasts of the effects of wildfires imposed on air quality, using techniques like Satellite-based (CALIPSO) light detection and ranging (McKendry et al., 2011), MODIS imagery combined with the Chemistry Transport Model (Ito, 2011), and the GEOS-Chem chemical transport model (Y. Chen et al., 2009) to build a meteorological analysis and forecast method, improving the accuracy of analyzing and predicting the influence of forest fires imposed on quality of air. Forest fires serve as a crucial type of disturbance that occurs in various forested ecosystems and can affect the structure and function of forests. Monitoring vegetation responses to fire disturbance is significant. Some researchers began to use MODIS imagery to conduct long-term monitoring of vegetation after fires (van Leeuwen et al., 2010). Radar-based remote sensing combined with multi-temporal spatial synthetic aperture radar data has been applied to analyze vegetation structure, regeneration characteristics, and recovery of fire-burned areas (Goetz et al., 2010). Landsat thematic mapper and reinforced thematic mapper time series statistics (He et al., 2011) and hyperspectral Earth Observation-1 satellite statistics have been applied to monitor and analyze the physiological features and spatial patterns of fire-disturbed vegetation (Numata et al., 2011). Therefore, remote sensing imagery has excellent potential for monitoring the growth and recovery of vegetation after fires.

Stage 2 (2015–2018): Since the beginning of the 20th century, average temperatures have increased by about 1.1 °C in California and Oregon and by about 0.8 °C in Washington state. As higher temperatures caused by climate change dry out vegetation, wildfires burn more intensely and spread quickly from suburban to urban areas. Severe heat and drought during that period led to frequent fires in California, Arizona, Oregon, and Washington. California is a major forest fire-prone area in the world, with multiple wildfires raging and causing significant damage during a long fire season that is becoming even longer. During this stage, remote sensing imagery was mainly used to monitor and analyze historical forest fires in the USA with the aim of realizing forest fire prevention and management. Since 2016, Landsat imagery has been used to accurately detect many fires in the USA and to distinguish between burning and non-burning areas (Meddens et al., 2016). By 2017, tree mortality caused by fires in various states of the United States was quantified using Above-Ground Carbon stocks and disturbance data from remote sensing, suggesting the need for continuous observing and describing of tree mortality rates in the coming decades to inform management of forest and greenhouse gas (Berner et al., 2017). Based on light detection and ranging and Landsat imagery, fuel loading was monitored and mapped through ML models such as random forest, so that fire behavior modeling at the landscape scale was realized (Bright et al., 2017). In the last decades, the United States has been able to restore pre-European settlement frequent fire regimes in many landscapes and improve forest resilience through various fuel treatments designed to reduce fuel loads as a part of forest management. Since 2018, researchers proposed a new fire burn index that allows low- and mixed-severity fires to be detected and described more accurately (McCarley et al., 2018). At the same time, with multi-temporal remote sensing statistics and cloud computing, the extent of burns from the 2013 Creek Fire was assessed and changes in land surface characteristics were tracked; as a result, fire treatments such as planned burning, commercial logging, forest thinning and resource-efficient burning, i.e. managed wildfires were found to be the most effective methods used in reducing the likelihood of dangerous fires and increasing post-fire recovery (Petrakis et al., 2018).

Stage 3 (2019–2024): Climate change has further exacerbated the threat of forest fires to biodiversity. All of the world will face longer fire seasons and more severe forest fires, and even areas that previously had few forest fires may become high-risk areas. In addition, population growth and irrational land use have made it more difficult to control forest fires. Monitoring the effects of fires, their onset, and recovery processes after fires is critical to recommending actions designed to mitigate the risks and impacts of these catastrophic events. Researchers have used land-use data combined with topography, climate, and human drivers to develop fire susceptibility maps, verifying the accuracy of fires detected by remote sensing to delineate fire danger areas and mitigate forest fires (Razavi-Termeh et al., 2020; Venkatesh et al., 2020). Meanwhile, to make up for the limitations of a single remote sensing satellite in monitoring fires, the researchers proposed the synergistic inversion and forest fire observation with multi-source remote sensing data (Tian et al., 2022b; Xie et al., 2022a). Moreover, deep learning, such as Convolutional Neural Network (CNN; McCarthy et al., 2021) and ML methods (Dahan et al., 2023; Deng et al., 2023), is used in conjunction with satellite imagery and spatial analyses to guarantee the forest fire detection at the early stage and facilitate response management. In addition, it becomes possible to monitor and model wildfires in a variety of terrestrial ecosystems because of the increasing remote sensing data availability. Important research began to use the spectral characteristics of remote sensing statistics from multiple sources to calculate land surface temperature, the normalized differential vegetation index, forest vegetation type, and temperature vegetation dryness index to construct a composite fire danger index (C. Chen et al., 2023). Burned area estimation products can be obtained using remote sensing statistics from multiple sources, which can quickly interpret and analyze the driving factors of the success of fire suppression and spread control (Crowley et al., 2019; Y. Zhao et al., 2023). Drivers are the key variables in building fire prediction models, and analyzing fire-driving factors can improve the accuracy of different fire monitoring systems (Chang et al., 2023). As wildfire activity continues to increase in frequency and severity, ecological resilience after fires decreases; ecosystems are at risk of collapse if they fail to recover after fires, so more research has begun to focus on the evaluation of the forests' recovery capacity from wildfire disasters. For example, Sentinel-2 satellite remote sensing imagery can be used to calculate greening, humidity, and fire severity indices, which can then be used to assess forest resilience after fire (Avetisyan et al., 2022); the use of satellite image monitoring can be used to develop new post-fire recovery-post-fire stability indices, methods, and so on (Gibson et al., 2022). The richness and diversity of vegetation can be used as one of the best indicators to estimate vegetation recovery after forest fires (Serra-Burriel et al., 2021). Using aperture radar backscatter (Sentinel-1) and multispectral emissivity fusion to estimate the vertical structural diversity of plant communities, vertical structural diversity monitoring has acted a crucial part in maintaining the restoration of ecosystem functions in fire-prone landscapes compared with post-fire vegetation restoration (Aydin-Kandemir & Demir, 2023). At the same time, extreme wildfires lead to a loss of wildlife habitat. Remote sensing data can be extracted from burned areas combined with pre-fire data such as species richness with fire data, which can then be analyzed and assessed for wildlife resilience and fire impacts on ecosystems (Fernández-Guisuraga et al., 2023). Research in this period of time provides important information related to monitoring wildfires with remote sensing and related risk research. Future research on forest fires will focus on four key areas: forest fire drivers, fire spread, fire index, and fire trends, aiming to enhance understanding and management through advanced technologies and interdisciplinary approaches.

Forest fire drivers primarily include natural factors (e.g., climate change, vegetation type, and topography, and anthropogenic factors (e.g., agricultural burning and urbanization). Existing studies have utilized remote sensing technologies with multi-source data (e.g., optical, thermal infrared, and radar) to quantify the spatial distribution and dynamics of these factors, coupled with machine learning algorithms to develop fire prediction models. However, challenges remain, such as inconsistencies in spatial, temporal, and spectral resolutions among different remote sensing data sources, which hinder data fusion. While current models perform well in specific regions, their accuracy diminishes when applied to other areas. Additionally, the spatial heterogeneity and dynamic nature of human activities (e.g., land-use changes) are difficult to precisely capture. To address these issues, future research should focus on developing unified data preprocessing frameworks to integrate multi-resolution remote sensing data, enhancing data consistency. Leveraging transfer learning and region-specific training methods can improve model generalizability while combining high-resolution satellite imagery (e.g., WorldView, Gaofen) and social media data can enable more accurate quantification of anthropogenic influences.

Fire spread is influenced by a combination of fuel, topography, and meteorological conditions. Remote sensing technologies, utilizing high spatiotemporal resolution data (e.g., UAV imagery and thermal infrared data), enable real-time monitoring of fire boundaries and intensity. When integrated with physical models (e.g., fluid dynamics) and numerical simulations, these technologies can reveal fire spread patterns. However, challenges remain, including the limited revisit cycles of current remote sensing systems, which hinder real-time monitoring, and the significant uncertainties in fuel, meteorological, and topographic parameters within fire spread models. Additionally, simulation accuracy is often low in complex terrains and vegetation conditions. To address these issues, UAVs and near-real-time satellite data (e.g., GOES, Himawari) can enhance monitoring frequency. Future efforts should focus on optimizing model parameters using ground-based measurements and machine learning algorithms, as well as integrating LiDAR and high-resolution DEM data to improve simulation accuracy in complex environments.

Fire indices (e.g., NDVI, NBR, FWI) are derived from remote sensing data to assess fire risk by evaluating vegetation status, meteorological conditions, and surface temperature (Z. Wang et al., 2024). However, most existing indices rely on static data, limiting their ability to reflect dynamic fire risks and their applicability across diverse ecosystems and climatic conditions. Future research will focus on developing region-specific fire indices tailored to different ecosystems and integrating real-time remote sensing and meteorological data to build robust, dynamic fire risk assessment models.

At present, Fire trend analysis primarily relies on long-term remote sensing data (e.g., MODIS, AVHRR) to reveal spatiotemporal patterns in fire frequency, intensity, and extent, combined with climate models to predict future trends. However, challenges such as sensor discrepancies, data gaps, and the complex relationship between climate change and fire trends persist. Quantifying the impacts of fires on carbon cycling, biodiversity, and ecosystem services faces issues like data insufficiency, model uncertainties, and interdisciplinary barriers. To address these challenges, future efforts will focus on developing data correction algorithms, leveraging multi-source data integration, and establishing long-term databases to enhance data quality and consistency. Additionally, comprehensive model development, multi-source data fusion, parameter optimization, quantification of human activities, and long-term monitoring and experiments will help reduce uncertainties, providing more reliable scientific insights into the climate-fire relationship. Building multi-source data integration systems, long-term monitoring networks, interdisciplinary collaborations, and data-sharing platforms will support holistic assessments and management of fire-related ecological impacts

4. Limitations

As for the limitations, this research only analyzed articles from the database WoS, which is a major weakness of CiteSpace, resulting in an incomplete literature search for this study and potentially biased results. Currently, most of the visualization work has been created according to WoS, which is the representative and most extensively used database in this area and therefore often adopted. Other data sources such as Scopus or Microsoft Academic Search are easily overlooked, while more data sources would provide a wider range of research for analysis. Second, due to the constraints of the project, the intervals between studies were not very long, with extracted articles published between 2009 and 2024. In addition, some of the potential publications were published recently, which made it difficult to retrieve and cite these research papers. Future research should be conducted using additional databases and different tools.

5. Discussion

This paper describes in detail the theoretical framework and new developments in the field of remote sensing monitoring of forest fires. We analyze countries, institutions, individuals, and the key themes in the relevant field, and predict new directions for future development in this field.

Sun Long, Guo Futao, and Mike D. Flannigan have great influence in the field of remote sensing monitoring of forest fires, which deserves the attention of researchers in related research fields. Sun Long and Guo Futao have studied the effects of forest fires on carbon and nitrogen cycles in larch forests in the Greater Khingan Mountains and their response mechanisms, focusing on soil cycles and vegetation recovery in burned areas. They led a team to develop key technologies for fire risk warnings and spread simulations, established a national forest and grassland fire warning system, and implemented it across most regions in China (H. Hu et al., 2016; T. Hu et al., 2017a). Mike D. Flannigan's research through future climate simulation has shown increased fire activity in many northern and temperate forests around the world. Climate change has a greater impact on forest fire activity in northern Canada and Russia, as well as grassland fire activity in Australia. Consequently, many researchers have begun to use Landsat, MODIS, lidar, multispectral and other remote sensing data to monitor fire activity and vegetation restoration in the region, which is used to scientifically guide forest resource management and reduce fire risk (Caccamo et al., 2015; S. Huang et al., 2019; Levin et al., 2021; Meng et al., 2018; Petrakis et al., 2018; Sever et al., 2012; Shah et al., 2023). After 2000, with the development of remote sensing technology and the increase in the amount of data, R language was used to process and analyze remote sensing data, including the monitoring and assessment of forest fires (Deng et al., 2023; Donager et al., 2018; Nisa et al., 2014). Since 2017, countries such as China, the United States, the European Union, the United Kingdom, and Japan have elevated AI to a national strategy and plan (Attard-Frost et al., 2024).With the development of remote sensing technology and the advancement of machine learning algorithms, researchers have begun to explore the application of machine learning technology to the monitoring and evaluation of forest fires. From the early days of traditional machine learning algorithms, such as support vector machines (SVMs; Anggraeni & Lin, 2011; Koetz et al., 2008) and random forests (Random Forest; Bright et al., 2017; João et al., 2018; Schroeder et al., 2017; Yao et al., 2018a), they are often used to identify fire signatures in remote sensing images. With the development of deep learning technology, deep learning models, such as convolutional neural networks (CNNs; J. Huang et al., 2022; Kang et al., 2022; McCarthy et al., 2021; Radman et al., 2023; Zikiou et al., 2024), long short-term memory networks (LSTMs; Bahadori et al., 2023), and long short-term memory networks (LSTMs; Bahadori et al., 2023; Duangsuwan & Klubsuwan, 2023; Fan et al., 2022; Hong et al., 2024; Muthukumar et al., 2022), are better able to process complex data to accurately identify fire signs and assess fire risks. More and more scientists have shifted their attention to how to better use machine learning and deep learning to improve the efficiency and accuracy of forest fire monitoring, a trend that reflects the significant increase in academic publications on the topic since 2020. On August 9, 2021, the United Nations Intergovernmental Panel on Climate Change (IPCC) released an updated scientific assessment report on climate change in Geneva, Switzerland, noting that drought is becoming more common in the future as world temperatures continue to rise. Extreme weather conditions have led to unprecedented temperatures and forest fires around the world, such as the wildfires in Australia and the Amazon, and habitat loss has led to the extinction of a large number of wild animals, which has had a huge impact on global ecosystems and species diversity. Since 2021, most researchers have begun to focus on the use of remote sensing data to monitor post-fire spatial changes, migration monitoring, and species activities (Aydin-Kandemir & Demir, 2023) and to analyze the spatial and temporal distribution drivers of forest fires, which is conducive to the formulation of fire prevention measures and decision-making (Rotich & Ojwang, 2021; Sikuzani et al., 2023; Tian et al., 2022a). At the same time, the use of remote sensing satellite data to monitor carbon emissions from forest fires has become a research hotspot (Liu et al., 2023). According to research statistics, the frequency of extreme fire events increased by 2.2 times from 2003 to 2023, and the last 7 years included the most extreme 6 years (Cunningham et al., 2024). In 2021, boreal forest burning in Eurasia and North America released a record 480 million tons of carbon dioxide, accounting for 23% of total global carbon dioxide emissions from fires (B. Zheng et al., 2023). In the future, we should focus on the risk of wildfires in the boreal forests, and establish remote sensing monitoring, forecasting, and evaluation systems for wildfire carbon emissions, to provide support for the formulation of scientific and effective wildfire management and regulation policies.

The United States Department of Agriculture (USDA), a federal government agency responsible for protecting agriculture, forestry, and pastoralism, has a large position in the number of publications and the level of cooperation between relevant research institutions. The USDA's affiliate, the United States Forest Service (USFS), established the Missoula Fire Science

Laboratory, and in 1998 began the Joint Fire Science Program with the Department of Agriculture's Forest Service, systematically developing fire prediction and analysis software, such as BehavePlus fire scenario prediction software and the National Fire Risk Rating System (NFDRS), whose laboratories are well-known in the field of remote sensing monitoring of forest fires (Andrews, 2014; Finney, 2005). As a world-class educational and scientific institution, the University of California system actively cooperates with the Center for Remote Sensing (CSTARS), the United States Forest Service, and the United States California Forest and Fire Protection Agency, such as the early fire detection system of the Geosynchronous Environmental Satellite (GOES), to the project to develop "Alert California AI" using artificial intelligence (AI) technology to monitor and prevent forest fires, and improve the forest fire prevention and extinguishing capabilities in United States California region. Forest fire losses are minimized. The Chinese Academy of Sciences is the highest academic institution of natural sciences in China, which has built a complete natural science system, including chemistry, materials science, physics, mathematics, environment and ecology, earth science and other disciplines are the world's most advanced projects, and has long been committed to the application of satellite remote sensing technology in forest fire prevention technology research. In the 80s of the 20th century, the research institute carried out forest fire monitoring, mainly involving the identification of smoke areas, the detection of ignition points, and the dynamic monitoring of forest fire combustion (Jiao et al., 2023; X. Li et al., 2015; X. Li et al., 2014; Qu et al., 2009; Z. Zhang et al., 2010; Y. Zhao et al., 2023).

Our analysis of publications and international cooperation networks shows that the United States is a major force in remote sensing monitoring of forest fires. The United States is in a typically Eastern Mediterranean climate, often exposed to heat, drought, and strong winds, especially in United States California, where forest fires occur every year. It has been concerned and studied by most researchers. Beginning in 1960, the United States National Aeronautics and Space Administration (NASA) launched TIROS and ERTS satellites, which began to be used for fire monitoring and disaster response. The subsequent launch of a series of Landsat satellites, MODIS and OLI has provided researchers around the world with high-resolution images to extract forest fire hotspots and monitor fire spread. NASA actively cooperates with other countries and international organizations to share forest fire remote sensing data and research results, which provides important support for promoting global forest fire monitoring, early warning, and response. With the advancement of remote sensing technology, a new generation of remote sensing sensors and platforms will be developed and deployed, these advanced sensors can provide higher quality data, including higher spatial resolution and wider spectral range, and more accurate forest fire monitoring methods will be studied in the future, focusing on the development of machine learning technology combined with traditional forest fires, and the development of efficient fire prevention, monitoring, early warning and response technologies and ecological restoration management planning.

Keywords that appear suddenly or change significantly at a specific time represent an emerging field of research or trend. Analyzing the trend of keywords over time can provide insight into the evolution of the field of study. The keywords of citation burst detection and its topic development point to the key research topics of remote sensing monitoring of forest fires, such as "history," "transport," "United States," "drivers," "growth," "spread" and so on. Among them, the word "history" is the most prominent, with an outbreak intensity of 28.12. From 2009 to 2017, researchers paid more attention to the impact of forest fires on human health and the environment, emphasizing the use of remote sensing to monitor forest fire disturbance factors, spatial patterns, and post-disaster vegetation detection and air quality assessment in the early stage. Research hotspots include "soil," "fire detection," "spread," and "diversity". Keywords such as "vegetation," "climate change," "boreal forest," "landscape," "patterns," and "wildfire" have become the main research topics of forest fire management. The shift in research hotspots from 2009–2019 to 2020–2024 reflects evolving challenges driven by climate change, technological advancements, and the need for integrated ecosystem management strategies in forest fire monitoring and mitigation. Monitoring post-fire soil health using remote sensing is critical for achieving global climate goals such as carbon neutrality and land degradation neutrality. Post-fire changes in soil properties, including organic matter content, water repellency, and nutrient cycling, directly influence vegetation regrowth, carbon sequestration, and hydrological processes. The increasing frequency and intensity of wildfires necessitate a deeper understanding of soil's role in ecosystem resilience and carbon storage. High-resolution remote sensing (e.g., UAVs, Sentinel-2) and machine learning enable detailed monitoring of soil characteristics and recovery dynamics. The integration of UAVs, thermal sensors, and AI (e.g., deep learning models) has revolutionized fire detection capabilities, enabling real-time monitoring and early warning systems. Understanding fire propagation is essential for effective firefighting, evacuation planning, and risk mitigation, reducing response times and resource allocation costs for fire management agencies. Furthermore, fire regimes significantly impact species composition, habitat availability, and ecosystem services. Research on fire-biodiversity relationships supports the development of conservation strategies and adaptive management practices, enhancing ecosystem resilience amid increasing wildfire risks. Researchers monitor land-use change through remote sensing, identify high-fire risk areas and the speed and direction of fire spread by understanding information such as forest density, vegetation type, and soil moisture, and develop new remote sensing indices to monitor the fire spread process and provide key information for decision-makers. Remote sensing can help researchers assess the impact of fires on the structure and function of forest ecosystems, as well as the recovery after fires. Under global climate change, the increasing frequency of wildfires worldwide requires enhanced monitoring and evaluation. Forest fire management agencies should strengthen interdisciplinary cooperation by integrating remote sensing, meteorological, and geographic information data to develop risk-based prevention strategies. Promote the construction of fire early warning systems and simulation models, optimize resource allocation, improve emergency response efficiency, strengthen international cooperation, and effectively respond to cross-border fire challenges.

6. Conclusions

To know the progress of forest fire monitoring using remote sensing, an analysis of document co-citation, author, country, and institution co-authorship, and keyword analysis was used to conduct a comprehensive econometric analysis. In this study, CiteSpace, a commonly used bibliometric software, was used as the research object for papers included in WoS from 2009 to 2024. The results show the yearly number of publications is increasing, though a slight decrease has been found recently. At the national level, the five nations with the largest volume of papers published on the focus topic were the USA, China, Canada, Spain, and Australia. The USA collaborated with most countries such as Brazil, Portugal, and Canada has made an outstanding contribution to international collaborative research. On the institutional scale, the NASA-centered network had the highest collaboration intensity, forming close partnerships with other institutions. At the researcher level, ten research groups were identified, with the highest intensity in groups including Oram D. E., Bauguitte S. J.-B., Palmer P. I., and Parrington M. as members, along with Flannigan M. D. and. Parisien M.-A as another group. In addition, the three most productive authors were Sun L. from Northeast Forestry University, China, Guo F. T. from Fujian Agriculture and Forestry University, China, and Flannigan M. D. from the University of Alberta, Canada. At the journal level, Forests ranked first with 382 publications followed by Remote Sensing and the International Journal of Wildland Fire with 314 and 313 publications, respectively. At the research field level, Environmental Sciences, Agricultural and Biological Sciences, and Remote sensing ranked highest with 1090, 942, and 314 publications.

Besides, the analysis of co-citation contained both previous studies and individual levels. In terms of the previous studies, the cluster literature co-citation analysis showed 10 research directions in the area of forest fire monitoring based on climate, fire emissions, mediterranean, remote sensing, post-fire effects, deep learning, fuel management, number of fires, viirs, and eucalypt. For example, the large wildfires' spatial dynamics can be explored with satellite-based active fire statistics, which is an efficient means to systematically obtain information on a global scale. Fire monitoring and modeling can be improved based on fire activity data, thus providing decisive data support for the vast majority of fire analysts. Based on the keyword cluster graph analysis, it was found that the years 2009–2024 could be categorized into ten main themes: particulate matter, deep learning, fire severity, remote sensing, organic matter, black carbon, forest fire, patterns, climate change, and machine learning. From 2003 to 2014, the main themes were transport, disturbance, boreal forest, history, and growth. From 2015 to 2018, the main themes were the United States and conservation as hot topics of research. From 2019 to 2024, the main themes were, index, biomass burning, drivers, spread, and trends as the hotspots that had the most frequent appearance over the past 6 years. Finally, an exploration of the research tendencies through the keyword time zone map was conducted to determine the influences of forest fires imposed on properties of soil, fire point detection, forest fire spread, and biodiversity are expected to be the next focus of this type of research. China occupied ten of the top twenty individual rankings, with L. Sun from the University of Northeast Forestry, China, ranking first with 16 citations in total.

CRediT Author Statement: Juan Zhang: Writing – original draft, Validation, Methodology, Formal analysis, and Conceptualization. **Yawen Dong:** Writing – review & editing. **Yan Liu:** Methodology and Writing – review & editing. **Yuelin Kang:** Writing – review & editing. **Shaofeng Xie:** Writing – review & editing. **Haizhou Xu:** Supervision, Funding acquisition, and Conceptualization.

Data Availability Statement: Not applicable.

Funding: This work was supported by the Scientific Research Project of Hunan Provincial Education Department (Grant No. 23B0244), Forest Quality Improvement and Efficiency Enhancement Demonstration Project of Hunan Province with Loan from European Investment Bank "The Assessment Techniques of Multifunctional Forest Benefits" (Grant No. OT-S-KTA4), the Research Start-up Project of Central South University of Forestry and Technology, and the Science and Technology Innovation Platform and Talent Plan Project of Hunan Province (Grant No. 2017TP1022).

Conflicts of Interest: The authors declare no conflict of interest.

Acknowledgments: Not applicable.

References

Abatzoglou, J. T., & Williams, A. P. (2016). Impact of anthropogenic climate change on wildfire across western US forests. *Proceedings of the National Academy of Sciences*, *113*(42), 11770–11775. https://doi.org/10.1073/pnas.1607171113

Abram, N. J., Henley, B. J., Gupta, A. S., Lippmann, T. J. R., Clarke, H., Dowdy, A. J., Sharples, J. J., Nolan, R. H., Zhang, T., Wooster, M. J., Wurtzel, J. B., Meissner, K. J., Pitman, A. J., Ukkola, A. M., Murphy, B. P., Tapper, N. J., & Boer, M. M. (2021). Connections of climate change and variability to large and extreme forest fires in southeast Australia. *Communications Earth & Environment*, *2*, 8. https://doi.org/10.1038/s43247-020-00065-8

Adab, H., Kanniah, K. D., & Solaimani, K. (2013). Modeling forest fire risk in the northeast of Iran using remote sensing and GIS techniques. *Natural Hazards*, *65*, 1723–1743. https://doi.org/10.1007/s11069-012-0450-8

Andrews, P. L. (2014). Current status and future needs of the BehavePlus Fire Modeling System. *International Journal of Wildland Fire*, *23*(1), 21–33. https://doi.org/10.1071/wf12167

Anggraeni, A., & Lin, C. (2011, February 26–28). Application of SAM and SVM techniques to burned area detection for Landsat TM images in Forests of South Sumatra. 2nd International Conference on Environmental Science and Technology (ICEST 2011), Singapore.

Attard-Frost, B., Brandusescu, A., & Lyons, K. (2024). The governance of artificial intelligence in Canada: Findings and opportunities from a review of 84 AI governance initiatives. *Government Information Quarterly*, *41*(2), 101929. https://doi.org/10.1016/j.giq.2024.101929

Attiya, A. A., & Jones, B. G. (2022). Impact of smoke plumes transport on air quality in Sydney during extensive bushfires (2019) in New South Wales, Australia using remote sensing and ground data. *Remote Sensing*, *14*(21), 5552. https://doi.org/10.3390/rs14215552

Avetisyan, D., Velizarova, E., & Filchev, L. (2022). Post-fire forest vegetation state monitoring through satellite remote sensing and in situ data. *Remote Sensing*, *14*(24), 6266. https://doi.org/10.3390/rs14246266

Aydin, B., Selvi, E., Tao, J., & Starek, M. J. (2019). Use of fire-extinguishing balls for a conceptual system of drone-assisted wildfire fighting. *Drones*, *3*(1), 17. https://doi.org/10.3390/drones3010017

Aydin-Kandemir, F., & Demir, N. (2023). 2021 Turkey mega forest Fires: Biodiversity measurements of the IUCN Red List wildlife mammals in Sentinel-2 based burned areas. *Advances in Space Research*, *71*(7), 3060–3075. https://doi.org/10.1016/j.asr.2023.01.031

Babu, K. N., Gour, R., Ayushi, K., Ayyappan, N., & Parthasarathy, N. (2023). Environmental drivers and spatial prediction of forest fires in the Western Ghats biodiversity hotspot, India: An ensemble machine learning approach. *Forest Ecology and Management*, *540*, 121057. https://doi.org/10.1016/j.foreco.2023.121057

Bahadori, N., Razavi-Termeh, S. V., Sadeghi-Niaraki, A., Al-Kindi, K. M., Abuhmed, T., Nazeri, B., & Choi, S.-M. (2023). Wildfire susceptibility mapping using deep learning algorithms in two satellite imagery dataset. *Forests*, *14*(7), 1325. https://doi.org/10.3390/f14071325

Bao, Y., Shinoda, M., Yi, K., Fu, X., Sun, L., Nasanbat, E., Li, N., Xiang, H., Yang, Y., DavdaiJavzmaa, B., & Nandintsetseg, B. (2023). Satellite-based analysis of spatiotemporal wildfire pattern in the Mongolian Plateau. *Remote Sensing*, *15*(1), 190. https://doi.org/10.3390/rs15010190

Beltrán-Marcos, D., Suárez-Seoane, S., Fernández-Guisuraga, J. M., Fernández-García, V., Marcos, E., & Calvo, L. (2023). Relevance of UAV and sentinel-2 data fusion for estimating topsoil organic carbon after forest fire. *Geoderma*, *430*, 116290. https://doi.org/10.1016/j.geoderma.2022.116290

Berner, L. T., Law, B. E., Meddens, A. J. H., & Hicke, J. A. (2017). Tree mortality from fires, bark beetles, and timber harvest during a hot and dry decade in the western United States (2003–2012). *Environmental Research Letters*, *12*(6), 065005. https://doi.org/10.1088/1748-9326/aa6f94

Bright, B. C., Hudak, A. T., Meddens, A. J. H., Hawbaker, T. J., Briggs, J. S., & Kennedy, R. E. (2017). Prediction of forest canopy and surface fuels from lidar and satellite time series data in a bark beetle-affected forest. *Forests*, *8*(9), 322. https://doi.org/10.3390/f8090322

Busby, S. U., Klock, A. M., & Fried, J. S. (2023). Inventory analysis of fire effects wrought by wind-driven megafires in relation to weather and pre-fire forest structure in the western Cascades. *Fire Ecology*, *19*, 58. https://doi.org/10.1186/s42408-023-00219-x

Caccamo, G., Bradstock, R., Collins, L., Penman, T., & Watson, P. (2015). Using MODIS data to analyse post-fire vegetation recovery in Australian eucalypt forests. *Journal of Spatial Science*, *60*(2), 341–352. https://doi.org/10.1080/14498596.2015.974227

Chang, C., Chang, Y., Xiong, Z., Ping, X., Zhang, H., Guo, M., & Hu, Y. (2023). Predicting grassland fire-occurrence probability in Inner Mongolia Autonomous Region, China. *Remote Sensing*, *15*(12), 2999. https://doi.org/10.3390/rs15122999

Chen, C., Dubin, R., & Kim, M. C. (2014). Emerging trends and new developments in regenerative medicine: A scientometric update (2000 - 2014). *Expert Opinion on Biological Therapy*, *14*(9), 1295–1317. https://doi.org/10.1517/14712598.2014.920813

Chen, C., Hu, Z., Liu, S., & Tseng, H. (2012). Emerging trends in regenerative medicine: A scientometric analysis in *CiteSpace*. *Expert Opinion on Biological Therapy*, *12*(5), 593–608. https://doi.org/10.1517/14712598.2012.674507

Chen, C., Xu, T., Sun, F., & Zhao, D. (2023). A fire danger index assessment method for short-term pre-warning of wildfires: A case study of Xiangxi, China. *Safety Science*, *167*, 106287. https://doi.org/10.1016/j.ssci.2023.106287

Chen, D., Billmire, M., Loughner, C. P., Bredder, A., French, N. H. F., Kim, H. C., & Loboda, T. V. (2023). Simulating spatio-temporal dynamics of surface $PM_{2.5}$ emitted from Alaskan wildfires. *Science of The Total Environment*, *898*, 165594. https://doi.org/10.1016/j.scitotenv.2023.165594

Chen, X., Vogelmann, J. E., Rollins, M., Ohlen, D., Key, C. H., Yang, L. M., Huang, C., & Shi, H. (2011). Detecting post-fire burn severity and vegetation recovery using multitemporal remote sensing spectral indices and field-collected composite burn index data in a ponderosa pine forest. *International Journal of Remote Sensing*, *32*(23), 7905–7927. https://doi.org/10.1080/01431161.2010.524678

Chen, Y., Li, Q., Randerson, J. T., Lyons, E. A., Kahn, R. A., Nelson, D. L., & Diner, D. J. (2009). The sensitivity of CO and aerosol transport to the temporal and vertical distribution of North American boreal fire emissions. *Atmospheric Chemistry and Physics*, *9*(17), 6559–6580. https://doi.org/10.5194/acp-9-6559-2009

Chuvieco, E., Mouillot, F., van der Werf, G. R., Miguel, J. S., Tanase, M., Koutsias, N., García, M., Yebra, M., Padilla, M., Gitas, I., Heil, A., Hawbaker, T. J., & Giglio, L. (2019). Historical background and current developments for mapping burned area from satellite Earth observation. *Remote Sensing of Environment*, *225*, 45–64. https://doi.org/10.1016/j.rse.2019.02.013

Crowley, M. A., Cardille, J. A., White, J. C., & Wulder, M. A. (2019). Generating intra-year metrics of wildfire progression using multiple open-access satellite data streams. *Remote Sensing of Environment*, *232*, 111295. https://doi.org/10.1016/j.rse.2019.111295

Cunningham, C. X., Williamson, G. J. & Bowman, D. M. J. S. (2024). Increasing frequency and intensity of the most extreme wildfires on Earth. *Nature Ecology & Evolution*, *8*, 1420–1425. https://doi.org/10.1038/s41559-024-02452-2

da Silva, J. A., Jr., Pacheco, A., da P., Ruiz-Armenteros, A. M., & Henriques, R. F. F. (2023). Evaluation of the ability of SLSTR (Sentinel-3B) and MODIS (Terra) images to detect burned areas using spatial-temporal attributes and SVM classification. *Forests*, *14*(1), 32. https://doi.org/10.3390/f14010032

Dahan, K. S., Kasei, R. A., Husseini, R., Said, M. Y., & Rahman, M. M. (2023). Towards understanding the environmental and climatic changes and its contribution to the spread of wildfires in Ghana using remote sensing tools and machine learning (Google Earth Engine). *International Journal of Digital Earth*, *16*(1), 1300–1331. https://doi.org/10.1080/17538947.2023.2197263

Dasgupta, S., Qu, J. J., Hao, X., & Bhoi, S. (2007). Evaluating remotely sensed live fuel moisture estimations for fire behavior predictions in Georgia, USA. *Remote Sensing of Environment*, *108*(2), 138–150. https://doi.org/10.1016/j.rse.2006.06.023

Demir, S., & Dursun, İ. (2024). Assessment of pre- and post-fire erosion using the RUSLE equation in a watershed affected by the forest fire on Google Earth Engine: The study of Manavgat River Basin. *Natural Hazards*, *120*, 2499–2527. https://doi.org/10.1007/s11069-023-06291-5

Deng, L., Yan, E., Jiang, J., & Mo, D. (2023). Estimating fine fuel load using Sentinel-2A imagery and machine Learning: A case study in the mountainous forests of Changsha, China. *Remote Sensing*, *15*(24), 5721. https://doi.org/10.3390/rs15245721

de Santana, M. M. M., de Vasconcelos, R. N., & Mariano-Neto, E. (2023). Fire propensity in Amazon savannas and rainforest and effects under future climate change. *International Journal of Wildland Fire*, *32*(2), 149–163. https://doi.org/10.1071/wf21174

Donager, J. J., Sankey, T. T., Sankey, J. B., Sanchez Meador, A. J., Springer, A. E., & Bailey, J. D. (2018). Examining forest structure with terrestrial lidar: Suggestions and novel techniques based on comparisons between scanners and forest treatments. *Earth and Space Science*, *5*(11), 753–776. https://doi.org/10.1029/2018ea000417

Dreessen, J., Sullivan, J., & Delgado, R. (2016). Observations and impacts of transported Canadian wildfire smoke on ozone and aerosol air quality in the Maryland region on June 9–12, 2015. *Journal of the Air & Waste Management Association*, *66*(9), 842–862. https://doi.org/10.1080/10962247.2016.1161674

Duangsuwan, S., & Klubsuwan, K. (2023). Accuracy assessment of drone real-time open burning imagery detection for early wildfire surveillance. *Forests*, *14*(9), 1852. https://doi.org/10.3390/f14091852

Eskandari, S., Pourghasemi, H. R., & Tiefenbacher, J. P. (2020). Relations of land cover, topography, and climate to fire occurrence in natural regions of Iran: Applying new data mining techniques for modeling and mapping fire danger. *Forest Ecology and Management*, *473*, 118338. https://doi.org/10.1016/j.foreco.2020.118338

Eskandari, S., Pourghasemi, H. R., & Tiefenbacher, J. P. (2021). Fire-susceptibility mapping in the natural areas of Iran using new and ensemble data-mining models. *Environmental Science and Pollution Research*, *28*, 47395–47406. https://doi.org/10.1007/s11356-021-13881-y

Fan, X., Gong, M., Pang, X., & Feng, H. (2022). Safety application platform of energy production surveillance based on data flow. *Big Data - Bigdata 2021*, 37–47. https://doi.org/10.1007/978-3-030-96282-1_3

Fernández-García, V., Marcos, E., Francos, M., Jimenez-Morillo, N. T., & Calvo, L. (2023). Editorial: Wildfire severity and forest soils: impacts and post-fire restoration strategies to mitigate climate change. *Frontiers in Forests and Global Change*, *6*, 1203411. https://doi.org/10.3389/ffgc.2023.1203411

Fernández-Guisuraga, J. M., Suárez-Seoane, S., & Calvo, L. (2023). Radar and multispectral remote sensing data accurately estimate vegetation vertical structure diversity as a fire resilience indicator. *Remote Sensing in Ecology and Conservation*, *9*(1), 117–132. https://doi.org/10.1002/rse2.299

Finney, M. A. (2005). The challenge of quantitative risk analysis for wildland fire. *Forest Ecology and Management*, *211*(1–2), 97–108. https://doi.org/10.1016/j.foreco.2005.02.010

Flannigan, M. (2015). Fire evolution split by continent. *Nature Geoscience*, *8*, 167–168. https://doi.org/10.1038/ngeo2360

Flannigan, M. D., Krawchuk, M. A., de Groot, W. J., Wotton, B. M., & Gowman, L. M. (2009). Implications of changing climate for global wildland fire. *International Journal of Wildland Fire*, *18*(5), 483–507. https://doi.org/10.1071/wf08187

Fodor, G., & Conde, M. V. (2023). Rapid deforestation and burned area detection using deep multimodal learning on satellite imagery [Preprint]. *Arxiv*. https://doi.org/10.48550/arXiv.2307.04916

Freitas, W. K., Gois, G., Pereira, E. R., Jr., Oliveira, J. F., Jr., Magalhães, L. M. S., Brasil, F. C., & Sobral, B. S. (2020). Influence of fire foci on forest cover in the Atlantic Forest in Rio de Janeiro, Brazil. *Ecological Indicators*, *115*, 106340. https://doi.org/10.1016/j.ecolind.2020.106340

Gibson, R. K., White, L. A., Hislop, S., Nolan, R. H., & Dorrough, J. (2022). The post-fire stability index; a new approach to monitoring post-fire recovery by satellite imagery. *Remote Sensing of Environment*, *280*, 113151. https://doi.org/10.1016/j.rse.2022.113151

Giglio, L., Schroeder, W., & Justice, C. O. (2016). The collection 6 MODIS active fire detection algorithm and fire products. *Remote Sensing of Environment*, *178*, 31–41. https://doi.org/10.1016/j.rse.2016.02.054

Goetz, S. J., Sun, M., Baccini, A., & Beck, P. S. A. (2010). Synergistic use of spaceborne lidar and optical imagery for assessing forest disturbance: An Alaska case study. *Journal of Geophysical Research-Biogeosciences*, *115*(G2), G00E07. https://doi.org/10.1029/2008jg000898

González, F., Morante-Carballo, F., González, A., Bravo-Montero, L., Benavidez-Silva, C., & Tedim, F. (2024). Assessment of forest fire severity for a management conceptual model: Case study in Vilcabamba, Ecuador. *Forests*, *15*(12), 2210. https://doi.org/10.3390/f15122210

Guo, L., Li, S., Wu, Z., Parsons, R. A., Lin, S., Wu, B., & Sun, L. (2022). Assessing spatial patterns and drivers of burn severity in subtropical forests in Southern China based on Landsat 8. *Forest Ecology and Management*, *524*, 120515. https://doi.org/10.1016/j.foreco.2022.120515

Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., Thau, D., Stehman, S. V., Goetz, S. J., Loveland, T. R., Kommareddy, A., Egorov, A., Chini, L., Justice, C. O., & Townshend, J. R. G. (2013). High-resolution global maps of 21st-century forest cover change. *Science*, *342*(6160), 850–853. https://doi.org/10.1126/science.1244693

He, L., Chen, J. M., Zhang, S., Gomez, G., Pan, Y., McCullough, K., Birdsey, R., & Masek, J. G. (2011). Normalized algorithm for mapping and dating forest disturbances and regrowth for the United States. *International Journal of Applied Earth Observation and Geoinformation*, *13*(2), 236–245. https://doi.org/10.1016/j.jag.2010.12.003

Hefeeda, M., & Bagheri, M. (2009). Forest fire modeling and early detection using wireless sensor networks. *Ad Hoc & Sensor Wireless Networks*, *7*, 169–224. https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=ff1ee3cff697f88f0c5b76fc7b10ec6faa269d75

Niklasson, M., Zin, E., Zielonka, T., Feijen, M., Korczyk, A. F., Churski, M., Samojlik, T., Jędrzejewska, B., Gutowski, J. M., & Brzeziecki, B. (2010). A 350-year tree-ring fire record from Białowieża Primeval Forest, Poland: Implications for Central European lowland fire history. *Journal of Ecology*, *98*(6),1319–1329. http://doi.org/10.1111/j.1365-2745.2010.01710.x

Herbert, C. (2022). Improving methods to validate forest growth and quantify landscape tradeoffs in fire prone ecosystems (Publication No. 29209375) [Doctoral dissertation, University of California, Berkeley]. ProQuest Dissertations and Theses Global.

Hong, Z., Tang, Z., Pan, H., Zhang, Y., Zheng, Z., Zhou, R., Zhang, Y., Han, Y., Wang, J., & Yang, S. (2024). Near real-time monitoring of fire spots using a novel SBT-FireNet based on Himawari-8 satellite images. *Ieee Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *17*, 1719–1733. https://doi.org/10.1109/JSTARS.2023.3338448

Hościło, A., & Turlej, K. (2014, Jul 13–18). Use of satellite data for monitoring fire events in Poland. 2014 IEEE Geoscience and Remote Sensing Symposium, Quebec City, Canada. https://web.archive.org/web/20150923031858id_/http://www.igik.edu.pl/upload/Image/teledetekcja/fire/IGARSS2014HOSCILO60na90.pdf

Hu, H., Hu, T., & Sun, L. (2016). Spatial heterogeneity of soil respiration in a Larix gmelinii forest and the response to prescribed fire in the Greater Xing'an Mountains, China. *Journal of Forestry Research*, *27*, 1153–1162. https://doi.org/10.1007/s11676-016-0215-4

Hu, T., Sun, L., Hu, H., & Guo, F. (2017a). Effects of fire disturbance on soil respiration in the non-growing season in a Larix gmelinii forest in the Daxing'an Mountains, China. *PLoS One*, *12*(6), e0177084. https://doi.org/10.1371/journal.pone.0180214

Hu, T., Sun, L., Hu, H., Weise, D. R., & Guo, F. (2017b). Soil respiration of the Dahurian Larch (*Larix gmelinii*) Forest and the response to fire disturbance in Da Xing'an Mountains, China. *Scientific Report*, *7*, 2967. https://doi.org/10.1038/s41598-017-03325-4

Hu, X., Liu, W., Wen, H., Yuen, K.-V., Jin, T., Nogueira, A. C., Jr., & Zhong, P. (2024). AF-Net: An active fire detection model using improved object-contextual representations on unbalanced UAV datasets. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *17*, 13558–13569. https://doi.org/10.1109/jstars.2024.3406767

Huang, J., Lu, X., Chen, L., Sun, H., Wang, S. H., & Fang, G. (2022). Accurate identification of pine wood nematode disease with a deep convolution neural network. *Remote Sensing*, *14*(4), 913. https://doi.org/10.3390/rs14040913

Huang, S., Ramirez, C., McElhaney, M., Clark, C., & Yao, Z. (2019). Quantifying spatiotemporal post-disturbance recovery using field inventory, tree growth, and remote sensing. *Earth and Space Science*, *6*(3), 489–504. https://doi.org/10.1029/2018ea000489

Huang, Z., Zhan, X., Ma, Y., Zhao, P., Tigabu, M., Wang, G., Lin, H., & Guo, F. (2024). Do plants directly absorb nitrogen derived from deposition of wildfire smoke? *Forest Ecology and Management*, *561*, 121882. https://doi.org/10.1016/j.foreco.2024.121882

Ikhsan, A. N., Hadmoko, D. S., & Widayani, P. (2023). Spatial modeling of forest and land fire susceptibility using the information value method in Kotawaringin Barat Regency, Indonesia. *Fire*, *6*(4), 170. https://doi.org/10.3390/fire6040170

Ito, A. (2011). Mega fire emissions in Siberia: Potential supply of bioavailable iron from forests to the ocean. *Biogeosciences*, *8*(6), 1679–1697. https://doi.org/10.5194/bg-8-1679-2011

Jain, P., Barber, Q. E., Taylor, S. W., Whitman, E., Acuna, D. C., Boulanger, Y., Chavardès, R. D., Chen, J., Englefield, P., Flannigan, M., Girardin, M. P., Hanes, C. C., Little, J., Morrison, K., Skakun, R. S., Thompson, D. K., Wang, X., & Parisien, M.-A. (2024). Drivers and impacts of the record-breaking 2023 wildfire season in Canada. *Nature Communications*, *15*, 6764. https://doi.org/10.1038/s41467-024-51154-7

Jain, P., Coogan, S. C. P., Subramanian, S. G., Crowley, M., Taylor, S., & Flannigan, M. D. (2020). A review of machine learning applications in wildfire science and management. *Environmental Reviews*, *28*(4), 478–505. https://doi.org/10.1139/er-2020-0019

Jiao, Q., Fan, M., Tao, J., Wang, W., Liu, D., & Wang, P. (2023). Forest fire patterns and lightning-caused forest fire detection in Heilongjiang Province of China using satellite data. *Fire*, *6*(4), 166. https://doi.org/10.3390/fire6040166

João, T., João, G., Bruno, M., & João, H. (2018). Indicator-based assessment of post-fire recovery dynamics using satellite NDVI time-series. *Ecological Indicators*, *89*, 199–212. https://doi.org/10.1016/j.ecolind.2018.02.008

Jolly, W. M., Cochrane, M. A., Freeborn, P. H., Holden, Z. A., Brown, T. J., Williamson, G. J., & Bowman, D. M. J. S. (2015). Climate-induced variations in global wildfire danger from 1979 to 2013. *Nature Communications*, *6*, 7537. https://doi.org/10.1038/ncomms8537

Jones, M. W., Kelley, D. I., Burton, C. A., Di Giuseppe, F., Barbosa, M. L. F., Brambleby, E., Hartley, A. J., Lombardi, A., Mataveli, G., McNorton, J. R., Spuler, F. R., Wessel, J. B., Abatzoglou, J. T., Anderson, L. O., Andela, N., Archibald, S., Armenteras, D., Burke, E., Carmenta, R., … Xanthopoulos, G. (2024). State of wildfires 2023–2024. *Earth System Science Data*, *16*(8), 3601–3685. https://doi.org/10.5194/essd-16-3601-2024

Kang, Y., Jang, E., Im, J., & Kwon, C. (2022). A deep learning model using geostationary satellite data for forest fire detection with reduced detection latency. *Giscience & Remote Sensing*, *59*(1), 2019–2035. https://doi.org/10.1080/15481603.2022.2143872

Koetz, B., Morsdorf, F., van der Linden, S., Curt, T., & Allgöwer, B. (2008). Multi-source land cover classification for forest fire management based on imaging spectrometry and LiDAR data. *Forest Ecology and Management*, *256*(3), 263–271. https://doi.org/10.1016/j.foreco.2008.04.025

Kondo, Y., Matsui, H., Moteki, N., Sahu, L., Takegawa, N., Kajino, M., Zhao, Y., Cubison, M. J., Jimenez, J. L., Vay, S., Diskin, G. S., Anderson, B., Wisthaler, A., Mikoviny, T., Fuelberg, H. E., Blake, D. R., Huey, G., Weinheimer, A. J., Knapp, D. J., & Brune, W. H. (2011). Emissions of black carbon, organic, and inorganic aerosols from biomass burning in North America and Asia in 2008. *Journal of Geophysical Research: Atmospheres*, *116*, D08204. https://doi.org/10.1029/2010jd015152

Kotel'nikov, R. V., Lupyan, E. A., Bartalev, S. A., & Ershov, D. V. (2020). Space monitoring of forest fires: History of the creation and development of ISDM-Rosleskhoz. *Contemporary Problems of Ecology*, *13*, 795–802. https://doi.org/10.1134/s1995425520070045

Laneve, G., Cadau, E., Ferrucci, F., Rongo, R., Guarino, A., Fortunato, G., Hirn, B., Di Bartola, C., Iavarone, L., & Loizzo, R. (2012). SIGRI - an integrated system for detecting, monitoring, characterizing forest fires and assessing damage by LEO-GEO data. *Italian Journal of Remote Sensing*, *44*(1), 19–25. https://www.researchgate.net/publication/277515421

Levin, N., Yebra, M., & Phinn, S. (2021). Unveiling the factors responsible for Australia's Black Summer fires of 2019/2020. *Fire*, *4*(3), 58. https://doi.org/10.3390/fire4030058

Liang, Y. D., Li, Y., Zhao, J., Wang, X. Y., Zhu, H. Z., & Chen, X. H. (2017). Study of acupuncture for low back pain in recent 20 years: A bibliometric analysis via CiteSpace. *Journal of Pain Research*, *10*, 951–964. https://doi.org/10.2147/jpr.S132808

Li, L., Girguis, M., Lurmann, F., Pavlovic, N., McClure, C., Franklin, M., Wu, J., Oman, L. D., Breton, C., Gilliland, F., & Habre, R. (2020). Ensemble-based deep learning for estimating $PM_{2.5}$ over California with multisource big data including wildfire smoke. *Environment International*, *145*, 106143. https://doi.org/10.1016/j.envint.2020.106143

Lin, H., Liu, X., Wang, X., & Liu, Y. (2018). A fuzzy inference and big data analysis algorithm for the prediction of forest fire based on rechargeable wireless sensor networks. *Sustainable Computing: Informatics & Systems*, *18*, 101–111. https://doi.org/10.1016/j.suscom.2017.05.004

Lin, H., Ma, Y., Zhao, P., Huang, Z., Zhan, X., Tigabu, M., & Guo, F. (2023). Nitrogen allocation in $PM_{2.5}$ smoke-exposed plants: Implications for ecosystem nitrogen cycling and stress response. *Fire Ecology*, *19*, 69. https://doi.org/10.1186/s42408-023-00229-9

Lin, J., Lin, H., & Wang, F. (2022). STPM_SAHI: A small-target forest fire detection model based on Swin Transformer and Slicing Aided Hyper Inference. *Forests*, *13*(10), 1603. https://doi.org/10.3390/f13101603

Liu, M., Chen, Y., Chen, K., & Chen, Y. (2023). Progress and hotspots of research on land-use carbon emissions: A global perspective. *Sustainability*, *15*(9), 7245. https://doi.org/10.3390/su15097245

Liu, M., Popescu, S., & Malambo, L. (2020). Feasibility of burned area mapping based on ICESAT-2 photon counting data. *Remote Sensing*, *12*(1), 24. https://doi.org/10.3390/rs12010024

Li, X., Jin, H., He, R., Wang, H., Sun, L., Luo, D., Huang, Y., Li, Y., Chang, X., Wang, L., & Wei, C. (2023). Impact of wildfire on soil carbon and nitrogen storage and vegetation succession in the Nanweng'he National Natural Wetlands Reserve, Northeast China. *Catena*, *221*, 106797. https://doi.org/10.1016/j.catena.2022.106797

Li, X., Jin, H., Sun, L., Wang, H., He, R., Huang, Y., & Chang, X. (2022). Climate warming over 1961–2019 and impacts on permafrost zonation in Northeast China. *Journal of Forestry Research*, *33*, 767–788. https://doi.org/10.1007/s11676-021-01403-y

Li, X., Song, W., Lian, L., & Wei, X. (2015). Forest fire smoke detection using back-propagation neural network based on MODIS data. *Remote Sensing*, *7*(4), 4473–4498. https://doi.org/10.3390/rs70404473

Li, X., Wang, J., Song, W., Ma, J., Telesca, L., & Zhang, Y. (2014). Automatic smoke detection in MODIS satellite data based on *K*-means clustering and Fisher Linear Discrimination. *Photogrammetric Engineering and Remote Sensing*, *80*(10), 971–982. https://doi.org/10.14358/pers.80.10.971

Luo, H., Cai, Z., Huang, Y., Song, J., Ma, Q., Yang, X., & Song, Y. (2021). Study on pain catastrophizing from 2010 to 2020: A bibliometric analysis via CiteSpace. *Frontiers in Psychology*, *12*, 759347. https://doi.org/10.3389/fpsyg.2021.759347

Lutz, J. A., van Wagtendonk, J. W., & Franklin, J. F. (2010). Climatic water deficit, tree species ranges, and climate change in Yosemite National Park. *Journal of Biogeography*, *37*(5), 936–950. https://doi.org/10.1111/j.1365-2699.2009.02268.x

Maffei, C., Lindenbergh, R., & Menenti, M. (2021). Combining multi-spectral and thermal remote sensing to predict forest fire characteristics. *ISPRS Journal of Photogrammetry and Remote Sensing*, *181*, 400–412. https://doi.org/10.1016/j.isprsjprs.2021.09.016

Masinda, M. M., Li, F., Qi, L., Sun, L., & Hu, T. (2022). Forest fire risk estimation in a typical temperate forest in Northeastern China using the Canadian forest fire weather index: Case study in autumn 2019 and 2020. *Natural Hazards*, *111*, 1085–1101. https://doi.org/10.1007/s11069-021-05054-4

Mastrolonardo, G., Castelli, G., Certini, G., Maxwald, M., Trucchi, P., Foderi, C., Errico, A., Marra, E., & Preti, F. (2024). Post-fire erosion and sediment yield in a Mediterranean forest catchment in Italy. *International Journal of Sediment Research*, *39*(3), 464–477. https://doi.org/10.1016/j.ijsrc.2024.03.008

McCarley, T. R., Smith, A. M. S., Kolden, C. A., & Kreitler, J. (2018). Evaluating the Mid-Infrared Bi-spectral Index for improved assessment of low-severity fire effects in a conifer forest. *International Journal of Wildland Fire*, *27*(6), 407–412. https://doi.org/10.1071/wf17137

McCarthy, N. F., Tohidi, A., Aziz, Y., Dennie, M., Valero, M. M., & Hu, N. (2021). A deep learning approach to downscale Geostationary satellite imagery for decision support in high impact wildfires. *Forests*, *12*(3), 294. https://doi.org/10.3390/f12030294

McKendry, I., Strawbridge, K., Karumudi, M. L., O'Neill, N., Macdonald, A. M., Leaitch, R., Jaffe, D., Cottle, P., Sharma, S., Sheridan, P., & Ogren, J. (2011). Californian forest fire plumes over Southwestern British Columbia: Lidar, sunphotometry, and mountaintop chemistry observations. *Atmospheric Chemistry and Physics*, *11*(2), 465–477. https://doi.org/10.5194/acp-11-465-2011

Meddens, A. J. H., Kolden, C. A., & Lutz, J. A. (2016). Detecting unburned areas within wildfire perimeters using Landsat and ancillary data across the northwestern United States. *Remote Sensing of Environment*, *186*, 275–285. https://doi.org/10.1016/j.rse.2016.08.023

Meng, R., Wu, J., Zhao, F., Cook, B. D., Hanavan, R. P., & Serbin, S. P. (2018). Measuring short-term post-fire forest recovery across a burn severity gradient in a mixed pine-oak forest using multi-sensor remote sensing techniques. *Remote Sensing of Environment*, *210*, 282–296. https://doi.org/10.1016/j.rse.2018.03.019

Milanović, S., Kaczmarowski, J., Ciesielski, M., Trailović, Z., Mielcarek, M., Szczygieł, R., Kwiatkowski, M., Bałazy, R., Zasada, M., & Milanović, S. D. (2023). Modeling and mapping of forest fire occurrence in the Lower Silesian Voivodeship of Poland based on machine learning methods. *Forests*, *14*(1), 46. https://doi.org/10.3390/f14010046

Miller, J. D., Knapp, E. E., Key, C. H., Skinner, C. N., Isbell, C. J., Creasy, R. M., & Sherlock, J. W. (2009). Calibration and validation of the relative differenced Normalized Burn Ratio (RdNBR) to three measures of fire severity in the Sierra Nevada and Klamath Mountains, California, USA. *Remote Sensing of Environment*, *113*(3), 645–656. https://doi.org/10.1016/j.rse.2008.11.009

Minaei-Bidgoli, B., Kortemeyer, G., & Punch, W. F. (2004, August 16–18). Enhancing online learning performance: An application of data mining methods. The 7th Iasted International Conference on Computers & Advanced Technology in Education, Kauai, Hawaii, USA. https://loncapa.org/papers/Behrouz_CATE2004.pdf

Mohajane, M., Costache, R., Karimi, F., Pham, Q. B., Essahlaoui, A., Nguyen, H., Laneve, G., & Oudija, F. (2021). Application of remote sensing and machine learning algorithms for forest fire mapping in a Mediterranean area. *Ecological Indicators*, *129*, 107869. https://doi.org/10.1016/j.ecolind.2021.107869

Muthukumar, P., Nagrecha, K., Comer, D., Calvert, C. F., Amini, N., Holm, J., & Pourhomayoun, M. (2022). PM2.5 air pollution prediction through deep learning using multisource meteorological, wildfire, and heat data. *Atmosphere*, *13*(5), 822. https://doi.org/10.3390/atmos13050822

Nisa, K. K., Andrianto, H. A., & Mardhiyyah, R. (2014, October, 18–19). Hotspot clustering using DBSCAN algorithm and shiny web framework. 2014 International Conference on Advanced Computer Science and Information Systems, Jakarta, Indonesia.

Numata, I., Cochrane, M. A., & Galvão, L. S. (2011). Analyzing the impacts of frequency and severity of forest fire on the recovery of disturbed forest using landsat time series and EO-1 Hyperion in the Southern Brazilian Amazon. *Earth Interactions*, *15*(13), 1–17. https://doi.org/10.1175/2010ei372.1

Nurlatifah, A., Kombara, P. Y., Pratama, A., Faristyawan, R., Rakhman, A. A., & Noviastuti, N. (2025). Utilisation of WRF-HYSPLIT modelling approach and GEMS to identify $PM_{2.5}$ sources in Central Kalimantan - study case: 2023 forest fire. *Journal of Southern Hemisphere Earth Systems Science*, *75*, Es24006. https://doi.org/10.1071/es24006

O'Shea, S. J., Allen, G., Gallagher, M. W., Bauguitte, S. J.-B., Illingworth, S. M., Le Breton, M., Muller, J. B. A., Percival, C. J., Archibald, A. T., Oram, D. E., Parrington, M., Palmer, P. I., & Lewis, A. C. (2013). Airborne observations of trace gases over boreal Canada during BORTAS: Campaign climatology, air mass analysis and enhancement ratios. *Atmospheric Chemistry and Physics*, *13*(24), 12451–12467. https://doi.org/10.5194/acp-13-12451-2013

Palmer, P. I., Parrington, M., Lee, J. D., Lewis, A. C., Rickard, A. R., Bernath, P. F., Duck, T. J., Waugh, D. L., Tarasick, D. W., Andrews, S., Aruffo, E., Bailey, L. J., Barrett, E., Bauguitte, S. J.-B., Curry, K. R., Di Carlo, P., Chisholm, L., Dan, L., Forster, G., … Young, J. C. (2013). Quantifying the impact of BOReal forest fires on Tropospheric oxidants over the Atlantic using Aircraft and Satellites (BORTAS) experiment: Design, execution and science overview. *Atmospheric Chemistry and Physics*, *13*(13), 6239–6261. https://doi.org/10.5194/acp-13-6239-2013

Parrington, M., Palmer, P. I., Lewis, A. C., Lee, J. D., Rickard, A. R., Di Carlo, P., Taylor, J. W., Hopkins, J. R., Punjabi, S., Oram, D. E., Forster, G., Aruffo, E., Moller, S. J., Bauguitte, S. J.-B., Allan, J. D., Coe, H., & Leigh, R. J. (2013). Ozone photochemistry in boreal biomass burning plumes. *Atmospheric Chemistry and Physics*, *13*(15), 7321–7341. https://doi.org/10.5194/acp-13-7321-2013

Partheepan, S., Sanati, F., & Hassan, J. (2023). Autonomous unmanned aerial vehicles in bushfire management: Challenges and opportunities. *Drones*, *7*(1), 47. https://doi.org/10.3390/drones7010047

Petrakis, R. E., Villarreal, M. L., Wu, Z., Hetzler, R., Middleton, B. R., & Norman, L. M. (2018). Evaluating and monitoring forest fuel treatments using remote sensing applications in Arizona, USA. *Forest Ecology and Management*, *413*, 48–61. https://doi.org/10.1016/j.foreco.2018.01.036

Qian, J., Lin, J., Bai, D., Xu, R., & Lin, H. (2023). Omni-Dimensional Dynamic Convolution meets Bottleneck Transformer: A novel improved high accuracy forest fire smoke detection model. *Forests*, *14*(4), 838. https://doi.org/10.3390/f14040838

Qu, J. J., Hao, X., Liu, Y., Riebau, A. R., Yi, H., & Qin, X. (2009). Remote sensing applications of wildland fire and air quality in China. *Developments in Environmental Science*, *8*, 277–288. https://doi.org/10.1016/s1474-8177(08)00013-2

Radman, A., Shah-Hosseini, R., & Homayouni, S. (2023). A deep convolutional neural network for burn progression mapping using Sentinel-1 SAR time-series. *International Journal of Remote Sensing*, *44*(7), 2196–2215. https://doi.org/10.1080/01431161.2023.2197131

Razavi-Termeh, S. V., Sadeghi-Niaraki, A., & Choi, S.-M. (2020). Ubiquitous GIS-based forest fire susceptibility mapping using artificial intelligence methods. *Remote Sensing*, *12*(10), 1689. https://doi.org/10.3390/rs12101689

Ross, C. W., Loudermilk, E. L., O'Brien, J. J., Flanagan, S. A., McDaniel, J., Aubrey, D. P., Lowe, T., Hiers, J. K., & Skowronski, N. S. (2024). Lidar-derived estimates of forest structure in response to fire frequency. *Fire Ecology*, *20*, 44. https://doi.org/10.1186/s42408-024-00279-7

Rotich, B., & Ojwang, D. (2021). Trends and drivers of forest cover change in the Cherangany hills forest ecosystem, western Kenya. *Global Ecology and Conservation*, *30*, e01755. https://doi.org/10.1016/j.gecco.2021.e01755

Rust, A. J., Saxe, S., McCray, J., Rhoades, C. C., & Hogue, T. S. (2019). Evaluating the factors responsible for post-fire water quality response in forests of the western USA. *International Journal of Wildland Fire*, *28*(10), 769–784. https://doi.org/10.1071/wf18191

Sahin, Y. G., & Ince, T. (2009). Early forest fire detection using radio-acoustic sounding system. *Sensors*, *9*(3), 1485–1498. https://doi.org/10.3390/s90301485

Schroeder, T. A., Schleeweis, K. G., Moisen, G. G., Toney, C., Cohen, W. B., Freeman, E. A., Yang, Z., & Huang, C. (2017). Testing a Landsat-based approach for mapping disturbance causality in US forests. *Remote Sensing of Environment*, *195*, 230–243. https://doi.org/10.1016/j.rse.2017.03.033

Serra-Burriel, F., Delicado, P., & Cucchietti, F. M. (2021). Wildfires vegetation recovery through satellite remote sensing and Functional Data Analysis. *Mathematics*, *9*(11), 1305. https://doi.org/10.3390/math9111305

Sever, L., Leach, J., & Bren, L. (2012). Remote sensing of post-fire vegetation recovery; a study using Landsat 5 TM imagery and NDVI in North-East Victoria. *Journal of Spatial Science*, *57*(2), 175–191. https://doi.org/10.1080/14498596.2012.733618

Seydi, S. T., Saeidi, V., Kalantar, B., Ueda, N., & Halin, A. A. (2022). Fire-net: A deep learning framework for active forest fire detection. *Journal of Sensors*, *2022*(1), 8044390. https://doi.org/10.1155/2022/8044390

Shah, S. U., Yebra, M., Van Dijk, A. I. J. M., & Cary, G. J. (2023). Relating McArthur fire danger indices to remote sensing derived burned area across Australia. *International Journal of Wildland Fire*, *32*(2), 133–148. https://doi.org/10.1071/wf21108

Shao, Y., Wang, Z., Feng, Z., Sun, L., Yang, X., Zheng, J., & Ma, T. (2023). Assessment of China's forest fire occurrence with deep learning, geographic information and multisource data. *Journal of Forestry Research*, *34*, 963–976. https://doi.org/10.1007/s11676-022-01559-1

Sikuzani, Y. U., Mukenza, M. M., Muteya, H. K., Cizungu, N. C., Malaisse, F., & Bogaert, J. (2023). Vegetation fires in the Lubumbashi charcoal production basin (The Democratic Republic of the Congo): Drivers, extent and spatiotemporal dynamics. *Land*, *12*(12), 2171. https://doi.org/10.3390/land12122171

Simpson, I. J., Akagi, S. K., Barletta, B., Blake, N. J., Choi, Y., Diskin, G. S., Fried, A., Fuelberg, H. E., Meinardi, S., Rowland, F. S., Vay, S. A., Weinheimer, A. J., Wennberg, P. O., Wiebring, P., Wisthaler, A., Yang, M., Yokelson, R. J., & Blake, D. R. (2011). Boreal forest

fire emissions in fresh Canadian smoke plumes: C_1–C_{10} volatile organic compounds (VOCs), CO_2, CO, NO_2, NO, HCN and CH_3CN. *Atmospheric Chemistry and Physics*, *11*(13), 6445–6463. https://doi.org/10.5194/acp-11-6445-2011
Singh, H., & Srivastava, S. K. (2025). Identification of forest fire-prone region in Lamington National Park using GIS-based multicriteria technique: Validation using field and Sentinel-2-based observations. *Geocarto International*, *40*(1), 2462484. https://doi.org/10.1080/10106049.2025.2462484
Sofowote, U., & Dempsey, F. (2015). Impacts of forest fires on ambient near-real-time $PM_{2.5}$ in Ontario, Canada: Meteorological analyses and source apportionment of the July 2011–2013 episodes. *Atmospheric Pollution Research*, *6*(1), 1–10. https://doi.org/10.5094/apr.2015.001
Steel, Z. L., Safford, H. D., & Viers, J. H. (2015). The fire frequency-severity relationship and the legacy of fire suppression in California forests. *Ecosphere*, *6*(1), 1–23. https://doi.org/10.1890/es14-00224.1
Sulla-Menashe, D., Kennedy, R. E., Yang, Z., Braaten, J., Krankina, O. N., & Friedl, M. A. (2014). Detecting forest disturbance in the Pacific Northwest from MODIS time series using temporal segmentation. *Remote Sensing of Environment*, *151*, 114–123. https://doi.org/10.1016/j.rse.2013.07.042
Sun, L., Hu, T., Kim, J. H., Guo, F., Song, H., Lv, X., & Hu, H. (2014). The effect of fire disturbance on short-term soil respiration in typical forest of Greater Xing'an Range, China. *Journal of Forestry Research*, *25*, 613–620. https://doi.org/10.1007/s11676-014-0499-1
Tian, Y., Wu, Z., Bian, S., Zhang, X., Wang, B., & Li, M. (2022a). Study on spatial-distribution characteristics based on fire-spot data in Northern China. *Sustainability*, *14*(11), 6872. https://doi.org/10.3390/su14116872
Tian, Y., Wu, Z., Li, M., Wang, B., & Zhang, X. (2022b). Forest fire spread monitoring and vegetation dynamics detection based on multi-dource remote sensing images. *Remote Sensing*, *14*(18), 4431. https://doi.org/10.3390/rs14184431
Tsiourlis, G., Andreadakis, S., & Konstantinidis, P. (2009). SITHON: A wireless network of *in situ* optical cameras applied to the early detection-notification-monitoring of forest fires. *Sensors*, *9*(6), 4465–4482. https://doi.org/10.3390/s90604465
van der Werf, G. R., Randerson, J. T., Giglio, L., Collatz, G. J., Mu, M., Kasibhatla, P. S., Morton, D. C., DeFries, R. S., Jin, Y., & van Leeuwen, T. T. (2010). Global fire emissions and the contribution of deforestation, savanna, forest, agricultural, and peat fires (1997–2009). *Atmospheric Chemistry and Physics*, *10*(23), 11707–11735. https://doi.org/10.5194/acp-10-11707-2010
van der Werf, G. R., Randerson, J. T., Giglio, L., van Leeuwen, T. T., Chen, Y., Rogers, B. M., Mu, M., van Marle, M. J. E., Morton, D. C., Collatz, G. J., Yokelson, R. J., & Kasibhatla, P. S. (2017). Global fire emissions estimates during 1997–2016. *Earth System Science Data*, *9*(2), 697–720. https://doi.org/10.5194/essd-9-697-2017
Van Eck, C. M., Nunes, J. P., Vieira, D. C. S., Keesstra, S., & Keizer, J. J. (2016). Physically-based modelling of the post-fire runoff response of a forest catchment in central Portugal: Using field versus remote sensing based estimates of vegetation recovery. *Land Degradation & Development*, *27*(5), 1535–1544. https://doi.org/10.1002/ldr.2507
van Leeuwen, W. J. D., Casady, G. M., Neary, D. G., Bautista, S., Alloza, J. A., Carmel, Y., Wittenberg, L., Malkinson, D., & Orr, B. J. (2010). Monitoring post-wildfire vegetation response with remotely sensed time-series data in Spain, USA and Israel. *International Journal of Wildland Fire*, *19*(1), 75–93. https://doi.org/10.1071/wf08078
Van Le, H., Hoang, D. A., Tran, C. T., Nguyen, P. Q., Tran, V. H. T., Hoang, N. D., Amiri, M., Ngo, T. P. T., Nhu, H. V., Hoang, T. V., & Bui, D. T. (2021). A new approach of deep neural computing for spatial prediction of wildfire danger at tropical climate areas. *Ecological Informatics*, *63*, 101300. https://doi.org/10.1016/j.ecoinf.2021.101300
Venkatesh, K., Preethi, K., & Ramesh, H. (2020). Evaluating the effects of forest fire on water balance using fire susceptibility maps. *Ecological Indicators*, *110*, 105856. https://doi.org/10.1016/j.ecolind.2019.105856
Verbesselt, J., Hyndman, R., Newnham, G., & Culvenor, D. (2010). Detecting trend and seasonal changes in satellite image time series. *Remote Sensing of Environment*, *114*(1), 106–115. https://doi.org/10.1016/j.rse.2009.08.014
von Nonn, J., Villarreal, M. L., Blesius, L., Davis, J., & Corbett, S. (2024). An open-source workflow for scaling burn severity metrics from drone to satellite to support post-fire watershed management. *Environmental Modelling & Software*, *172*, 105903. https://doi.org/10.1016/j.envsoft.2023.105903
Wang, B., Spessa, A. C., Feng, P., Hou, X., Yue, C., Luo, J.-J., Ciais, P., Waters, C., Cowie, A., Nolan, R. H., Nikonovas, T., Jin, H., Walshaw, H., Wei, J., Guo, X., Liu, D. L., & Yu, Q. (2022). Extreme fire weather is the major driver of severe bushfires in southeast Australia. *Science Bulletin*, *67*(6), 655–664. https://doi.org/10.1016/j.scib.2021.10.001
Wang, J., & Zhang, X. (2020). Investigation of wildfire impacts on land surface phenology from MODIS time series in the western US forests. *ISPPRS Journal of Photogrammetry and Remote Sensing*, *159*, 281–295. https://doi.org/10.1016/j.isprsjprs.2019.11.027
Wang, Y., Yang, L., Zhao, L., & Deng, Y. (2018). Design of simulation training system for remote sensing large data processing of natural disasters [Special issue]. *Journal of Coastal Research*, *83*, 328–334. https://doi.org/10.2112/si83-054.1
Wang, Y., Zou, X., Deng, C., Tang, W., Li, Y., Zhang, Y., & Feng, J. (2020). A novel method for mitigating the GPS multipath effect based on a multi-point Hemispherical grid model. *Remote Sensing*, *12*(18), 3045. https://doi.org/10.3390/rs12183045
Wang, Z., Ma, T., Shao, Y., Sun, L., Li, Y., Zhang, X., Zhang, L., Zhang, G., Fan, W., & Feng, Z. (2024). Future oriented smart forestry in China: Evolution and development trends of observation instrument systems (In Chinese). *Scientia Silvae Sinicae*, *60*(4), 1–15.
Wei, M., Guo, X., Ma, Y., Tigabu, M., Zheng, W., Liu, M., & Guo, F. (2023). Impact of forest fire on radial growth of tree rings and their element concentrations of *Pinus sylvestris* and *Larix gmelinii* in northern China. *Frontiers in Forests and Global Change*, *6*, 1136039. https://doi.org/10.3389/ffgc.2023.1136039
Westerling, A. L., Hidalgo, H. G., Cayan, D. R., & Swetnam, T. W. (2006). Warming and earlier spring increase western US forest wildfire activity. *Science*, *313*(5789), 940–943. https://doi.org/10.1126/science.1128834
Wotton, B. M. (2009). Interpreting and using outputs from the Canadian Forest Fire Danger Rating System in research applications. *Environmental and Ecological Statistics*, *16*, 107–131. https://doi.org/10.1007/s10651-007-0084-2
Xiang, M., Xiao, C., Feng, Z., & Ma, Q. (2023). Global distribution, trends and types of active fire occurrences. *Science of the Total Environment*, *902*, 166456. https://doi.org/10.1016/j.scitotenv.2023.166456
Xie, J., Qi, T., Hu, W., Huang, H., Chen, B., & Zhang, J. (2022a). Retrieval of live fuel moisture content based on multi-source remote sensing data and ensemble deep learning model. *Remote Sensing*, *14*(17), 4378. https://doi.org/10.3390/rs14174378
Xie, J., Yu, F., Wang, H., & Zheng, H. (2022b). Class Activation Map-Based data augmentation for satellite smoke scene detection. *Ieee Geoscience and Remote Sensing Letters*, *19*, 6510905. https://doi.org/10.1109/lgrs.2022.3179013

Xu, H., Zhang, G., Zhou, Z., Zhou, X., Zhang, J., & Zhou, C. (2022). Development of a novel Burned-Area Subpixel Mapping (BASM) workflow for fire scar detection at subpixel level. *Remote Sensing*, *14*(15), 3546. https://doi.org/10.3390/rs14153546

Xue, W., Li, H., Ali, R., & Rehman, R. U. (2020). Knowledge mapping of corporate financial performance research: A visual analysis using Cite Space and Ucinet. *Sustainability*, *12*(9), 3554. https://doi.org/10.3390/su12093554

Yao, J., Brauer, M., Raffuse, S., & Henderson, S. B. (2018a). Machine learning approach to estimate hourly exposure to fine particulate matter for urban, rural, and remote populations during wildfire seasons. *Environmental Science & Technology*, *52*(22), 13239–13249. https://doi.org/10.1021/acs.est.8b01921

Yao, J., Raffuse, S. M., Brauer, M., Williamson, G. J., Bowman, D. M. J. S., Johnston, F. H., & Henderson, S. B. (2018b). Predicting the minimum height of forest fire smoke within the atmosphere using machine learning and data from the CALIPSO satellite. *Remote Sensing of Environment*, *206*, 98–106. https://doi.org/10.1016/j.rse.2017.12.027

Yin, J., He, R., Zhao, F., & Ye, J. (2023). Research on forest fire monitoring based on multi-source satellite remote sensing images. *Spectroscopy and Spectral Analysis*, *43*(3), 917–926. https://doi.org/10.3964/j.issn.1000-0593(2023)03-0917-10

Yousefi, S., Pourghasemi, H. R., Emami, S. N., Pouyan, S., Eskandari, S., & Tiefenbacher, J. P. (2020). A machine learning framework for multi-hazards modeling and mapping in a mountainous area. *Scientific Reports*, *10*, 12144. https://doi.org/10.1038/s41598-020-69233-2

Yuan, G., Shi, J., Jia, Q., Shi, S., Zhu, X., Zhou, Y., Shi, S., & Hu, Y. (2021). Cardiac rehabilitation: A bibliometric review from 2001 to 2020. *Frontiers in Cardiovascular Medicine*, *8*, 672913. https://doi.org/10.3389/fcvm.2021.672913

Yuchi, W., Yao, J., McLean, K. E., Stull, R., Pavlovic, R., Davignon, D., Moran, M. D., & Henderson, S. B. (2016). Blending forest fire smoke forecasts with observed data can improve their utility for public health applications. *Atmospheric Environment*, *145*, 308–317. https://doi.org/10.1016/j.atmosenv.2016.09.049

Zhang, J. H., Lin, S., Kong, L. H., & Chen, Y. P. (2012). Application of remote sensing on monitoring of forest fire. *Advanced Materials Research*, *468*, 290–293. https://doi.org/10.4028/www.scientific.net/AMR.468-471.290

Zhang, Z., Yu, H., Hu, Z., Zhou, B., & Han, M. (2010, Jun 18–20). Agricultural burning detection using remote sensing: A case study in Zhejiang Province, China. 2010 4th international conference on bioinformatics and biomedical engineering, Chengdu, China. https://doi.org/10.1109/ICBBE.2010.5516543

Zhan, X., Ma, Y., Huang, Z., Zheng, C., Lin, H., Tigabu, M., & Guo, F. (2023). Temporal and spatial dynamics in emission of water-soluble ions in fine particulate matter during forest fires in Southwest China. *Frontiers in Forests and Global Change*, *6*, 1250038. https://doi.org/10.3389/ffgc.2023.1250038

Zhao, F., Sun, R., Zhong, L., Meng, R., Huang, C., Zeng, X., Wang, M., Li, Y., & Wang, Z. (2022). Monthly mapping of forest harvesting using dense time series Sentinel-1 SAR imagery and deep learning. *Remote Sensing of Environment*, *269*, 112822. https://doi.org/10.1016/j.rse.2021.112822

Zhao, L., Liu, J., Peters, S., Li, J., Oliver, S., & Mueller, N. (2022). Investigating the impact of using IR bands on early fire smoke detection from Landsat imagery with a lightweight CNN model. *Remote Sensing*, *14*(13), 3047. https://doi.org/10.3390/rs14133047

Zhao, P., Zhang, F., Lin, H., & Xu, S. (2021). GIS-based forest fire risk model: A case study in Laoshan National Forest Park, Nanjing. *Remote Sensing*, *13*(18), 3704. https://doi.org/10.3390/rs13183704

Zhao, Y. (2023). *Understanding fire-climate-land surface interactions: From monitoring to prediction*. UC Irvine. https://escholarship.org/uc/item/0s73z39b

Zhao, Y., Huang, Y., Sun, X., Dong, G., Li, Y., & Ma, M. (2023). Forest fire mapping using multi-source remote sensing data: A case study in Chongqing. *Remote Sensing*, *15*(9), 2323. https://doi.org/10.3390/rs15092323

Zheng, B., Ciais, P., Chevallier, F., Yang, H., Canadell, J. G., Chen, Y., van der Velde, I. R., Aben, I., Chuvieco, E., Davis, S. J., Deeter, M., Hong, C., Kong, Y., Li, H., Li, H., Lin, X., He, K., & Zhang, Q. (2023). Record-high CO_2 emissions from boreal fires in 2021. *Science*, *379*(6635), 912–917. https://doi.org/10.1126/science.ade0805

Zheng, Y., Zhang, G., Tan, S., Yang, Z., Wen, D., & Xiao, H. (2023). A forest fire smoke detection model combining convolutional neural network and vision transformer. *Frontiers in Forests and Global Change*, *6*, 1136969. https://doi.org/10.3389/ffgc.2023.1136969

Zhong, C., Guo, M., Zhou, F., Li, J., Yu, F., Guo, F., & Li, W. (2023). Forest succession trajectories after fires in valleys and on slopes in the Greater Khingan Mountains, China. *Journal of Forestry Research*, *34*, 623–640. https://doi.org/10.1007/s11676-023-01602-9

Zikiou, N., Rushmeier, H., Capel, M. I., Kandakji, T., Rios, N., & Lahdir, M. (2024). Remote sensing and machine learning for accurate fire severity mapping in Northern Algeria. *Remote Sensing*, *16*(9), 1517. https://doi.org/10.3390/rs16091517

Agricultural & Rural Studies

Article

Bayesian Data Fusion Framework for Soil Moisture Interpolation in Entre Ríos, Argentina: Analysis of Topographic Indices

César Augusto Aguirre [1,2,3,]*, Guillermo Antonio Rondán [1], Carlos Germán Sedano [1], Macarena Cardozo [1] and Tatiana Rut [1]

1 Agricultural Sciences School, National University of Entre Ríos, Oro Verde 3101, Argentina; guillermo.rondan@uner.edu.ar (G.A.R.); carlos.sedano@uner.edu.ar (C.G.S.); macacr1368@gmail.com (M.C.); tatuu2427@gmail.com (T.R.)
2 Paraná Regional School, National Technology University, Paraná 3100, Argentina; cesaraguirre@frp.utn.edu.ar
3 National Scientific and Technical Research Council, Paraná 3100, Argentina
* Correspondence: cesar.aguirre@uner.edu.ar

Abstract: The estimation of soil moisture contents on crop growth is the most important variable and, in many cases, determines yields. Many simulation models predict this variable by considering atmospheric conditions, crop water needs, and soil characteristics. In general, these models simulate soil moisture content for an average plant in the cultivated field without taking into account spatial variability. Relief is one of the characteristics that can explain this variability, so obtaining maps of soil moisture in the root zone has been addressed in this work through spatial interpolations obtained in sampling campaigns, together with the application of the Bayesian data fusion technique. In this work, soil moisture measurements were carried out in the first half of 2021 and the second half of 2022. With these data, several topographic indices were analyzed, finding that the inverse of the topographic wetness index and the digital terrain model best explain the spatial variability of soil moisture. Subsequently, data fusion techniques were applied by combining the results of the Ordinary Kriging interpolation method and these topographic indices. An analysis of the estimation errors was carried out using an independent set of data that did not participate in the spatial interpolations. It is observed that the application of the Bayesian data fusion method, considering these topographic indices, improves the soil moisture estimates compared to the use of the Ordinary Kriging interpolation method alone.

Keywords: soil moisture; spatial variability; geostatistics; Ordinary Kriging; topography

Check for updates

Citation: Aguirre, C. A., Rondán, G. A., Sedano, C. G., Cardozo, M., & Rut, T. (2025). Bayesian Data Fusion Framework for Soil Moisture Interpolation in Entre Ríos, Argentina: Analysis of Topographic Indices. *Agricultural & Rural Studies*, 3(2), 24. https://doi.org/10.59978/ar03020009

Received: 12 December 2024
Revised: 4 April 2025
Accepted: 7 April 2025
Published: 28 May 2025

1. Introduction

In agricultural practices aimed at achieving good results in the yield of crops of greater economic interest, one important issue is the estimation of soil moisture in the root zone, as it is essential for the restoration of vegetation, irrigation scheduling, and hydrological modeling (Li, Xu, et al., 2019). It is a vital resource that plays a central role in agricultural areas because it determines the partition of available energy between latent, sensible, and soil heat fluxes and the distribution of precipitation in surface runoff or infiltration, which is a crucial factor for crop growth (Álvarez-Mozos et al., 2005). Different methodologies can be used to obtain three-dimensional soil moisture maps in the cultivated area. The most commonly used are gravimetric measurements at specific sites or the use of soil moisture indices derived from satellite images (Sayago et al., 2017).

Crop growth simulation models are a very useful tool for determining the conditions of growth, development, and the available resources of water and nutrients in the soil. Most of these models are one-dimensional since they simulate the physiological processes of plants considering an average plant in the cultivated area. Heat and moisture fluxes in the soil and at the soil-plant-atmosphere interface are simulated with this criterion (Noilhan & Planton, 1989; Bougeault et al., 1991a, 1991b). However, for several years now, the concept of "precision agriculture" has been in use, with the main objective of incorporating the spatial variability of soil properties in the dosage of products such as fertilizers or spraying and sowing. In this sense, models that allow obtaining estimates of soil temperature and moisture have also evolved, incorporating the resolution of heat and water flow equations in a vertical direction but considering the spatial variability of the agro-hydrological and thermal soil properties in a horizontal direction (Smirnova et al., 1997; Xiu & Pleim, 2001; Chen & Dudhia, 2001a, 2001b; Pleim & Xiu, 2003; Pleim & Guilliam, 2009; Li & Vanapalli, 2021). One of the problems in the use of these models is the initialization of the soil temperature and moisture values since it needs a three-dimensional matrix of values at the start of the simulation. One solution is to consider that the soil is at "field capacity" when there is abundant and intense rainfall. The problem is that in dry climates this situation is practically impossible, so a large number of soil moisture measurements must be carried out in the region of interest with the consequent cost that this procedure entails. The number of soil moisture samples required to obtain detailed maps is large, making this practice costly in time and resources. An alternative is to sample soil at a few sites and use a spatial interpolation method to obtain soil moisture values at the remaining unsampled sites. Geostatistical concepts (Journel, 1989) are used to apply spatial interpolation methods with rigorous analytical criteria. Karumuri et al. (2023) used this methodology to address uncertainty in input data when experimental measurements of simple and inexpensive physical properties are to be correlated with expensive material properties such as yield strength. Among the most commonly used methods, Ordinary Kriging (OK) can be mentioned (Desbarats et al., 2002; Liao et al., 2016). However, the low density of sampling sites presents some typical configurations such as the so-called "bull's eyes" that show circles around very low or very high soil moisture values. These configurations are often unrealistic, so the application of secondary data using fusion techniques of primary data (measurements of the variable to be interpolated) and secondary data (such as variables that indirectly explain the behavior of the primary variable). This fusion approach, combining measured data of the primary variable with secondary variables' data, is widely used in various applications. Among different data fusion methods, the "Evidence theory", also known as the Dempster-Shafer theory is an imprecise reasoning theory (Zhang et al., 2025), the weighting/voting fusion is often adopted to extract inconsistency features (Feng et al., 2009), neural network fusion, and fuzzy-logic inference. Zamani et al. (2023) use Bayesian Maximum Entropy-based Fusion specifically for the study of water quality variables in a water reservoir. Alizamir et al. (2025) use an innovative data fusion framework based on Bayesian model averaging to monitor dissolved oxygen levels in water. However, in the spatial interpolation of soil moisture, the Bayesian data fusion (BDF) framework is often used for this purpose, taking into account the variations explained by secondary variables related to soil moisture (Zhao et al., 2025) that can be obtained across the entire soil grid—for example, topography (Bogaert & Fasbender, 2007; Fasbender et al., 2008; Peeters et al., 2010; Wang et al., 2018; Li, Wang, et al., 2019) — or updating high-resolution images with coarser image time series using Bayesian data fusion (Fasbender et al., 2009). The limitations in the use of this technique are undoubtedly the availability of soil moisture sample data and a Digital Terrain Model (DTM) with high spatial resolution. Due to this, the DTM is first obtained from aerial photographic survey data carried out in the area with a spatial resolution of 5 m. The objective of this work is to analyze topographic indices to be used as secondary variables within the BDF framework and to use this technique to obtain spatial interpolations of soil moisture in the root zone in the experimental field of the Agricultural Sciences School of Entre Ríos National University (FCA-UNER) during the first months of 2021 and the last months of 2022 that was characterized as "La Niña" period in terms of precipitation variability, with values well below normal.

2. Materials and Methods

2.1. Location of the Study Area and Soil Moisture Sampling Sites

In the experimental farm of the FCA-UNER named Ramón Roldán, located north of the Diamante Department as shown in Figure 1, gravimetric measurements of soil moisture were carried out every 0.2 m depth up to the first meter using a stratified sampling design considering the classes "hill," "middle hill," and "low" according to the Topographic Index (TPI) suggested by Weiss (2001) and applied to the experimental field by Tóffoli et al. (2022). Three repetitions of soil moisture data collection were carried out at each sampling site at each visit using the gravimetric method. Soil moisture sampling began on February 25, 2021, and was conducted at 9 sites in the study area. Sampling was conducted at the same sites on March 12 and 19, April 20 and 30, and May 7, 14, and 31, 2021. During the second half of that year, sampling was interrupted due to the health situation caused by the COVID-19 pandemic, which led to the suspension of academic and research activities due to quarantine. Subsequently, during the second half of 2022, soil moisture sampling tasks were resumed at the sites established on August 19, September 9, October 2, 17, and 28, November 18, and December 2, 2022. Each sample was carefully conditioned and taken to the FCA-UNER Soil Laboratory to be weighed, dried in an oven at 105 °C until its weight remained constant, and then weighed again. Gravimetric humidity at location s was obtained by weight difference. The data were subsequently expressed as volumetric moisture using layer-wise bulk density determinations. In addition, soil moisture measurements were carried out in the surface layer (0–0.20 m depth), called AP, during the second half of 2022 with the sole purpose of validating the interpolation methods, that is, these data did not participate in the spatial interpolation process. For this second set of soil moisture data, 5 sites were selected as shown in Figure 2.

The location of the Ramón Roldán farm classified by the TPI (Tóffoli et al., 2022) and both soil moisture sample datasets in the rectangular study area whose dimensions are 1060 m x 880 m are shown in Figure 2. The brown points are located equally in the "hilltop," "half hill," and "low" areas according to the TPI, while the white points indicate the sites of additional soil moisture measurements in the AP layer that do not participate in the spatial interpolation processes.

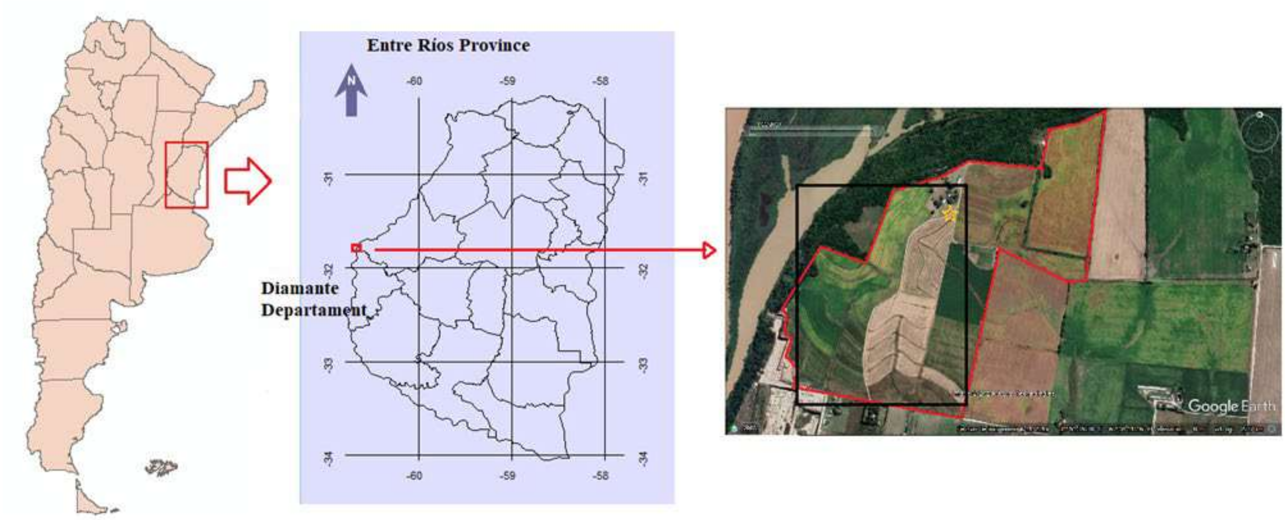


Figure 1. Geographic location of Ramón Roldán experimental farm. The satellite image on the right was obtained on 2019/04/11 from Maxar Technologies Google Earth Pro. The red polygon delimited the perimeter experimental farm and the black rectangle is the study area. ★: Installation site of automatic weather station.

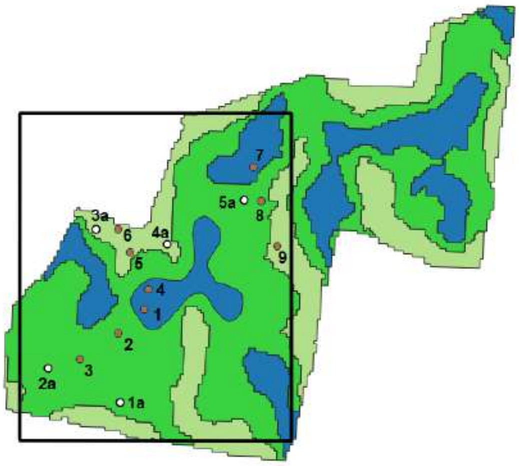


Figure 2. Ramón Roldán experimental farm is classified according to the Topographic Index (TPI), following the methodology of Tóffoli et al. (2022).
: "Hilltop"; : "Half Hill"; : Low; : Area of soil moisture interpolations.
● : sampling sites involved in the interpolations of soil moisture.
○ : sampling additional sites for calculating interpolation errors.

2.2. Spatial Interpolation of Soil Moisture

An ordinary Kriging geostatistical interpolation method (OK) was used to perform spatial interpolations of the soil moisture samples. In this case, interpolated soil moisture data grids were generated with a spatial resolution of 10 m × 10 m. This resolution was adopted because the results of the interpolations will be used in combination with data obtained from the analysis of satellite images with this resolution to be used as initial conditions in the soil moisture balance model runs. In addition to the soil moisture values using OK, the standard deviation of the soil moisture interpolations has been calculated for the entire three-dimensional grid and all sampling dates. The OK method was chosen because it has proven useful and popular in many fields. This method produces visually appealing maps from irregularly spaced data. OK attempts to express the suggested trends in the data using the variogram function, which is a mathematical model that indicates the direction in which the data tend to vary most rapidly. Therefore, the variogram is a function of direction. In this case, one might think that the slope of the land would be associated with a greater variation in soil moisture. It is also logical to assume that the direction of each sampling point towards the lower areas (drainage network) could be represented by a variogram. A detailed description of this method can be found in Cressie (1991) or Journel and Huijbregts (1978). Journel (1989) presents a concise introduction to geostatistics and particularly the Kriging method with its variants. Isaaks and Srivastava (1989) also provide a clear introduction to the subject.

2.3. Bayesian Data Fusion Framework

The technique of data fusion from topographic indices was used to improve the results of spatial interpolations of soil moisture obtained by ordinary kriging (OK). The technique that allows incorporating another set of data from other sources (such as topographic data) into the analysis of spatial variability is known as Bayesian data fusion (BDF). BDF was proposed within its theoretical framework by Bogaert and Fasbender (2007) and was specifically applied in hydrology by Fasbender et al. (2008) to analyze water table depth data measured in the Dijle River basin in northern Belgium. Peeters et al. (2010) also used this technique to improve spatial interpolations of water table depth data in an aquifer located in central Belgium. This method hypothesizes that topographical data can provide information about soil moisture variations that can help improve spatial interpolations of measured data. It is based on the assumption that part of the variability in soil moisture is explained by topography. To prevent other environmental variables from influencing the result, soil moisture sampling should be carried out on a specific day when there are no changes in weather conditions while the sampling process is taking place. In this way, the variability of soil moisture is limited to topographical characteristics.

The data fusion method proposes the estimation of the variable to be analyzed (in this case the soil moisture η_0) at an unsampled site x_0 based on n observations (sample data) $\eta_s = \{\eta_1, \eta_2, \dots, \eta_n\}$ that were taken at locations $x_s = \{x_1, x_2, \dots, x_n\}$ using some spatial interpolation techniques such as OK and complementing the result of the interpolation with the help of magnitudes obtained indirectly from the entire study area, such as topographic indices. Soil moisture values are obtained from a fitting statistical analysis of a secondary function $g_{(y)}$ that depends on the secondary variable $y = \{y_0, y_1, y_2, \dots, y_m\}$ and that correspond to the sites $x = \{x_0, x_1, x_2, \dots, x_m\}$ where m is the total number of pixels covered by the horizontal extent of the grid for a soil layer. This process must be repeated for all soil layers that make up the soil depth. Thus, at the sampling sites x_s, the soil moisture values obtained from the secondary variable are available. The pairs (η_s, y_s) are used to find the fitting function $g_{(y)}$. Then, under the assumption of mutual independence between the secondary variable data and the measured soil moisture data, Bogaert and Fasbender (2007) show that an "a posteriori" probability density function $pdf = f\left({}^{\eta_0}/_{y_0}\right)$ at the unsampled site x_0 can be derived given a value of the secondary variable at the same site y_0 from the "a priori" probability density function $pdf = f(\eta_0)$ and the conditional probability density functions $pdf = f\left({}^{\eta_0}/_{y_{0,j}}\right)$:

$$f\left(\eta_0 / y_0\right) \propto \frac{1}{\left|f\left(\eta_0\right)\right|^{p-1}} \prod_{i=1}^{p} f\left(\eta_0 / y_{0,j}\right), \tag{1}$$

where p is the number of variables that can be considered in the conditional probability density function, including the one calculated using the OK interpolation method. Thus, it can be seen that all the variables that are desired can participate in the fusion. However, sometimes a secondary variable that has a low correlation with soil moisture can negatively affect the result. For this reason, it is advisable to first perform a correlation analysis to identify the secondary variables that most accurately explain the variability of soil moisture. Assuming that $f(\eta_0), f\left({}^{\eta_0}/_{y_s}\right)$ and the $f\left({}^{\eta_0}/_{y_{0,j}}\right)$ have Gaussian distributions, one can calculate the mean μ_{BDF} and the variance σ_{BDF}^2 proposed and used by Bogaert and Fasbender (2007); Fasbender et al. (2008) and Peeters et al. (2010):

$$\mu_{BDF} = \left(\frac{\mu_k}{\sigma_k^2} + \sum_{j=1}^{p-1} \frac{\mu_{y0,j}}{\sigma_{y0,j}^2} - \frac{\mu_s}{\sigma_s^2} \right) \sigma_{BDF}^2 , \tag{2}$$

$$\sigma_{BDF}^2 = \left(\frac{1}{\sigma_k^2} + \sum_{j=1}^{p-1} \frac{1}{\sigma_{y0,j}^2} - \frac{1}{\sigma_s^2} \right)^{-1}, \quad (3)$$

where μ_k and σ_k^2 are the mean and variance of the spatial interpolation of data by OK, $\mu_{y0,j}$ and $\sigma_{y0,j}^2$ are the means and variances of the j secondary variables $g_{(y)}$ obtained from the data y and μ_s, σ_s^2 are the mean and variance of the data observed in the sampling characterizing the initial or "a priori" probability density distribution. In this way, the μ_{BDF} value obtained in each pixel of the study area will be the most probable value of the soil moisture η_0.

2.4. Topographic Indices

Topographic indices were obtained throughout the spatial grid of the study area from a Digital Terrain Model (DTM) calculated from a Digital Elevation Model (DEM) available on the National Geographic Institute (IGN) website:
https://www.ign.gob.ar/NuestrasActividades/Geodesia/ModeloDigitalElevaciones/Mapa
with a spatial resolution of 10 m. The DEMs were created by this institute based on topographic and photogrammetric surveys of the study area in 2013 (IGN, 2017, 2019; Tocho et al., 2020). From the DTM, four topographic indices were calculated: the Topographic Position Index (TPI) proposed by Weiss (2001), the Topographic Wetness Index (TWI) of Beven and Kirkby (1979), the Euclidean distance to the drainage channels (d_stream), and an index that relates d_stream with the slope called dDTM, both proposed by Fasbender et al. (2008). All these products were obtained using the QGIS 3.24 software.

2.4.1. Obtaining the Digital Terrain Model (DTM) of the Study Area

A DTM represents the bare ground surface above mean sea level without any ground objects such as plants and buildings. A Digital Surface Model (DSM) captures the natural and built/artificial features of the environment above the DTM. A Digital Elevation Model (DEM) is often used as a generic term for DSM and DTM, thus it only represents height information without any additional definition of the surface (Hirt, 2016). The average height of plants or trees can be obtained from the difference between DSM and DTM. In forest management, a Canopy Height Model (CHM) is a leaf area ceiling model derived from elevation data. In forested areas, the difference between the DSM and the DTM can be viewed as a CHM representing the height of trees above ground level or the canopy height. As mentioned above, the IGN provides DEM data with a spatial resolution of 5 meters in the study area that was obtained from analysis of aerial photographs, so the elements on the ground are included in these products. In rural areas where there are no large buildings, these images resemble a DSM, so the DTM was obtained by first digitizing the tree areas using a very high spatial resolution image such as those provided by Google Earth Engineering™. Subsequently, a field survey was carried out to estimate the height of the canopy. These areas were assimilated into a CHM. A roughness image as proposed by Wilson et al. (2007) can be obtained from the so-called "roughness" algorithm of the GDAL plugins in QGIS (see Figure 3a). This algorithm calculates the largest difference between cells of a central pixel and the values of the surrounding cells. The obtained roughness image allows knowing the maximum difference between the height of a pixel and its neighbors when the DEM is processed (not to be confused with the roughness parameter z_0). In Figure 3a, the ravine can be distinguished in dark tones to the northwest and center-west on the image, with values greater than 20 m. Leaving aside the area that goes from the ravine to the river, a group of trees to the east of the ravine are between 7.5 m and 10 m high (orange area), while another group to the northwest is up to 5 m high (light grey area). The row of trees to the southwest is 10 m high while the group of trees near the university offices and storage sheds is 7.5 m; with some scattered 5 m high. To the west of the ravine, a group of trees with different heights ranging from 7.5 m to 15 m (orange, green and blue) can be seen. Figure 3b shows the satellite image obtained from Maxar Technologies Google Earth Pro on 2022/12/12. Figure 4 shows two zoom views of the Figure 3b. It can be observed that the southern part of the ravine has a steeper slope than the central and northern parts. From the above analysis, an approximate CHM can be derived (Figure 5).

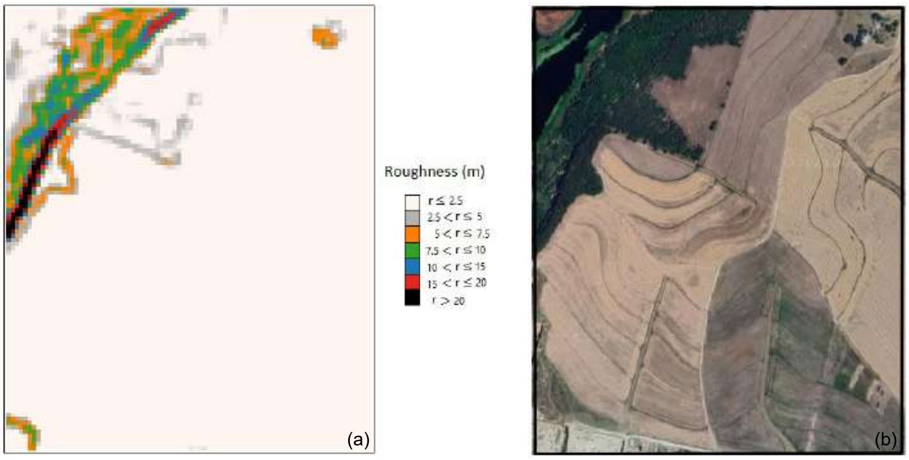


Figure 3. (a): Roughness image (r) obtained from GDAL plugins showing the maximum height differences between each pixel and the surrounding cells. (b): Satellite image obtained from Maxar Technologies Google Earth Pro on 2022/12/12.

Figure 4. Zoom view of Figure 3b. The southern part of the ravine (left) and the central part (right).

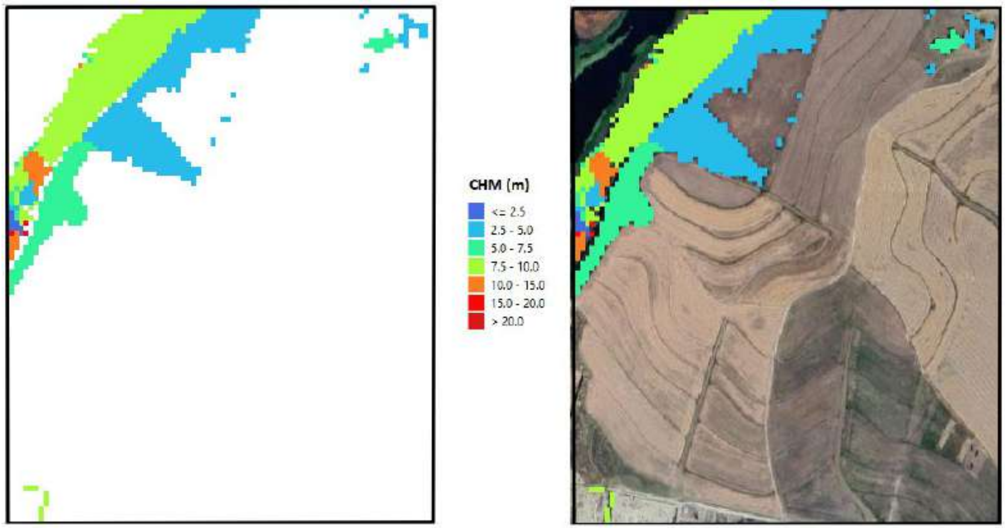


Figure 5. Left: Canopy height model (CHM) obtained from a digitized vector layer using the satellite image (right) from Maxar Technologies Google Earth Pro on 2022/12/12 rasterized using the GDAL tool in QGIS software.

As mentioned above, the DTM was obtained as a difference between the DEM and the CHM. However, due to the error that can occur when estimating the height of tree groups, it is advisable to filter the obtained image using a low-pass filter to remove possible unwanted edges of the tree area. This type of filter was used with a circular kernel of 2 pixels. Figure 6 on the left shows the DTM after performing the difference between DTM and CHM, while the one on the right shows the same image after the filtering process.

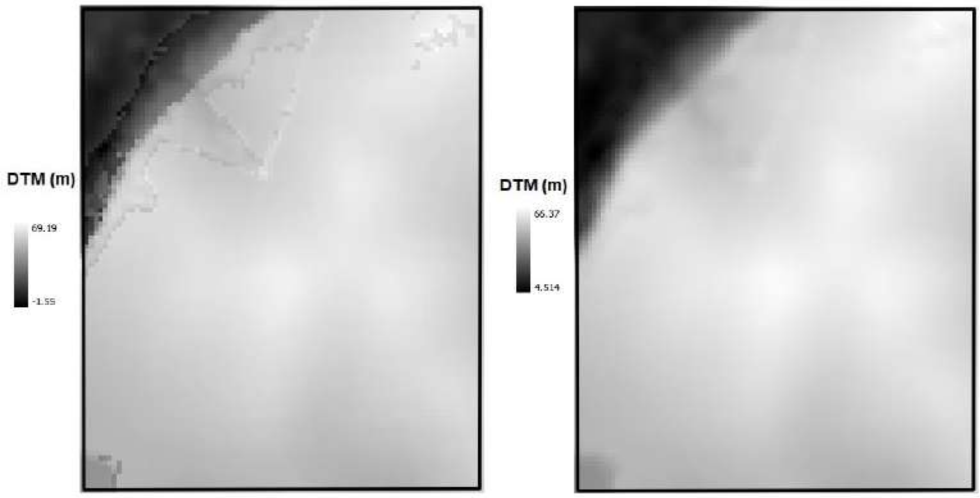


Figure 6. Left: Digital Terrain Model (DTM) obtained from the difference between the DEM and CHM models. Right: Same DTM after having performed the low-pass filtering process.

The DTM is also necessary for the simulation of heat and water fluxes at the soil-plant-atmosphere interface since it takes into account terrain variations as a boundary condition in the simulation of airflow over the terrain for the calculation of evapotranspiration. In turn, the CHM is used in Computational Fluid Dynamics (CFD) codes, such as the Advanced Regional Prediction System (ARPS), to determine the average tree height in an area with natural vegetation, in order to estimate the roughness parameter (z_0) of the wind profile.

2.4.2. Calculation and Selection of Topographic Indices

The following topographic variables have been selected to be analyzed as a source of secondary data in the BDF method for estimating soil moisture:

- The digital terrain model (DTM): In this case, the hypothesis is raised that pixels with a lower elevation value are more likely to receive surface drainage water, so they would have greater soil moisture compared to the higher ones.
- The Topographic Position Index (TPI) proposed by Weiss (2001): Computes the elevation of a cell relative to the average of neighboring cells within a specified internal and external radius. $TPI_{(5,25)}$ the internal radius from the cell center is 5 meters and the external radius of the ring is 25 meters. This indicates that the computation area for the average of the elevations of the neighboring cells has been taken as 2 pixels. In this way, if the value is negative it would indicate that the pixel is at a lower elevation than the surrounding area (valley) while a positive value indicates that the pixel is at a higher elevation than the surrounding area (peak). This computation was performed with the "Topographic Position Index" module of SAGA™.
- The Topographic Wetness Index (TWI) proposed by Beven and Kirkby (1979): Describes the tendency of a cell to accumulate surface runoff water from other cells. This index is computed as: $TWI = ln\left(\frac{SCA}{tan\emptyset}\right)$, where *SCA* is the Specific water Catchment Area for each pixel and $\emptyset$ is the slope of the pixel. The basic concept of TWI is a mass balance: *SCA* is a parameter of the tendency to receive water, while the local slope together with the drainage (implicit in *SCA*) describes the tendency to evacuate the received water. Both the SCA and $\emptyset$ are computed from the DTM. There is an algorithm in SAGA™ called "TWI one step" that calculates the TWI in a single step as shown by Mattivi et al. (2019).
- The Euclidean distance to water drainage channels (*d_stream*): In this case, the hypothesis is that the cells (or pixels) that are further away from the excess surface water drainage courses would have lower soil moisture than those located very close to them. The location of the segments that represent the channels for evacuating excess surface water must first be computed. These are the pixels that receive the greatest amount of water from their neighbours. Once these channels (stream) have been identified, the Euclidean distance from each pixel in the study area to the corresponding drainage channel is calculated. The drainage channel (or segment) layer can be obtained from the "r.watershead" module included in the GRASS™ plugin. The Euclidean distance layer to these segments is obtained from the "proximity" module of GDAL 3.8.3.
- The slope-penalized distance to water drainage channels (d_{DTM}) proposed by Fasbender et al. (2008) and modified in this work: *d_stream* indicates the Euclidean distance from each sector of the study area to the drainage channels; however, it can be thought that the excess water

would drain superficially faster towards these channels when their slope is greater than in other sites with a lower slope. For example, on the hilltop, a relationship between the terrain elevation and the soil moisture is not justified even when the Euclidean distance from the top to the drainage course is small. On the contrary, in areas with wide valleys, the soil moisture will be close to the ground level, even if the Euclidean distance to the drainage channels is large. Therefore, this indicator hypothesizes that the vertical percolations of water in areas with a high slope are lower and, therefore, result in lower soil moisture. In this way, the distance to the drainage channels can be penalized considering the slope as proposed by Fasbender et al. (2008) and applied by Peeters et al. (2010). However, the authors do not specify the penalty algorithm they use. In this paper, the use of the LS factor is proposed, which takes into account the effect of slope on soil erosion (Wishmeier & Smith, 1978). Moore et al. (1991) present a simplified form: $LS=(n+1).\left(\frac{A_s}{22{,}13}\right)^n \left(\frac{\tan\emptyset}{0{,}0896}\right)^m$, where $n = 0.4$ and $m = 1.3$. $A_s = 100$ m^2 is the pixel area. Penalizing the distance to the drainage courses by this factor gives: $d_{DTM} = d\_stream\,(1 + LS)$, then when the slope is zero $d_{DTM} = d\_stream$.

These topographic indices were obtained using the SAGATM module in the QGIS software. From the analysis of the behavior of these topographic indicators it is observed that, except for the TWI, all the others are inversely proportional to the soil moisture.

2.5. Correlation Analysis of Topographic Indices and Doil Moisture Data Sampling

The study area presents two different soil types: La Juanita and Tezanos Pintos. Figure 7 shows a map of the area for each of them. Because of this, the difference between soil moisture at saturation and measured soil moisture was chosen as the target variable to be analyzed: $HSsat = \eta_{sat} - \eta$. Therefore, this difference is directly proportional to the values taken by the topographic indices except for the TWI. For this index, it is proposed the inverse of TWI, which is named TWI^{-1}. The values of soil moisture at saturation η_{sat}, field capacity η_{fc} and wilting point η_w of the soil layers "Tezanos Pintos" and "La Juanita" are shown in Table 1:

Table 1. Agro-hydrological properties of the Tezanos Pintos and La Juanita soil series.

	Tezanos Pintos			**La Juanita**		
Layer depth (m)	η_{sat}	η_{fc}	η_w	η_{sat}	η_{fc}	η_w
AP: 0.0 – 0.2	0.4792	0.3959	0.2064	0.6226	0.3180	0.1700
Bt1: 0.2 – 0.4	0.4720	0.4121	0.2321	0.5472	0.4680	0.2700
Bt2: 0.4 – 0.6	0.4870	0.4138	0.2367	0.5472	0.3996	0.2460
BC1: 0.6 – 0.8	0.5104	0.4248	0.3032	0.6226	0.3000	0.1970
BC2: 0.8 – 1.0	0.5162	0.4312	0.2412	0.5472	0.3516	0.2220
> 1.0	0.5162	0.4312	0.2412	0.5472	0.3516	0.2220

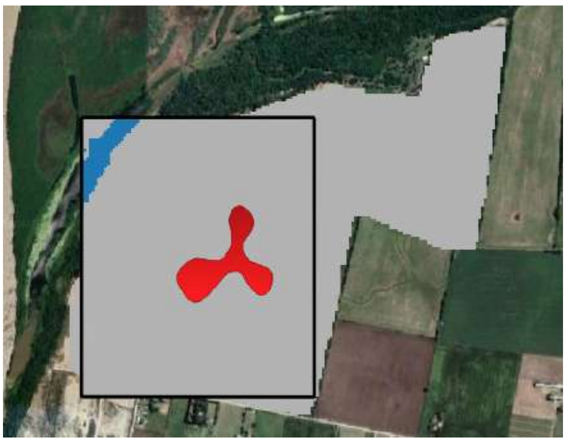


Figure 7. Soil types in the study area. (red): "La Juanita", (grey): "Tezanos Pintos", (blue): Water.

For the sampling dates, the *HSsat* calculation was performed, which was correlated with the topographic indices to obtain the functions of the secondary variables $\boldsymbol{g}_{\boldsymbol{sat(y)}}$ that allow *HSsat* to be estimated using topographic indices:

- $g_{sat(DTM)}$: *HSsat* estimation as a function of DTM.

- $g_{sat(TPI)}$: *HSsat* estimation as a function of TPI.
- $g_{sat(TWI^{-1})}$: *HSsat* estimation as a function of TWI^{-1}.
- $g_{sat(d\_stream)}$: HSsat estimation as a function of d_stream.
- $g_{sat(d_{DTM})}$: HSsat estimation as a function of d_{DTM}.

These secondary functions were fitted using soil moisture measurements at the 9 sampling sites. Twenty-seven tuning functions were tested: lineal, Square root-Y, Exponential, Inverse-Y, Y-Square, Square root-X, Double square root, Log-Y Square root-X, Inverse-Y Square root-X, Square-Y Square root-X, Log-X, Square root-Y Log-X, Multiplicative, Inverse-Y Log-X, Y-Square Log-X, Inverse-X, Square root-Y Inverse-X, S-curve, Double Inverse, Y-Square Inverse-X, X-Square, Square root-Y X-Square, Log-Y X-Square, Inverse-Y X-Square, Double Square, Logistic and Log-probit. A correlation analysis has been performed to select the topographic indices that best explain the spatial variability of soil moisture. Equations (2) and (3) can then be applied to obtain maps of the mean value and variance of soil moisture.

2.6. Validation of Interpolation Methods

In order to evaluate different combinations of the BDF method according to the topographic indices with the best correlation of soil moisture as well as to validate the OK results, the relative soil moisture errors have been calculated using the cross-validation method and by an independent set of data sampled in the surface layer $\eta_{s(ad)}$ that does not participate in the interpolations.

2.6.1. Cross-Validation (CV)

The process consisted of estimating soil moisture and its variance using the OK and the secondary functions and their associated variances of the topographic index at observation position x_1 without taking into account the moisture data η_1. Then, the interpolated soil moisture value $\eta_{1,-1}$ and the measured value η_1 are used to calculate the interpolation error $\hat{e}_{1(CV)} = \eta_1 - \eta_{1,-1}$. The first observation is then reintroduced into the dataset and the second observation is removed. Using the remaining data (including the first observation) and the specified algorithm, a value is interpolated $\eta_{2,-2}$ at the second observation position x_2. Using the known observation value at this location η_2, the interpolation error is calculated as before $\hat{e}_{2(CV)} = \eta_2 - \eta_{2,-2}$. The second observation is re-entered into the data set and the process continues in the same way for the third, fourth, fifth observation, etc., up to and including observation *N*. Then, *N* = *9 (s = 1, N)* is obtained using this method for each sampling date f and each of the five layers of the soil profile: $\hat{e}_{s(CV)} = \eta_s - \eta_{s,-s}$.

2.6.2. Independent Data Set (Vad)

These data were obtained at *N* = *5* sites during the second half of 2022. From the interpolated grid, the soil moisture value at each position x_0 is obtained, coinciding with the additional measurement of the extra data set that did not participate in the interpolation process $\eta_{0(ad)}$. Since the soil moisture values $\eta_{s(ad)}$ at these sites are known, the interpolation error is calculated for each sample *s*: $\hat{e}_{s(ad)} = \eta_{s(ad)} - \eta_{0(ad)}$.

2.6.3. Standard Interpolation Error

Subsequently, with the calculations of the interpolation errors $\hat{e}_{s(m)}$, where (*m*) is the method used*:* (*m*) = (CV) or (Vad), the standard root means square error for each date separately ($RMSE_d$) was performed for OK and BDF. In addition, the relative error ($RRMSE_d$) to the spatial mean value of measured data $\overline{\eta}_{s(m)_d}$ equation (4) has been obtained. Equations (5), (6), and (7) are used to calculate the errors of the soil moisture interpolations.

$$\overline{\eta}_{s(m)_d} = \begin{cases} \frac{1}{9}\sum_{s=1}^{9} \eta_{s(CV)d}\,(CV) \\ \frac{1}{5}\sum_{s=1}^{5} \eta_{s(ad)d}\,(\text{Vad}) \end{cases} \tag{4}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{s=1}^{N}\left(\hat{e}_{s(m)}\right)^2} \tag{5}$$

$$RMSE_{\mathrm{d}} = \sqrt{\frac{1}{N}\sum_{s=1}^{N}\left(\hat{e}_{s(m)d}\right)^2} \quad (6)$$

$$RRMSE_d\,(\%) = 100\frac{RMSE_d}{\overline{\eta}_{s(m)_d}} \quad (7)$$

3. Results and Discussion

3.1. Topographic Indices

Figure 8 shows the TPI using a saturation grey-scale palette $\overline{\mathrm{TPI}} \pm 2\ \mathrm{S_{TPI}} = -0{,}001258 \pm 2\ (0{,}476)$ to appreciate the variability in the cultivated area. Figure 9a represents the TWI using the same criterion for representing gray tones $\overline{\mathrm{TWI}} \pm 2\ \mathrm{S_{TWI}} = 7{,}5656 \pm 2\ (1{,}4872)$. It is notable that the highest TWI values coincide with the drainage channels (red lines), indicating that these pixels have a positive water balance because they receive a greater amount of water by surface runoff relative to the rate of water evacuation. This can be observed in Figure 9b. Figure 10a presents the *d_stream* in grey-scale and the drainage channels of the study area in red. Figure 10b shows the $\overline{d}_{DTM}$ with the drainage channels. The effect of the slope penalty considered in the LS factor on the *d_stream* is shown.

3.2. Statistical Analysis of Topographic Indices and Obtaining Secondary Functions

A correlation analysis was performed between the sampled *HSsat* soil moisture saturation deficit data and the five topographic indices.

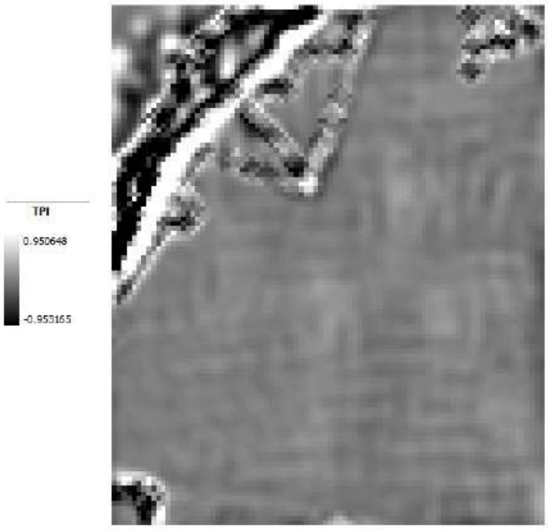


Figure 8. Topographic Position Index (TPI).

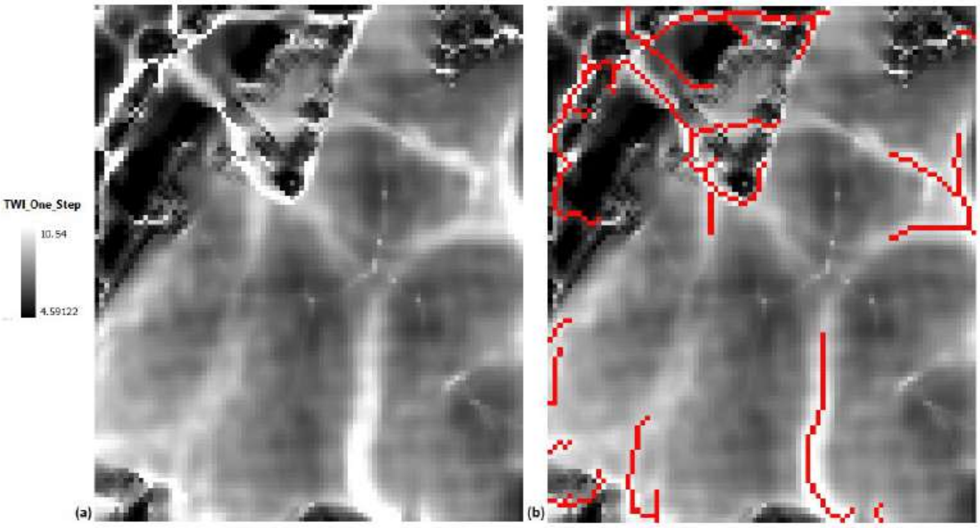


Figure 9. (a) Topographic moisture index (TWI) and (b) overlay of TWI with excess water surface drainage channels.

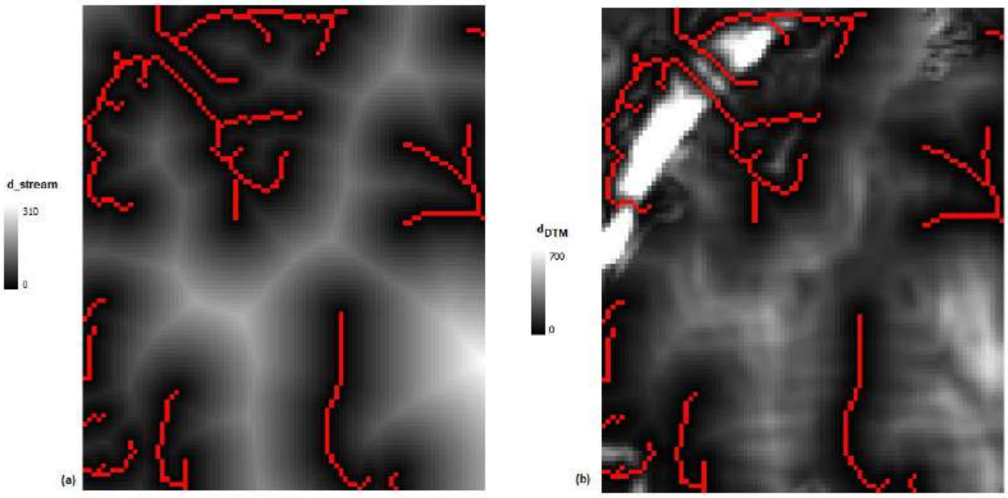


Figure 10. (a) Euclidean distance to excess water drainage channels (*d_stream*) and (b) distance penalized by the LS factor that takes into account the d_{DTM} slope.

From the analysis of the correlation coefficients, it was observed that the topographic indices that best explain the variability of the *HSsat* for all sampling dates are the DTM and the TWI^{-1}. These two indices were used as secondary variables for the fusion with the interpolation of spatial data using the OK method. For both the DTM and the TWI^{-1} indices, the most frequent *HSsat* fitting function on the observation dates is Double-Square. However, it was observed that the intercept coefficient of the Double-Square function is generally negative for DTM, which implies that the square root of the function has no solution when the value of DTM is low. For this, X-Square function was chosen for this topographic index after verifying that the values of the correlation coefficient are slightly lower than those obtained with the Double-Square function. Table 2 shows the correlation coefficients. The secondary variable functions for both indices are:

$$g_{sat(DTM)} = a + b \cdot DTM^2 \quad (8)$$

$$g_{sat(TWI^{-1})} = \sqrt{a + b \cdot \left(TWI^{-1}\right)^2} \quad (9)$$

It can be observed in Table 2 that to homogenize the calculation method of the secondary functions, it was decided to use X-Square and Double-Square functions fitting for DTM and TWI^{-1} topographic indices respectively on all sampling dates.

Table 2. Correlation coefficients of X-Square function for the DTM index and Double-Square function for the TWI^{-1} index.

Sampling dates	Topographic Index			
	DTM		TWI^{-1}	
	$g_{sat(DTM)}$	ρ	$g_{sat(TWI^{-1})}$	ρ
2021/02/25	X-Square	0.6325	Double-Square	0.6931
2021/03/12	X-Square	0.6382	Double-Square	0.6604
2021/03/19	X-Square	0.7094	Double-Square	0.7069
2021/04/20	X-Square	0.7007	Double-Square	0.7009
2021/04/30	X-Square	0.7297	Double-Square	0.6849
2021/05/07	X-Square	0.7200	Double-Square	0.7345
2021/05/14	X-Square	0.7392	Double-Square	0.7576
2021/05/31	X-Square	0.7172	Double-Square	0.7007
2022/08/19	X-Square	0.7367	Double-Square	0.7440
2022/09/09	X-Square	0.6532	Double-Square	0.6282
2022/10/02	X-Square	0.7663	Double-Square	0.8041
2022/10/17	X-Square	0.7959	Double-Square	0.8438
2022/10/28	X-Square	0.8257	Double-Square	0.8085
2022/11/18	X-Square	0.5952	Double-Square	0.5476
2022/12/02	X-Square	0.7411	Double-Square	0.7192
AVERAGE		0.7134		0.7156

The BDF method by using OK spatial interpolation and two secondary variables, DTM and TWI^{-1}, equation (1) yield:

$$f(\eta_0 / y_0) \propto \frac{1}{\left|f(\eta_0)\right|^2}\left[f(\eta_0 / y_s)\, f\left(\eta_0 / g_{(DTM)}\right) f\left(\eta_0 / g_{\left(TWI^{-1}\right)}\right)\right] \quad (10)$$

where $f\left({}^{\eta_0}/_{y_s}\right)$ is the Probability Density Function (PDF) of the soil moisture obtained at the unsampled site x_0 based on observations x_s through the OK spatial interpolation method and the other PDFs in the second member are the probability density functions of soil moisture for the same site obtained from the secondary functions $g_{(DTM)}$ and $g_{(TWI^{-1})}$. From equation (10), the mean value and variance of the BDF are obtained with equation (2) and equation (3) assuming Gaussian distribution. It is observed that not only the mean values of the secondary variables $\mu_{y0,j}$, ($g_{(y)}$ functions) are involved but also their variances $\left(\sigma^2_{y0,j}\right)$. These can be calculated by considering that the secondary functions respond to a normal probability distribution. From the statistical analysis of the sampled data, it is possible to use normal distribution models to calculate the variances as a function of the secondary variable. This calculation has been carried out for all sampling dates by finding the piecewise fit functions of the standard deviations using parabolic equations for DTM and TWI^{-1} variables. Figure 11 shows the $g_{(y)}$ functions, standard deviation, and 95% confidence for DTM and TWI^{-1} (respectively calculated from soil profile samples) during two 2021 sampling dates (February 25 [summer] and May 31 [winter]) and two 2022 sampling dates (August 19 [summer] and December 2 [winter]), illustrating the analytical approach. Figure 12 shows the standard deviation σ_{DTM} (left) and $\sigma_{TWI^{-1}}$ (right).

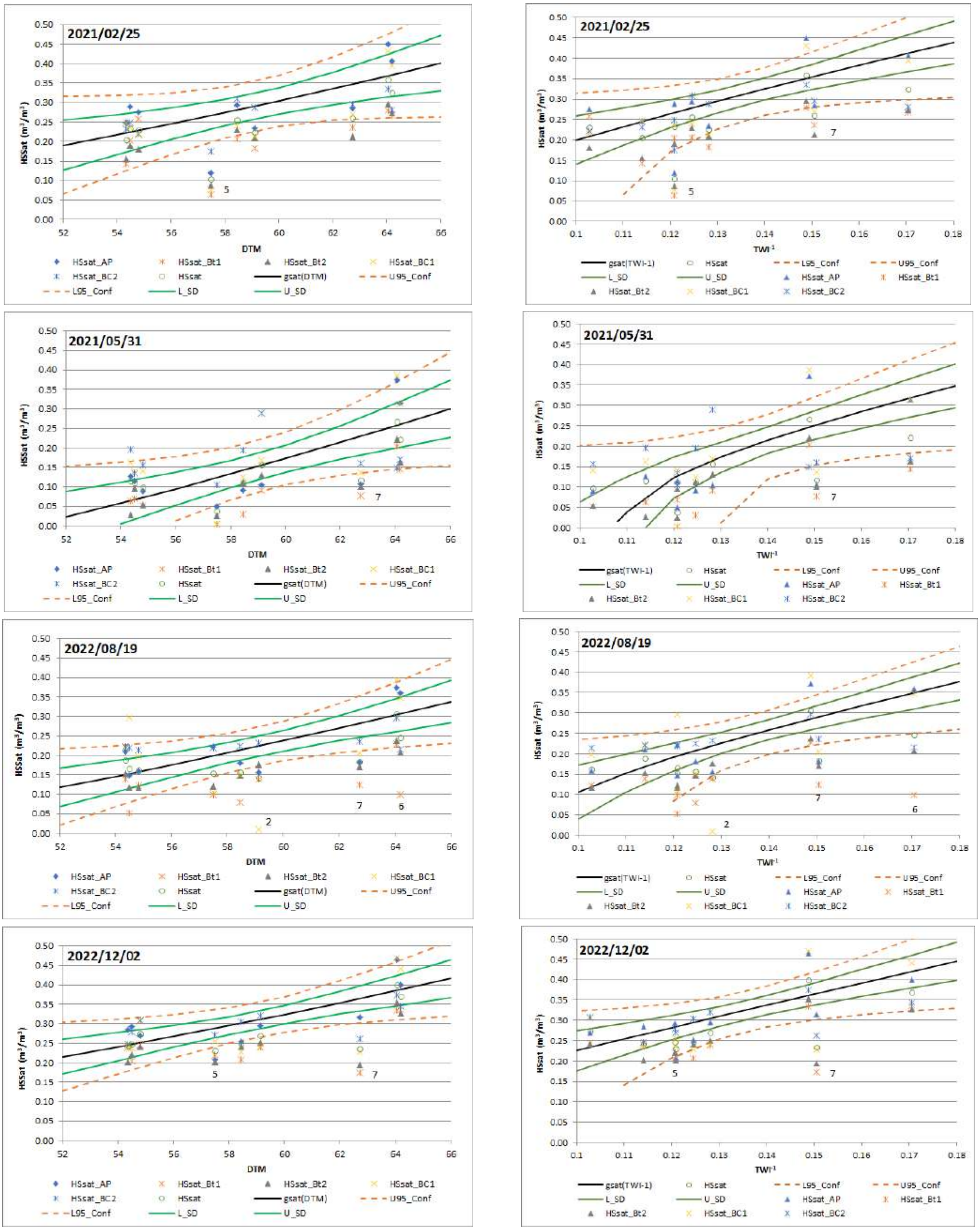


Figure 11. Curves of $g_{sat(DTM)}$ (left) and $g_{sat(TWI^{-1})}$ (right) functions, Standard Deviation Lower and Upper limits (L_SD; U_SD), 95% Confidence Lower and Upper limits (L95_Conf; U95_Conf), and *HSsat* values (symbols) were obtained from soil moisture measurements on 25 February 2021, 31 May 2021, 19 August 2022, and 2 December 2022.

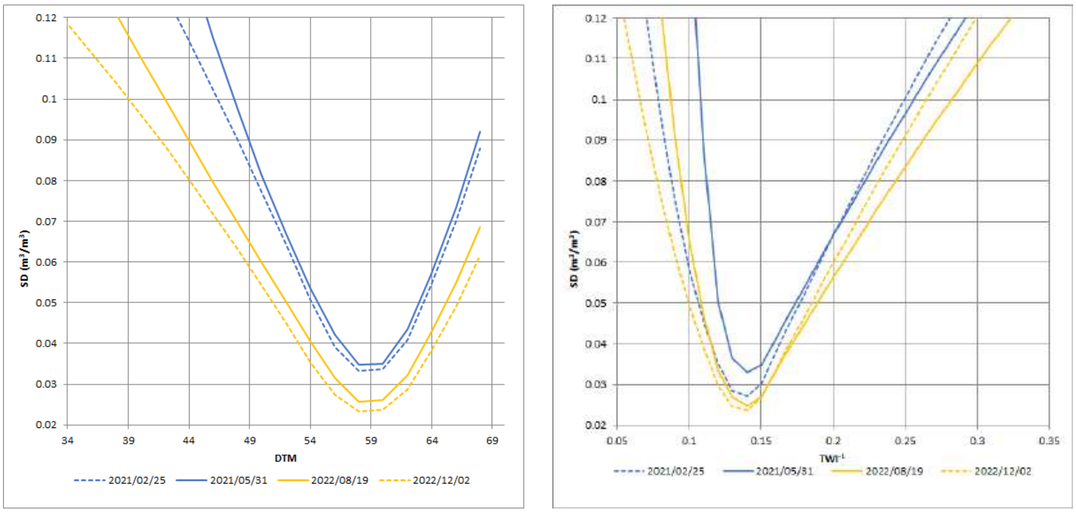


Figure 12. Fitted Standard Deviation curves of σ_{DTM} (left) and $\sigma_{TWI^{-1}}$ (right) using piecewise parabolic equations for summer days (dashed lines) and winter days (solid lines) in the 2021 and 2022 years.

It can be observed in Figure 11 for the 2021 sampling dates that there is variability that is not explained by the secondary variable DTM at sampling site 5, where all soil moisture values obtained from samples in February and a large part of them in May, are close to saturation beyond the 95% confidence limit. This behavior can also be seen on site 7 from mid-April 2021 and in the second half of 2022. This may be due to different land covers between the sampled sites. At sites 7 and 5 there were corn and soybean crops that were planted in November 2020 respectively with dense leaf cover at the time of soil moisture sampling and that completely covered the soil, unlike the other sites where soybeans were planted in February 2021, so the plant cover did not completely cover the soil because the crop was in its early vegetative stages. This year, it is also observed that during March and April, the precipitation was greater than the reference evapotranspiration (computed by Penman-Monteith method modified by Allen et al., 1998; Figure 13, left panel). Consequently, the soil moisture curves are closer to saturation. During the second half of 2022, there was a marked precipitation deficit (Figure 13, right panel), so the curves in this semester indicate a drier soil profile (see Figure 11, December 2022). For both the topographic variables DTM and TWI^{-1}, there are deviations towards wetter soil situations in sites 2, 6, and 7 in August 2022. However, a difference is observed when comparing Figure 11 in this semester. The TWI^{-1} index does not show a significant deviation at site 5 on December 2022, while the DTM has greater deviations towards low values outside the 95% confidence level limit, which may indicate that TWI^{-1} tends to depict better than the DTM part of the differences in coverage between sampling sites.

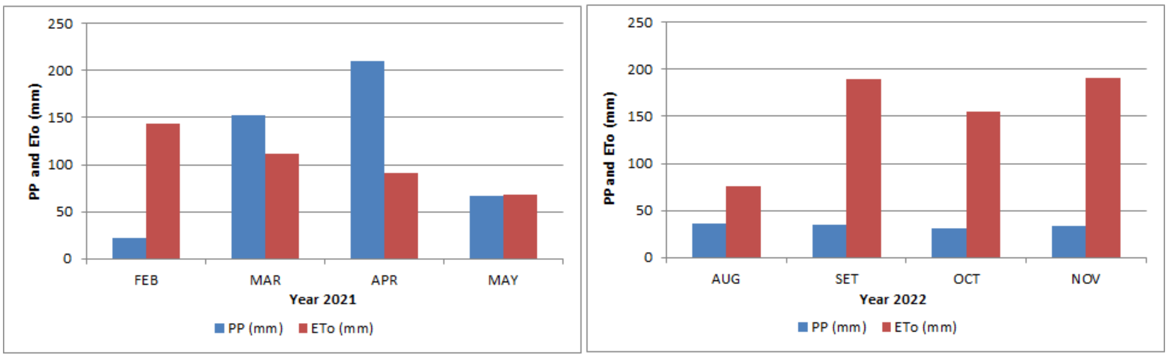


Figure 13. Relationship between Precipitation (PP) and Reference Evapotranspiration (ETo) for the first months of 2021 and the last months of 2022 in the study area.

3.3. Selected Secondary Functions Maps

The mean and standard deviation models of the secondary functions $g_{sat(y)}$ were used to obtain the soil moisture maps predicted by the variables $g_{(y)} = \eta_{sat} - g_{sat(y)}$. Maps of mean soil moisture for the AP layer depicted by the secondary functions $g_{(DTM)}$ and $g_{(TWI^{-1})}$ have been obtained for the 15 sampling dates. As an example, those corresponding to February 25, 2021; May 31, 2021; August 19, 2022; and December 2, 2022, are presented in Figure 14. Figure 15 presents the standard deviation maps for the AP surface layer at the same sampling dates. It is worth noting that the standard deviations of the variables $g_{sat(y)}$ are the same as those of the variables $g_{(y)}$ since both differ by a constant η_{sat}. This is due to the property of the linear combination of the variances: $\sigma^2_{(a+b.x)} = \frac{1}{b}\sigma^2_{(x)}$ where in this case: $a = \eta_{sat}$ and $b = 1$.

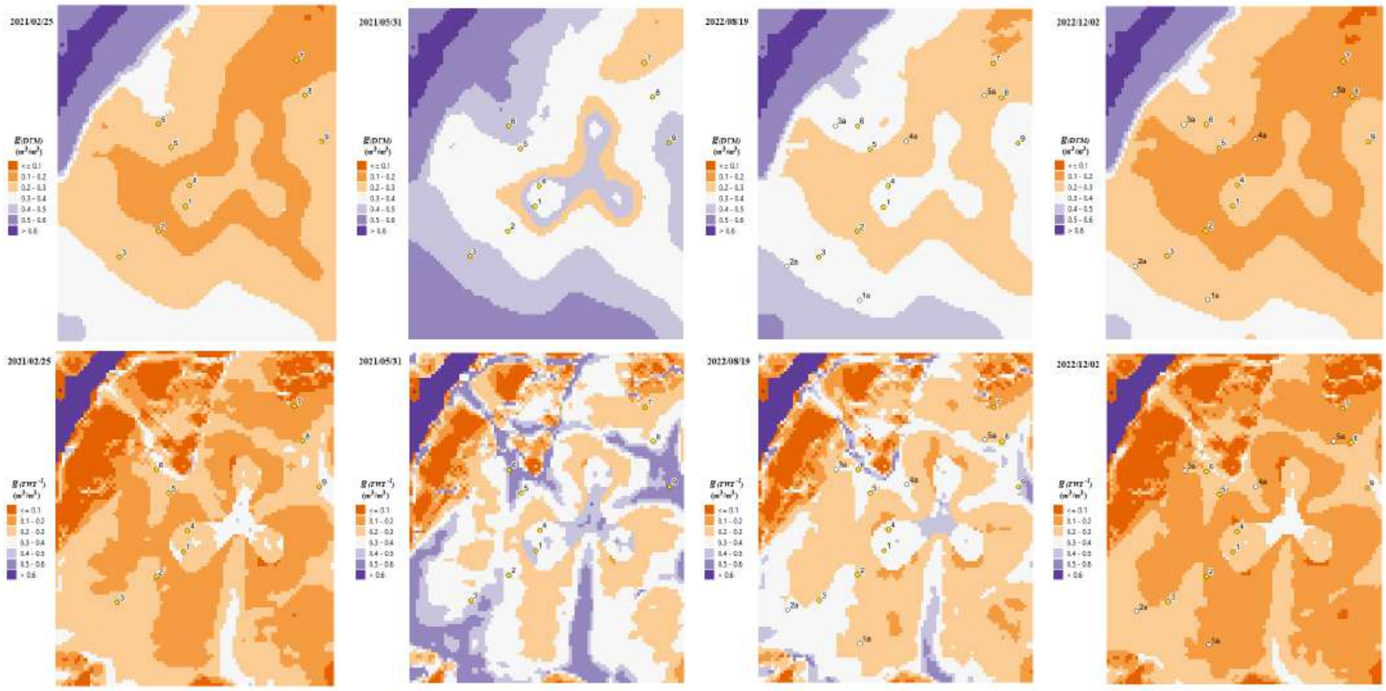


Figure 14. Maps of mean soil moisture for the AP layer depicted by the secondary functions $g_{(MDT)}$ (up) and $g_{(TWI^{-1})}$ (down). Sampling dates: 2021/02/25; 2021/05/31; 2022/08/19; 2022/12/02. The points indicate the soil moisture sampling sites.

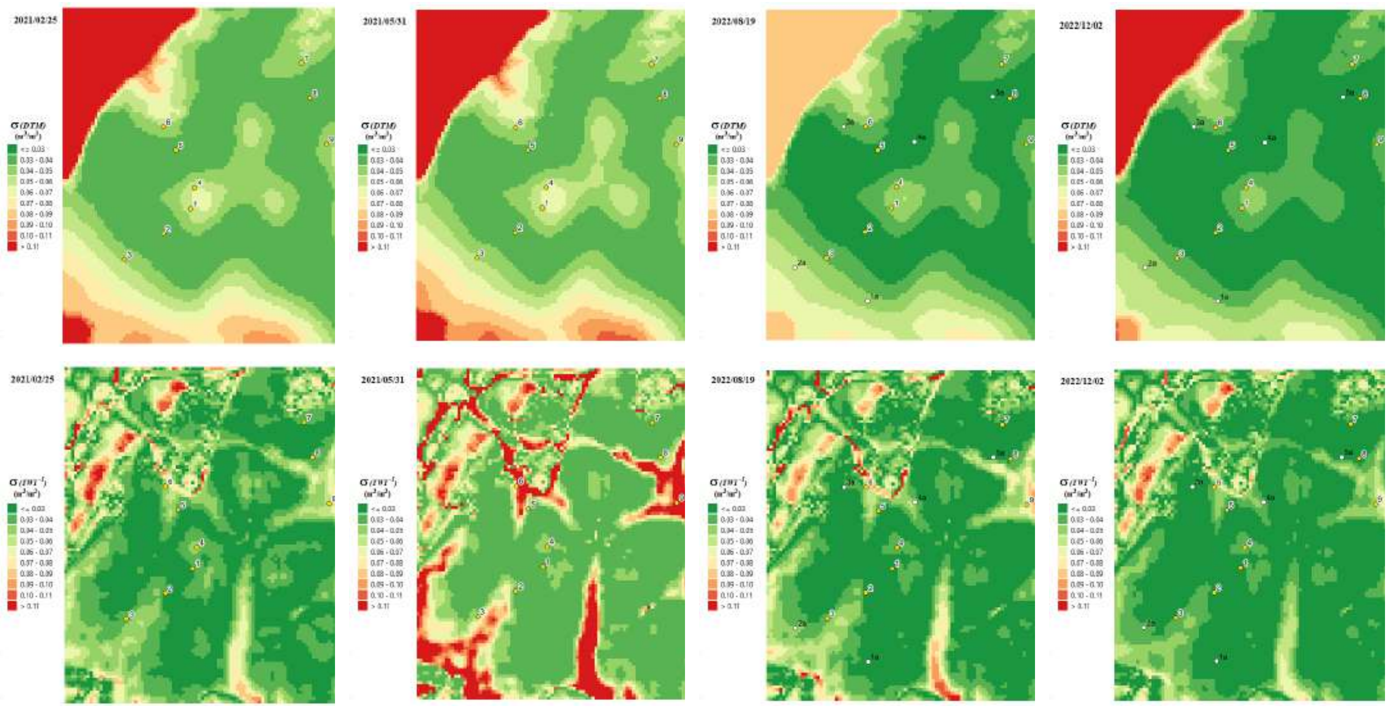


Figure 15. Maps of Standard Deviation soil moisture for the AP layer depicted by the secondary functions $g_{(MDT)}$ (left) and $g_{(TWI^{-1})}$ (right). Sampling dates: 2021/02/25, 2021/05/31, 2022/08/19, 2022/12/02. The points indicate the soil moisture sampling sites.

The temporal evolution of the mean soil moisture value maps (depicted by both secondary variables in Figure 14, μ_y: $g_{(MDT)}$ and $g_{(TWI^{-1})}$) shows that in the summer months (February and March 2021,) the values are low, possibly due to the influence of solar radiation and temperature in the AP soil surface layer. In April and May, a moisture recharge is shown in this profile, possibly due to the lower demand for water by evapotranspiration. In 2022, a progressive drying of the layer is observed as the year progresses. It is seen that the soil moisture explained by TWI^{-1} follows the trace of the excess water surface drainage channels in greater detail than the DTM. Both secondary variables show the difference in moisture by soil type. The differences in spatial variability of soil moisture between the years 2021 and 2022 are more evident in Figure 15 than in Figure 14. As shown previously, water stress situations in 2022 cause the spatial variability in soil moisture to be much lower than in 2021. Comparing the spatial variability of soil moisture for samples taken in the first half of 2021 with those of the second half of 2022, it is observed that these differences are larger for the secondary variable TWI^{-1}.

3.4. Spatial Interpolation of Soil Moisture Measurements Using Ordinary Kriging (OK)

Spatial interpolations using the OK method for all sampling dates were performed using Surfer 9.0 software. This software also allows obtaining standard deviation maps using the experimental variograms. Linear models of variograms were chosen because the number of soil moisture samples in the sub-basins is insufficient for the plotting of local directional variograms based on the terrain slopes. As an example, Figure 16 and Figure 17 show the mean value (left) and standard deviation (right) maps of the soil moisture interpolations using the OK method (μ_k, σ_k) for same dates.

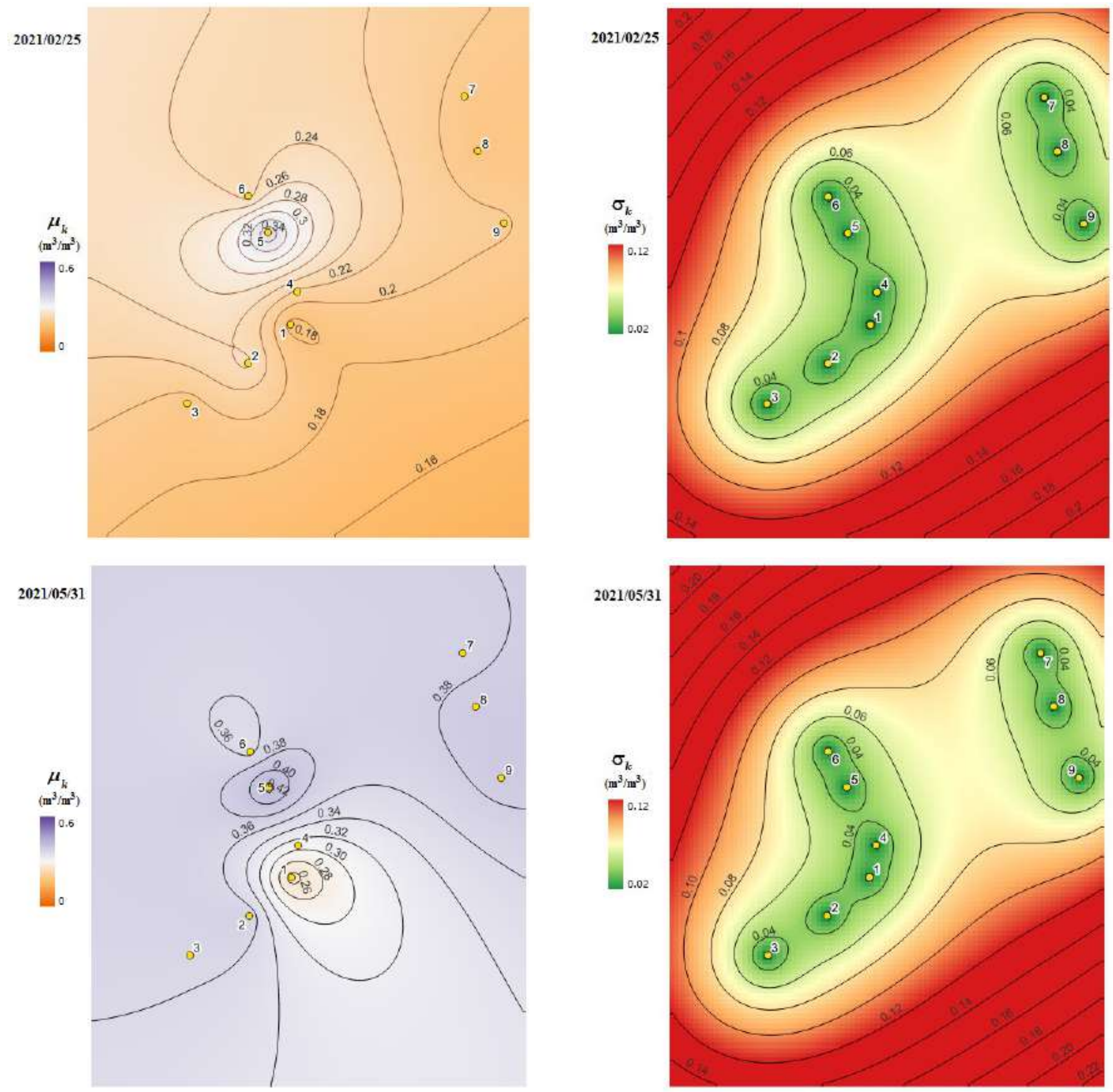


Figure 16. Soil moisture values in AP interpolated using OK: μ_k (left) and σ_K (right). Sampling dates: 2021/02/25 and 2021/05/31. The points indicate the soil moisture sampling sites.

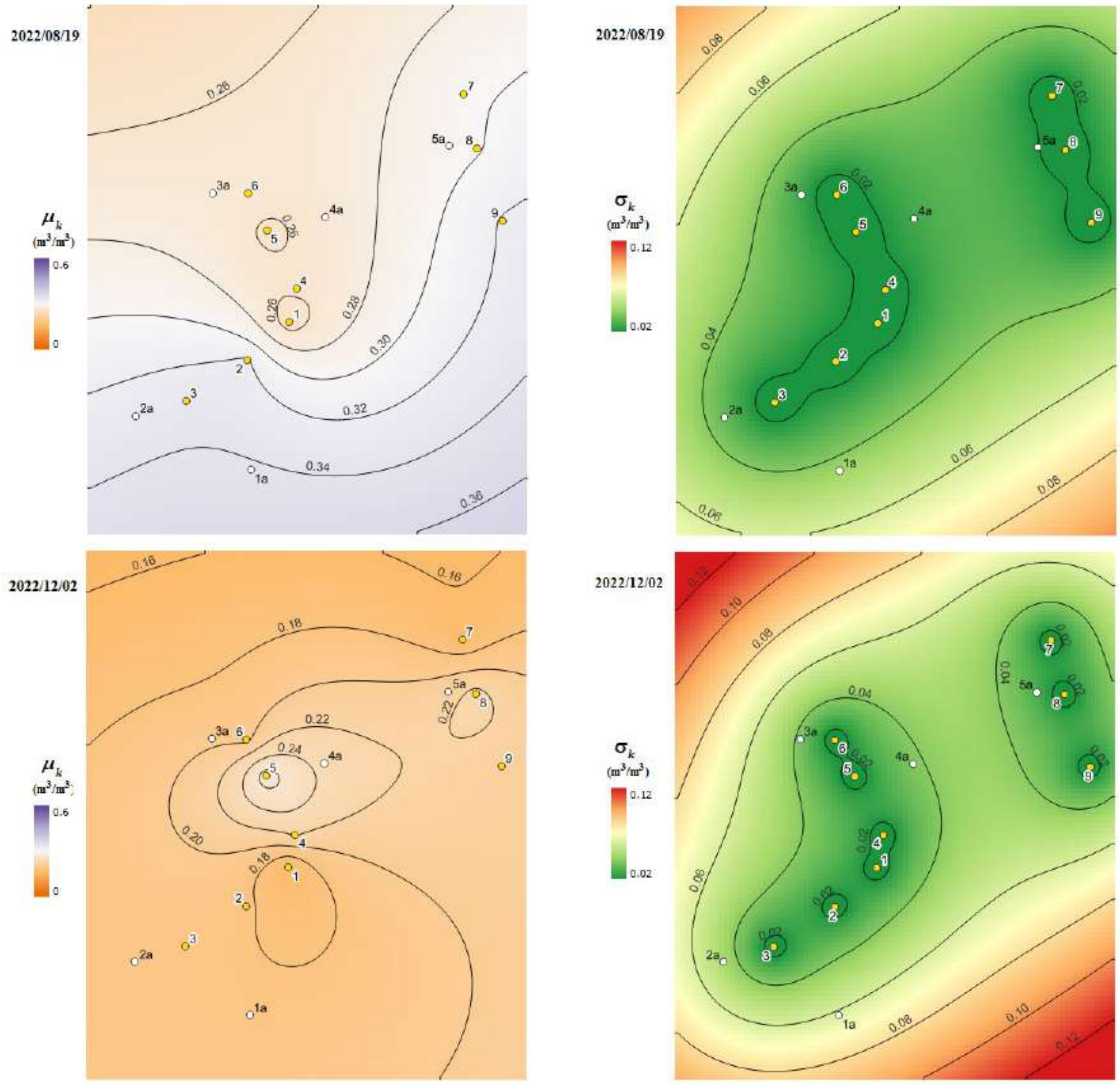


Figure 17. Soil moisture values in AP interpolated using OK: μ_k (left) and σ_K (right). Sampling dates: 2022/08/19 and 2022/12/02. The points indicate the soil moisture sampling sites.

Analysis of the interpolation maps using the OK method (see Figures 16 and 17), reveals that the low sampling site density presents the typical configurations called "bull's eyes" that correspond to circles around very low or very high soil moisture values. These configurations are unrealistic, which justifies the application of the BDF method to improve the OK results. The problem of low sample density can also be observed in the standard deviation maps since the dispersion around the interpolated values increases very rapidly as one moves away from the sampling sites. This is observed very markedly in 2021(Figure 16, right panel) and less evident in 2022 (Figure 17, right panel), because in this year the spatial variability of soil moisture in the study area was lower due to the occurrence of low rainfall throughout the region (see Figure 13).

3.5. Validation of the Bayesian Data Fusion Method

Using equations (4), (5), (6), and (7) the Relative Root Mean Square Standard Error $RRMSE_d$ was calculated for the soil moisture data sampling dates using the Cross-validation method (CV) and data set of independent samples (Vad) that were not included in the OK spatial interpolation. In the last method, these data marked on the previous maps of the year 2022 as 1a to 5a were taken in the surface layer of the AP soil profile. This validation methodology was used to compare the results of the OK and BDF interpolations using equations (2) and (3) considering three data fusion alternatives:

(1) OK and DTM;
(2) OK and TWI^{-1};
(3) OK and both secondary variables (DTM and TWI^{-1}).

Table 3 shows $RRMSE_d$ and the average over the sampling dates using the (CV) method. An improvement is observed in the interpolation errors of secondary topographic variables in the estimation of soil moisture using BDF. When the OK spatial interpolation method is compared with the BDF by using (CV) error estimation, it can be observed that in general the estimation error is greater in the summer months and is lower in the winter months. Considering the average of the soil moisture estimation errors in all the observations, it can be seen that the BDF method has a lower *RRMSE* than the OK method, although the differences are very small. Comparing the different combinations in the BDF, it is observed that the (OK-DTM) has the lowest *RRMSE*. When analyzing the years 2021 and 2022 separately, it can be seen that in 2021 the *RRMSE* is higher than in 2022, which affirms that the spatial variability is greater in 2021, possibly due to the fact that rainfall was greater than in the second half of 2022. In the comparison between the different interpolation methods, it is observed that for the first half of 2021, the FDB method with the combination (KO-DTM) is the one with the lowest *RRMSE*. In the second half of 2022, the one with the lowest *RRMSE* is the FDB method with the combination (OK-DTM-TWI^{-1}).

Table 3. Relative root mean square errors $RRMSE_d$ calculated using the interpolation errors by Cross-validation (CV) method for the Ordinary Kriging (OK) and Bayesian Data Fusion (BDF).

Sampling dates (*d*)	**$RRMSE_d$ (%)**			
	OK	**BDF**		
		OK-DTM	**OK-TWI^{-1}**	**OK-DTM-TWI^{-1}**
2021/02/25	32.59689	31.97403	31.57704	31.21643
2021/03/12	16.63304	16.69337	16.79643	16.94355
2021/03/19	18.91018	18.38758	18.51472	18.28422
2021/04/20	14.92306	14.96444	15.62951	15.71715
2021/04/30	12.89757	12.83425	13.47868	13.42929
2021/05/07	16.68387	16.67366	17.62583	17.60853
2021/05/14	10.19849	10.43183	11.34280	11.68066
2021/05/31	15.78390	15.56965	15.97378	15.98117
2022/08/19	7.30308	7.43519	7.72497	7.89307
2022/09/09	16.99758	17.14755	17.35412	17.52723
2022/10/02	13.19149	12.97038	12.63427	12.56903
2022/10/17	13.72735	13.68217	13.28364	13.43625
2022/10/28	15.35997	14.64658	14.32769	14.10953
2022/11/18	18.35396	18.24952	18.19721	18.16677
2022/12/02	22.84751	22.01082	21.90845	21.43883
AV. 2021–2022	**16.42720**	**16.24473**	**16.42461**	**16.40011**
AV. 2021	**17.32837**	**17.19110**	**17.61735**	**17.60763**
AV. 2022	**15.39728**	**15.16317**	**15.06148**	**15.02010**

Table 4 shows the $RRMSE_d$ and their average of the sampling dates using the independent set of soil samples (Vad). It can be seen that the lowest average $RRMSE_d$ is observed when using the BDF method with the variables (OK-TWI^{-1}) combination, even though on certain dates, the BDF method using (OK-DTM) variables has the best result (three of the seven dates analyzed: August 19, November 18, and December 2).

Figure 18 (left) shows a scatter diagram of the errors calculated by CV for the estimation of soil moisture in the AP layer using the OK methods and the topographic variables DTM and TWI^{-1}. Figure 18 (right) presents the scatter diagram of the errors considering the OK method and the FDB method with the combinations (OK-DTM), (OK-TWI^{-1}), and (OK-DTM-TWI^{-1}). The measured data from all sampling dates are represented on the abscissas and the simulated data with spatial interpolation methods are represented on the ordinate. These figures show the lowest error dispersion for the BDF interpolation methods compared to the soil moisture estimation using only the topographic variables separately. The fusion of these with the OK is evidenced in these figures.

Table 4. Relative root mean square errors $RRMSE_d$ calculated using the interpolation errors by Validation with an additional data set *(*Vad*)* for the Ordinary Kriging (OK) and Bayesian Data Fusion (BDF).

Sampling dates (*d*)	*RRMSEd (%)*			
	OK	BDF		
		OK-DTM	$OK\text{-}TWI^{-1}$	$OK\text{-}DTM\text{-}TWI^{-1}$
2022/08/19	13.68492	13.09942	15.70013	14.80832
2022/09/09	18.33629	17.09313	14.23506	14.81375
2022/10/02	12.01752	14.13030	6.41038	7.39070
2022/10/17	13.26676	20.86311	14.43126	18.16939
2022/10/28	21.29076	29.69339	17.26534	24.03038
2022/11/18	9.80441	7.85816	13.26226	12.26633
2022/12/02	14.68534	10.74759	15.96717	10.76994
AV. 2022	**14.72657**	**16.21216**	**13.89594**	**14.60697**

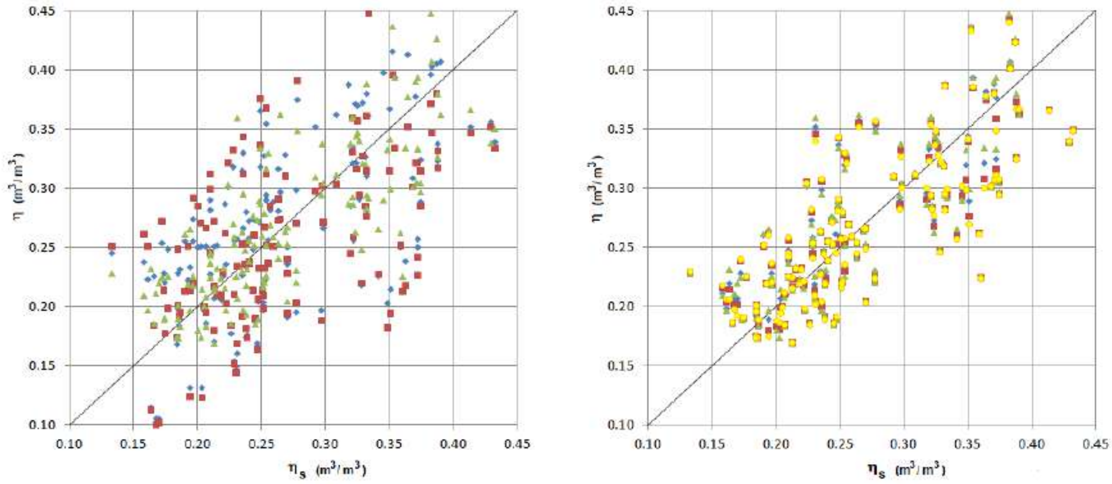


Figure 18. Scatter diagram of the errors calculated by CV method in the estimation of soil moisture.
Left: ▲ OK, ◆ *g(*DTM*)*, ■ *g(*TWI^{-1}*)*.
Right: ▲ OK, ◆ BDF(OK-DTM), ■ BDF(OK-TWI^{-1}), ● BDF(OK-DTM-TWI^{-1}).

3.6. Soil Moisture Maps Obtained with Bayesian Data Fusion Combination (OK-DTM-TWI^{-1})

The soil moisture maps of all layers and all sampling dates are obtained by using the BDF for (OK-DTM-TWI^{-1}) combinations. Figures 19–22 show the AP layer maps of all sampling dates.

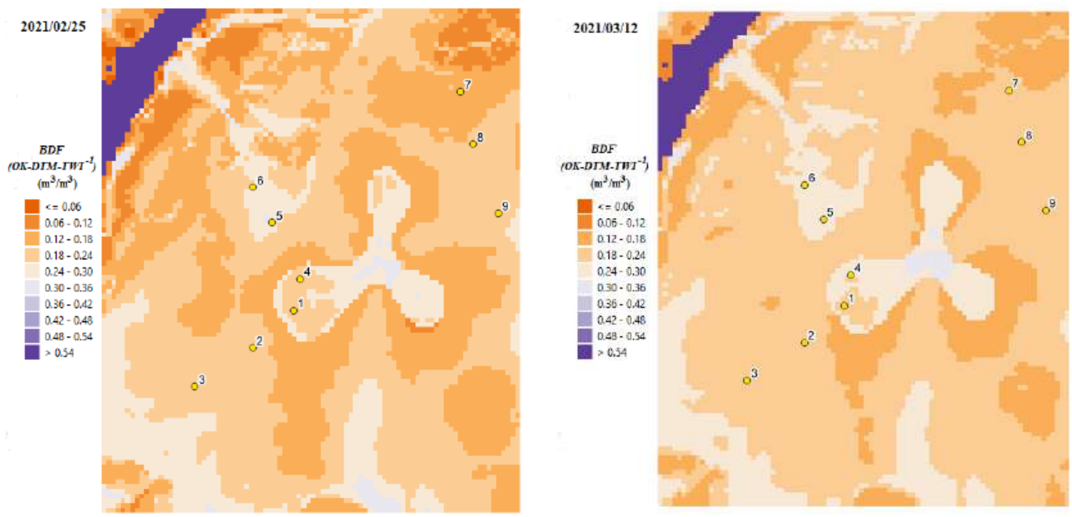


Figure 19. Maps of soil moisture on the AP layer estimated by Bayesian Data Fusion method BDF(OK-DTM-TWI^{-1}). Soil moisture sampling date: February 25 and March 12, 2021. The points indicate the soil moisture sampling sites.

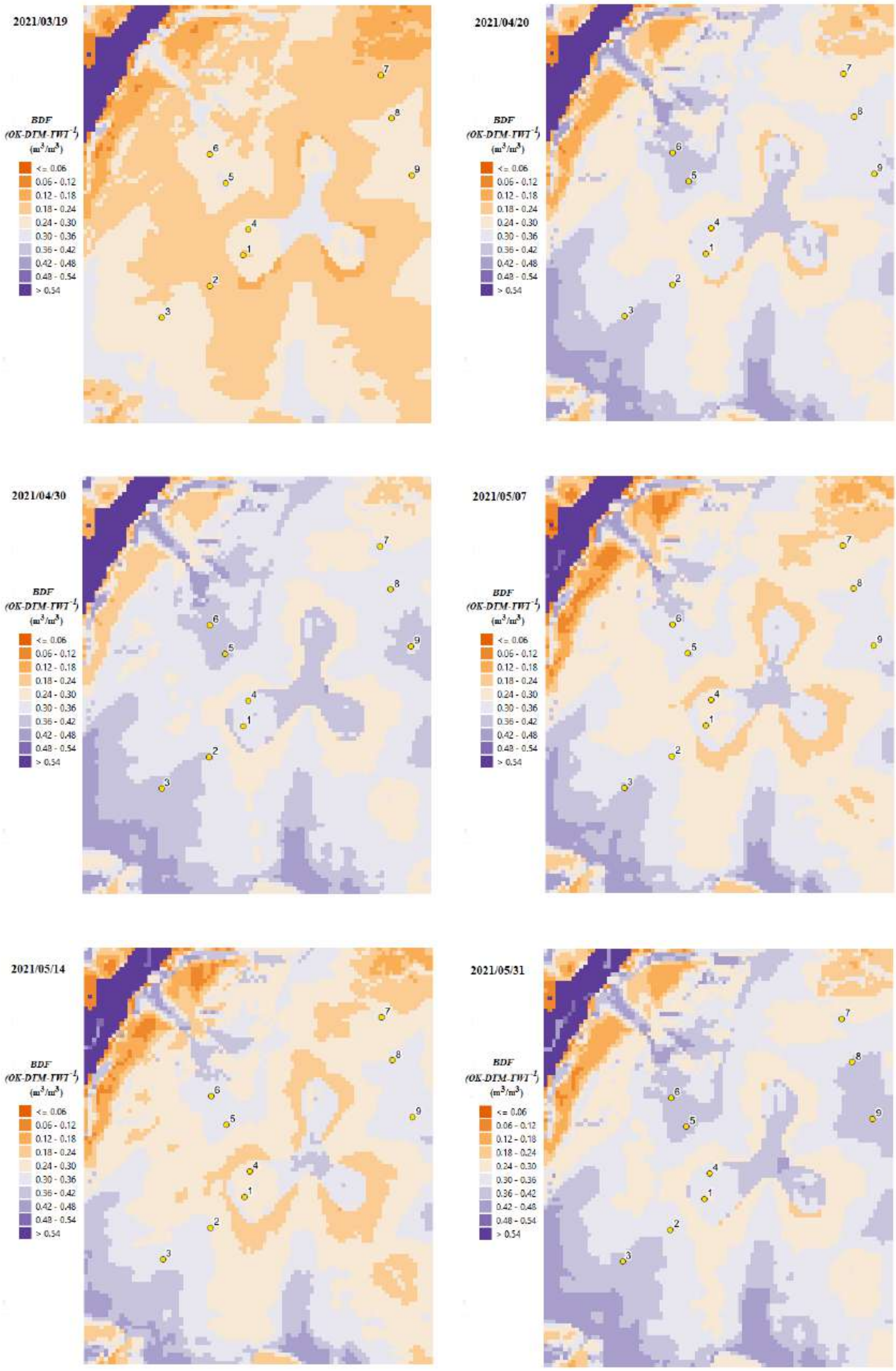


Figure 20. Maps of soil moisture on the AP layer estimated by Bayesian Data Fusion method BDF(OK-DTM-TWI^{-1}). Soil moisture sampling dates: March 19, April 30, May 5, 14, and 31, 2021. The points indicate the soil moisture sampling sites.

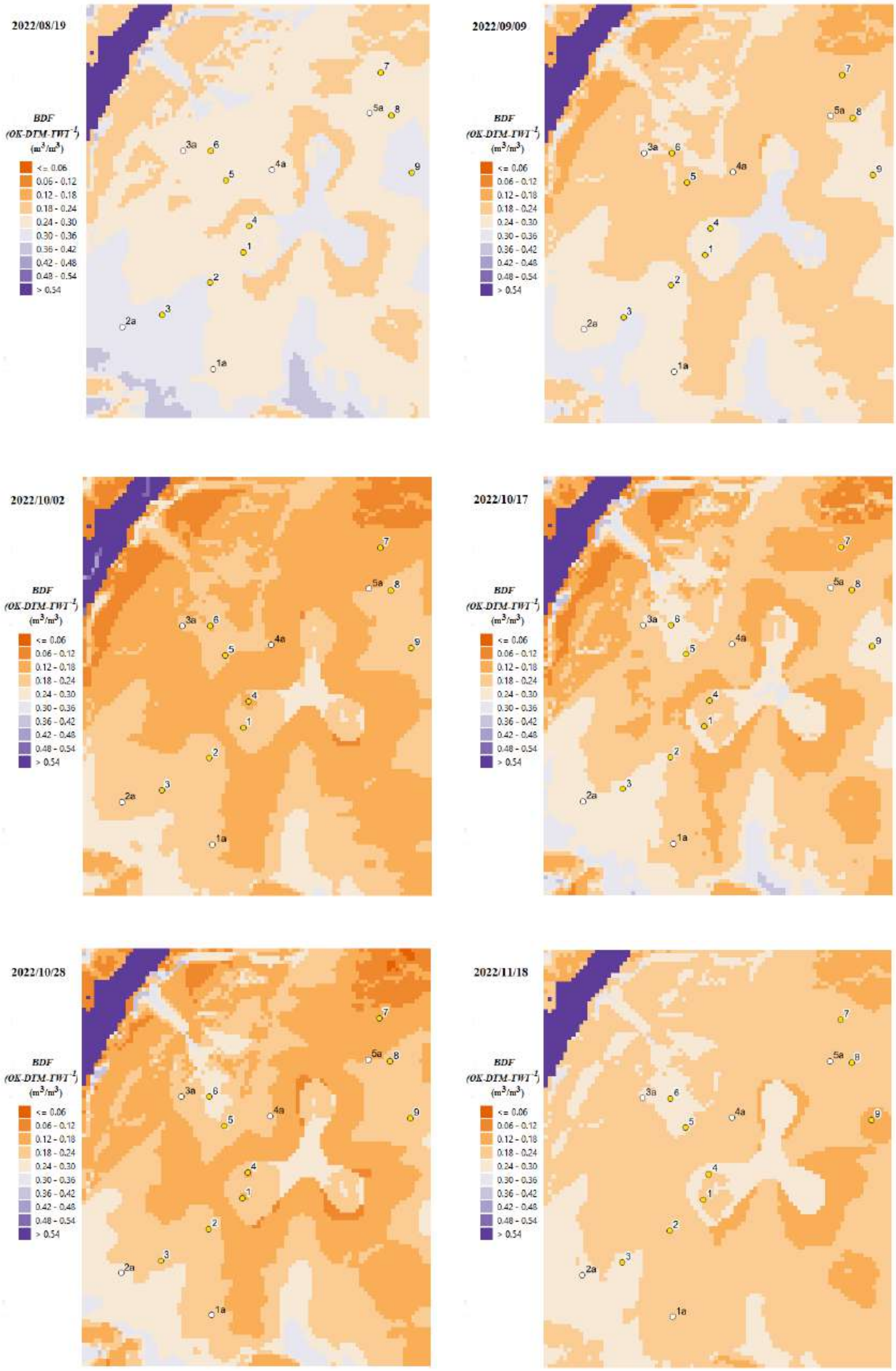


Figure 21. Maps of soil moisture on the AP layer estimated by Bayesian Data Fusion method BDF(OK-DTM-TWI^{-1}). Soil moisture sampling dates: August 19, September 9, October 2, 17, 28, and November 18, 2022. The points indicate the soil moisture sampling sites.

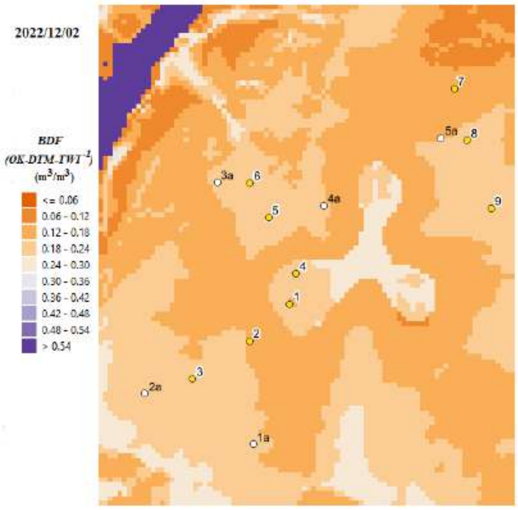


Figure 22. Maps of soil moisture on the AP layer estimated by Bayesian Data Fusion method BDF(OK-DTM-TWI^{-1}). Soil moisture sampling dates: December 2, 2022.

From Figures 16, 17, and 19–22, it can be seen that data fusion substantially improves the results of spatial interpolations of soil moisture when used instead of the OK method alone. By comparing the combinations of the BDF method from the estimation errors, it can be seen that in the months of the second half of 2022, the BDF(KO-TWI^{-1}) has lower relative errors than the others, but during the first half of 2021 the BDF(KO-DTM) combination has the lowest error. In any case, the differences are not very significant. Considering a classification in the performance of the estimation methods proposed by Despotovic et al. (2016), all three combinations are classified as "GOOD" with 10 % > *RRMSE* % < 20 % on average. In addition, the combination of both secondary variables could be considered redundant since the TWI^{-1} index is obtained from the DTM with the addition of a water flow balance on the sub-basins.

4. Conclusions

A methodology that combines different data sources based on Bayesian Data Fusion (BDF) is applied to incorporate topographic information into the spatial interpolation of soil moisture data.

A statistical analysis of 5 topographic indices derived from a digital terrain model (DTM) was performed to evaluate the capacity to explain the spatial variability of soil moisture.

The topographic wetness index (TWI) and the DTM presented better results according to a statistical correlation analysis.

In this paper, it was observed that both topographic indices reflect well the spatial variability of soil moisture when combined with spatial interpolations using OK in the BDF framework.

A soil moisture data set independent of spatial interpolation was used to calculate the interpolation errors by the OK method and the alternative applications of the BDF: OK-DTM, OK-TWI$^{-1,}$ and OK-DTM-TWI^{-1}.

The interpolation methodology presented and applied in this paper shows that using different data sources for soil moisture interpolation within the Bayesian data fusion framework, even with limited data, allows obtaining more realistic maps by incorporating topographic information.

The fusion of multiple sources of information provides significant advantages over data from a single source, as the estimation is improved relative to the application of a simple method of spatial interpolation of soil moisture data obtained from soil samples.

The practical innovation lies in the use of topographic indices as secondary variables to obtain improved soil moisture maps and can be used in a Bayesian data fusion framework as a valuable tool to reliably predict the most likely soil moisture. Its theoretical value lies in the application of these indices in the Bayesian data fusion framework, both individually and in combination.

The results obtained will serve as data for setting the initial conditions of multi-layer soil moisture simulation models.

5. Future Works

An extension of the research conducted in this paper will be the use of these topographic indices within the Bayesian fusion framework at other sites with different soil properties and topography characteristics.

Furthermore, the aspect and curvature of the relief as secondary variables will be the subject of research in future work.

The use of other interpolation methods for primary soil moisture data such as Co-Kriging, Universal Kriging, and Radial-Basis Function will be another subject of future works.

The results of this work will be used as input for soil temperature models and estimates of the thermal profile in subsurface layers for the initialization of multi-layer simulation models of soil moisture and temperature.

Supplementary Materials: The following supporting information can be downloaded: All Figures https://drive.google.com/file/all_Figures, Figures.rar.
The collection soil moisture data and analysis can be downloaded at: https://docs.google.com/spreadsheets/Atanor_Data_Soil_Moisture: HS_Atanor_Data_and_analysis.xlsx.

CRediT Author Statement: César Augusto Aguirre: Conceptualization, Methodology, Writing-original draft, Software, and Supervision; **Carlos Germán Sedano:** Visualization, Investigation, and Validation; **Guillermo Antonio Rondán**: Data collection, Data curation, and Investigation; **Macarena Cardozo:** Investigation and Software; **Tatiana Rut:** Investigation and Software.

Data Availability Statement: The Digital Elevation Model can be obtained from Instituto Geográfico Nacional at: https://www.ign.gob.ar/NuestrasActividades/Geodesia/ModeloDigitalElevaciones/Mapa

Funding: This research was funded by Fund for Scientific and Technological Research, Argentine (FONCyT), Argentina and National University of Entre Ríos (FCA-UNER), Argentine.

Conflicts of Interest: The authors declare no conflict of interest.

Acknowledgments: This study was financially supported by PICTO UNER-UADER 011 project of Fund for Scientific and Technological Research, Argentine and PID UNER 2242 project of National University of Entre Ríos, Argentine.

References

Alizamir, M., Moradveisi, K., Othman Ahmed, K., Bahrami, J., Kim, S., & Heddam, S. (2025). An efficient data fusion model based on Bayesian model averaging for robust water quality prediction using deep learning strategies. *Expert Systems with Applications*, *261*, 125499. https://doi.org/10.1016/j.eswa.2024.125499

Allen, R. G., Pereira, L. S., Raes, D., & Smith, M. (1998). *Crop evapotranspiration - Guidelines for computing crop water requirements - FAO Irrigation and drainage paper 56.* Food and Agriculture Organization of the United Nations. https://www.fao.org/4/X0490E/x0490e00.htm

Álvarez-Mozos, J., Casalí, J., & González-Audícana, M. (2005). Teledetección radar como herramienta para la estimación de la humedad superficial del suelo en cuencas agrícolas [Radar remote sensing as a tool for surface soil moisture estimation in agricultural watersheds]. *Revista de Teledetección*, (23), 27–42. https://www.aet.org.es/revistas/revista23/AET23-03.pdf

Beven, K. J., & Kirkby, M. J. (1979). A physically based, variable contributing area model of basin hydrology. *Hydrological Sciences Bulletin*, *24*(1*)*, 43–69. https://doi.org/10.1080/02626667909491834

Bogaert, P., & Fasbender, D. (2007). Bayesian data fusion in a spatial prediction context: A general formulation. *Stochastic Environmental Research and Risk Assessment*, *21*, 695–709. https://doi.org/10.1007/s00477-006-0080-3

Bougeault, P., Noilhan, J., Lacarrère, P., Mascart, P. (1991a). An experiment with an advanced surface parameterization in a Mesobeta-Scale Model. Part I: Implementation. *Monthly Weather Review*, *119*(10), 2358–2373. https://doi.org/10.1175/1520-0493(1991)119<2358:AEWAAS>2.0.CO;2

Bougeault, P., Bret, B., Lacarrère, P., Noilhan, J. (1991b). An experiment with an advanced surface parameterization in a Mesobeta-Scale Model. Part II: The 16 June 1986 Simulation. *Monthly Weather Review*,*119*(10), 2374–2392. https://doi.org/10.1175/1520-0493(1991)119<2374:AEWAAS>2.0.CO;2

Chen, F., & Dudhia, J. (2001a). Coupling an advanced land surface-hydrology model with the Penn State-NCAR MM5 modeling system. Part I: Model implementation and sensitivity. *Monthly Weather Review*, *129*(4), 569–585. https://doi.org/10.1175/1520-0493(2001)129<0569:CAALSH>2.0.CO;2

Chen, F., & Dudhia, J. (2001b). Coupling an advanced land surface-hydrology model with the Penn State-NCAR MM5 modeling system. Part II: Preliminary model validation. *Monthly Weather Review*, *129*(4), 587–604. https://doi.org/10.1175/1520-0493(2001)129<0587:CAALSH>2.0.CO;2

Cressie, N. A. C. (1991). *Statistics for spatial data*. John Wiley and Sons, Inc. https://doi.org/10.1002/9781119115151

Desbarats, A. J., Logan, C. E., Hinton, M. J., & Sharpe, D. R. (2002). On the kriging of water table elevations using collateral information from a digital elevation model. *Journal of Hydrology*, *225*(1–4), 25–38. https://doi.org/10.1016/S0022-1694(01)00504-2

Despotovic, M., Nedic, V., Despotovic, D., & Cvetanovic, S. (2016). Evaluation of empirical models for predicting monthly mean horizontal diffuse solar radiation. *Renewable and Sustainable Energy Reviews*, *56*, 246–260. https://doi.org/10.1016/j.rser.2015.11.058

Fasbender, D., Obsomer, V., Bogaert, P., & Defourny, P. (2009). Updating scarce high resolution images with time series of coarser images: A Bayesian data fusion solution. In N. Milisavljević (Ed.), *Sensor and Data Fusion*. I-Tech Education and Publishing. https://doi.org/10.5772/6581

Fasbender, D., Peeters, L., Bogaert, P., & Dassargues, A. (2008). Bayesian data fusion applied to water table spatial mapping. *Water Resource Research*, *44*(12), W12422. https://doi.org/10.1029/2008WR006921

Feng, F., Hu, X., Hu, L., Hu, F., Li, Y., & Zhang, L. (2009). Propagation mechanisms and diagnosis of parameter inconsistency within Li-Ion battery packs. *Renewable and Sustainable Energy Reviews*, *112*, 102–113. https://doi.org/10.1016/j.rser.2019.05.042

Hirt, C. (2016). Digital Terrain Models. In E. Grafarend (Ed.), *Encyclopedia of Geodesy* (pp. 1–6). Springer Cham.

https://doi.org/10.1007/978-3-319-02370-0_31-1
Instituto Geográfico Nacional. (2017). Modelo Digital de Elevaciones Aerofotogramétrico de Río Paraná (Sector 3.5) [Computer software]. https://www.ign.gob.ar/NuestrasActividades/Geodesia/ModeloDigitalElevaciones/Mapa
Instituto Geográfico Nacional. (2019). Modelo Digital de Elevaciones de la República Argentina versión 2.0 [Computer software]. Dirección de Geodesia.
Isaaks, E. H., & Srivastava, R. M. (1989). *An introduction to Applied Geostatistics*. Oxford University Press.
Journel, A. G. (1989). *Fundamentals of geoestatistics in five lessons*. American Geophysical Union. https://doi.org/10.1029/SC008
Journel, A. G., & Huijbregts, C. (1978). *Mining geostatistics*. Academic Press.
Karumuri, S., McClure, Z. D., Strachan, A., Titus, M., & Bilionis, I. (2023). Hierarchical Bayesian approach to experimental data fusion: Application to strength prediction of high entropy alloys from hardness measurements. *Computational Materials Science*, *217*, 111851. https://doi.org/10.1016/j.commatsci.2022.111851
Liao, K., Lai, X., Liu, Y., & Zhu, Q. (2016). Uncertainty analysis in near-surface soil moisture estimation on two typical land-use hillslopes. *Journal of Soils and Sediments*, *16*, 2059–2071. https://doi.org/10.1007/s11368-016-1405-6
Li, D.-Q., Wang, L., Cao, Z.-J., & Qi, X.-H. (2019). Reliability analysis of unsaturated slope stability considering SWCC model selection and parameter uncertainties. *Engineering Geology*, *260*, 105207. https://doi.org/10.1016/j.enggeo.2019.105207
Li, X., Xu, X., Liu, W., Xu, C., Zhang, R., & Wang, K. (2019). Prediction of profile soil moisture for one land use using measurements at a soil depth of other land uses in a karst depression. *Journal of Soils and Sediments*, *19*, 1479–1489. https://doi.org/10.1007/s11368-018-2138-5
Li, Y., & Vanapalli, S. K. (2021). A novel modeling method for the bimodal soil-water characteristic curve. *Computers and Geotechnics*, *138*, 104318. https://doi.org/10.1016/j.compgeo.2021.104318
Mattivi, P., Franci, F., Lambertini, A., & Bitelli, G. (2019). TWI computation: A comparison of different open source GISs. *Open Geospatial Data, Software and Standards*, *4*, 6. https://doi.org/10.1186/s40965-019-0066-y
Moore, I. D., Grayson, R. B., & Ladson, A. R. (1991). Digital terrain modeling: A review of hydrological, geomorphological, and biological applications. *Hydrological Processes*, *5*(1), 3–30. https://doi.org/10.1002/hyp.3360050103
Noilhan, J., & Planton, S. (1989). A simple parameterization of land surface processes for meteorological models. *Monthly Weather Review*, *117*(3), 536–549. https://doi.org/10.1175/1520-0493(1989)117<0536:ASPOLS>2.0.CO;2
Peeters, L., Fasbender, D., Batelaan, O., & Dassargues, A. (2010). Bayesian data fusion for water table interpolation: Incorporating a hydrogeological conceptual model in kriging. *Water Resources Research*, *46*(8), W08532. https://doi.org/10.1029/2009WR008353
Pleim, J. E., & Guilliam, R. (2009). An indirect data assimilation scheme for deep soil temperature in the Pleim–Xiu land surface model. *Journal of Applied Meteorology and Climatology*, *48*(7), 1362–1376. https://doi.org/10.1175/2009JAMC2053.1
Pleim, J. E., & Xiu, A. (2003). Development of a land surface model. Part II: Data assimilation. *Journal of Applied Meteorology*, *42*(12), 1811–1822. https://doi.org/10.1175/1520-0450(2003)042<1811:DOALSM>2.0.CO;2
Sayago, S., Ovando, G., & Bocco, M. (2017). Landsat images and crop model for evaluating water stress of rainfed soybean. *Remote Sensing of Environment*, *198*, 30–39. https://doi.org/10.1016/j.rse.2017.05.008
Smirnova, T. G., Brown, J. M., & Benjamin, S. G. (1997). Performance of different soil model configurations in simulting ground surface temperature and surface fluxes. *Monthly Weather Review*, *125*(8), 1870–1884. https://doi.org/10.1175/1520-0493(1997)125<1870:PODSMC>2.0.CO;2
Tocho, C. N., Antokoletz, E. D., & Piñón, D. A. (2020). Towards the realization of the International Height Reference Frame (IHRF) in Argentina. *International Association of Geodesy Symposia*, *152*. https://doi.org/10.1007/1345_2020_93
Tóffoli, M. B., Hernández, J. P., Kindeknecht, L. E., Befani, M. R., & Bressan, M. P. (2022). Caracterización edáfica y topográfica para la determinación de ambientes en función del agua disponible [Edaphic and topographic characterization for the determination of environments according to available water.]. *Revista Científica Agropecuaria*, *25*(2), 30–40. https://pcient.uner.edu.ar/index.php/rca/article/view/1535
Wang, L., Cao, Z.-J., Li, D.-Q., Phoon, K.-K., & Au, S.-K. (2018). Determination of site-specific soil-water characteristic curve from a limited number of test data – A Bayesian perspective. *Geoscience Frontiers*, *9*(6), 1665–1677. https://doi.org/10.1016/j.gsf.2017.10.014
Weiss, A. (2001, July). Topographic position and landform analysis [Poster presentation]. ESRI users Conference, San Diego, CA.
Wilson, M. F. J, O'Connell, B., Brown, C., Guinan, J. C., & Grehan, A. J. (2007). Multiscale terrain analysis of multibeam bathymetry data for habitat mapping on the continental slope. *Marine Geodesy*, *30*(1–2), 3–35. https://doi.org/10.1080/01490410701295962
Wishmeier, W. H. & Smith, D. D. (1978). *Predicting rainfall erosion Losses. A guide to conservation planning*. Science and Education Administration, United States Department of Agriculture. https://www.govinfo.gov/content/pkg/GOVPUB-A-PURL-gpo31516/pdf/GOVPUB-A-PURL-gpo31516.pdf
Xiu, A., & Pleim, J. E. (2001). Development of a land surface model. Part I: Application in a mesoscale meteorological model. *Journal of Applied Meteorology and Climatology*, *40*(2), 192–209. https://doi.org/10.1175/1520-0450(2001)040<0192:DOALSM>2.0.CO;2
Zamani, M. G., Reza Nikoo, M., Niknazar, F., Al-Rawas, G., Al-Wardy, M., & Gandomi, A. H. (2023). A multi-model data fusion methodology for reservoir water quality based on machine learning algorithms and bayesian maximum entropy. *Journal of Cleaner Production*, *416*, 137885. https://doi.org/10.1016/j.jclepro.2023.137885
Zhang, Q., Zhang, P., & Li, T. (2025). Information fusion for large-scale multi-source data based on the Dempster-Shafer evidence theory. *Information Fusion*, *115*, 102754. https://doi.org/10.1016/j.inffus.2024.102754
Zhao, T., Yang, Y., Xu, L., & Sun, P. (2025). Bayesian identification of the optimal soil-water characteristic curve (SWCC) model and reliability analysis of unsaturated loess slope from extremely sparse measurements. *Engineering Geology*, *349*, 107975. https://doi.org/10.1016/j.enggeo.2025.107975

Agricultural & Rural Studies

Article

The Impact of Non-Agricultural Management Experience on Eco-Friendly Practices in Chinese Family Farms

Jia Yue [1,2,†], Siyao Chen [1,2,†], Qiang Liu [3,*] and Zhixiong Weng [4,*]

1 School of Business, Xiangtan Institute of Technology, Xiangtan 411100, China; yuejia5211@gmail.com
2 Graduate School, University of Perpetual Help System DALTA, Las Piñas 1740, Philippines; echocsy11@gmail.com
3 Rural Revitalization Academy of Zhejiang Province, Zhejiang A&F University, Hangzhou 311300, China
4 Institute of Circular Economy, Beijing University of Technology, Beijing 100124, China
* Correspondence: niumeng119@zju.edu.cn (L.Q.); wengzx564@163.com (Z.W.)
† These authors contributed equally to this work.

Abstract: Encouraging and supporting family farms to embrace eco-friendly agricultural production methods can have a significant positive impact on sustainable agricultural development. This study analyzes data from 433 family farms across five Chinese provinces (Zhejiang, Anhui, Shandong, Hunan, and Sichuan) in 2022. Using an econometric model, it examines how non-agricultural management experience influences the adoption of specific eco-friendly practices within family farms. The results highlight the significance of non-agricultural management experience for farmers in determining the extent to which organic fertilizers are employed on family-owned farms. The role of farmers' green cognition in mediating this relationship is shown to be partial. Additionally, other variables such as gender, educational level, years of farming experience, scale of land management, demonstration farm status, and agricultural insurance ownership can impact the use of organic fertilizers on family farms. In order to promote the application of organic fertilizers on family farms, it is crucial to support individuals with non-agricultural management experience in managing family farms, continually promote awareness of environmentally friendly practices, and optimize the resource allocation of family farms.

Keywords: family farm; non-agricultural management experience; green cognition; eco-friendly practices

Citation: Yue, J., Chen, S., Liu, Q., & Weng, Z. (2025). The Impact of Non-Agricultural Management Experience on Eco-Friendly Practices in Chinese Family Farms. *Agricultural & Rural Studies*, *3*(2), 18. https://doi.org/10.59978/ar03020010

Received: 14 February 2025
Revised: 11 May 2025
Accepted: 21 May 2025
Published: 13 June 2025

1. Introduction

Rapid global warming and frequent climate events pose severe threats to human health, agriculture, and ecosystems (Furtak & Wolińska, 2023; Mora et al., 2022; Tong et al., 2022). It has become a consensus among countries worldwide that green and low-carbon development is one of the effective means to mitigate climate change (Lee et al., 2022). For example, the UK launched the Low Carbon Transformation Plan in 2009, which is its national strategic plan to address climate change (Geels, 2022). Meanwhile, Denmark is among the few countries that have achieved remarkable results in low-carbon development (Johnstone et al., 2021). However, China, being a large developing country, has relatively high total greenhouse gas emissions and global share. As per the 2021 World Energy Statistical Yearbook, China's total carbon dioxide emissions in 2020 were 9.899 billion tons, accounting for 30.7% of the world's total emissions. Therefore, China's obligations to address climate change and reduce emissions are also increasing (Cheng et al., 2022). Promoting green and low-carbon development is of great significance to reducing carbon dioxide emissions and mitigating global climate warming.

The agricultural sector is a significant contributor to greenhouse gas emissions, but it also has the potential to be a massive carbon sink system (Yang et al., 2022). While agricultural carbon emissions make up 17% of total emissions in China, 7% in the United States, and 11% globally (Huang et al., 2019), it is possible to make a significant difference by adopting green and low-carbon practices in agriculture. Sustainable agricultural practices not only help reduce carbon emissions but also improve the carbon sink capacity of the agricultural system (Cui et al., 2022; de Moraes Sá et al., 2017; Dou, 2018). By adopting these practices, we can store carbon in the soil for an extended period while improving agricultural productivity (Shah & Wu, 2019). The introduction of green agricultural technology and the protection of agricultural ecosystems can enhance the quality and yield of agricultural products while creating more significant economic benefits for farmers. This promotes sustainable agricultural development, which is critical to our planet's well-being (Y. Liu et al., 2020). Additionally, the promotion of organic agriculture is also considered an effective measure to slow down the release of greenhouse gases by increasing the application of organic fertilizers and reducing dependence on chemical fertilizers and pesticides (Durán-Lara et al., 2020).

Family farms play a crucial role in promoting eco-friendly practices and achieving green and low-carbon agricultural development (Ke & Huang, 2023; X. Li et al., 2023; L. Wang et al., 2023). Eco-friendly practices on family farms can help stabilize agricultural ecosystems, resist pests and diseases, and reduce the dependence on chemical pesticides (Yu et al., 2021b). Furthermore, such practices can mitigate the negative impact on the external environment by decreasing soil erosion, improving the water retention capacity of the soil, and reducing the loss of organic carbon (Holka et al., 2022). Eco-friendly practices on family farms also have a positive impact on the global carbon balance. They help reduce greenhouse gas emissions by increasing the organic carbon content of the soil and promoting carbon sequestration in farmland (Yu et al., 2020).

Numerous scholars have conducted extensive research on the implementation of eco-friendly practices on family farms, both theoretically and empirically. Firstly, the inherent characteristics of family farms determine their willingness to adopt eco-friendly practices. Family farmers are generally younger and better educated, possess the traits of "ideal farmers", and tend to be receptive to new technologies and knowledge (H. Li et al., 2023b; Yu et al., 2023). Secondly, policy guidance has a significant impact on the adoption of eco-friendly practices. Policies such as green production subsidies and agricultural product quality control measures have a significant influence on the adoption of eco-friendly practices by family farms (Gao et al., 2020; Yu et al., 2021a). Thirdly, resource endowment is a crucial factor limiting the adoption of eco-friendly practices by family farms. Factors such as the farmer's social network relationship and the farm's land management scale can significantly affect the adoption of eco-friendly practices on family farms (Elahi et al., 2021; Gao et al., 2019; H. Wang et al., 2021).

Researchers have identified several factors that influence the adoption of eco-friendly practices on family farms. Among them, non-agricultural management experience has gained significant attention. Farmers with non-agricultural management experience tend to be more aware of ecological environmental protection and are more willing to use eco-friendly production technologies (C. Li et al., 2022; C. Li et al., 2021). The extent of the effect increases with the richness of the farmer's non-agricultural management experience (Zheng et al., 2022). Additionally, farmers with such experience are more likely to adopt green control technologies (Gao et al., 2019). However, some scholars have found that non-agricultural management experience does not significantly affect the willingness of farmers to improve farmland pollution control (Lu, 2019).

In summary, research suggests that family farms are well-suited to adopt eco-friendly practices and that non-agricultural management experience can further encourage green production on these farms. However, existing studies have primarily focused on the overall environmentally friendly behavior of family farms, with non-agricultural management experience only being evaluated as a control variable. As a result, the direct impact of non-agricultural management experience on specific eco-friendly practices has been largely overlooked. With the Chinese government's support for farmers returning to rural areas to start businesses, the impact of their previous work experience on environmentally friendly production practices has become increasingly important after their return to the countryside. Clarifying this impact is important, as it has significant implications for the type of farmers that are cultivated and for the continuous promotion of low-carbon agricultural development.

Compared to previous work, the academic contribution of our research is mainly reflected in three aspects as follows:

(1) This study aims to investigate how farmers make decisions regarding the use of organic fertilizers on their family farms, and how they can be encouraged to intensify its application. By promoting the use of organic fertilizers, we can help reduce disparities in environmentally friendly behavior among farmers. This will enable a better understanding of how to increase the use of organic fertilizers on family farms and address the issue of excessive use of chemical fertilizers in China. Essentially, this study aims to uncover the reasons behind the low intensity of organic fertilizer application and high reliance on chemical fertilizers in China.

(2) The use of organic fertilizers on family farms is closely linked to farmers' awareness of environmental issues, known as "green cognition". To investigate whether this awareness affects their non-agricultural management practices, it was included in the model to determine the mediating effect that non-agricultural experience has on the use of organic fertilizers.

(3) This study addresses the issue of selection bias caused by farmers' "self-selection". Using the Probit model, a propensity score matching (PSM) model is established to measure the effect of farmers' non-agricultural management experience on the use of organic fertilizers in family farms. Compared to other methods, this approach addresses selection bias caused by farmers'

self-selection and more accurately measures the impact of farmers' non-agricultural management experience on the use of organic fertilizers on family farms.

The paper is structured as follows: Section 2 contains a review of the literature, Section 3 introduces the materials and methods, Section 4 presents the results, Section 5 discusses the main findings, and Section 6 concludes and provides policy implications.

2. Literature Review and Theoretical Framework

Several research studies have explored the topic of environmentally friendly behavior on family farms and have produced valuable findings. These studies analyze eco-friendly practices, identify the factors of influence these behaviors, and assess the potential impact of non-agricultural management experiences. Together, they provide a broad perspective for a more comprehensive understanding of eco-friendly practices on family farms.

2.1. Definition of Environmentally Friendly Behavior on Family Farms

To ensure the sustainable development of agriculture, it is important to promote environmentally friendly agricultural production models. Scholars have suggested paying attention to protecting land and water resources and promoting organic agriculture (Bhatt & John, 2023; X. Li et al., 2021; Miao et al., 2023). Some studies have focused on improving the utilization efficiency of agricultural systems to reduce their adverse impact on the environment by emphasizing energy and resource use efficiency (S. Sarkar et al., 2020; Song et al., 2021). Another definition highlights ecosystem protection, emphasizing the harmonious symbiosis between family farms and the natural environment (Zheng & Zhuang, 2021).

The use of information and advisory centers, innovative technologies, and digital agriculture is also emphasized to highlight the benefits of scientific and technological advancements in improving agricultural production efficiency while reducing environmental impact. This includes practices such as soil testing and formulated fertilization technology, organic fertilizer substitution technology, and green pest and disease prevention and control technology (Rana et al., 2024; Benyam et al., 2021; Liu & Liu, 2024; Northrup et al., 2021). These definitions provide a comprehensive and diverse understanding of eco-friendly practices on family farms, enriching our knowledge of sustainable agriculture.

2.2. Factors Influencing Environmentally Friendly Behavior on Family Farms

The environmentally friendly behavior of family farms is influenced by various factors, which have been extensively studied from different perspectives. Firstly, the educational level of farmers has been found to be significantly associated with eco-friendly practices. Previous research has indicated that farmers with higher levels of education are more likely to adopt sustainable agricultural practices (Slijper et al., 2023). Secondly, the size of family farmland operations also affects environmentally friendly behavior. Studies have shown that large-scale family farms are more likely to adopt ecologically friendly farming practices than small-scale family farms (Ren et al., 2019).

It has also been found that there is a close link between the financial status of farmers and their eco-friendly practices. Research has shown that relatively wealthy farmers are more capable of investing in resource-efficient technologies that help reduce negative environmental impacts (Yuan et al., 2021). In addition, sociocultural factors are considered significant in influencing eco-friendly practices (Adnan et al., 2019). Furthermore, studies have revealed that the degree of adoption of innovative technologies and digital agriculture also plays a role in environmentally friendly behavior (Northrup et al., 2021; Shang et al., 2021). These studies provide valuable insights into the various and interrelated factors that affect eco-friendly practices on family farms.

2.3. Impact of Non-agricultural Management Experience on Eco-friendly Practices in Family Farms

According to some scholars, farmers who have gained work experience in non-agricultural fields may have established a wider social network and acquired more information and resources. This can help them better understand and respond to environmental challenges (Yeleliere et al., 2023). By gaining management experience outside of agriculture, farmers are more likely to introduce advanced management concepts and technologies. This can lead to an increased adoption of environmentally friendly agricultural practices (Sun et al., 2022). However, it's important to note that the impact of non-agricultural management experience on eco-friendly practices may vary depending on regional differences and cultural factors (Zhong et al., 2021). Additionally, non-agricultural management experience can help improve farmers' environmental awareness, making them more inclined to adopt eco-friendly practices (Lei et al., 2023).

In summary, previous research has shed light on environmentally friendly practices on family farms, and some studies have discussed the factors that influence such practices. The potential impact of non-agricultural management experience and green cognition on eco-friendly practices has also been mentioned. However, few studies have utilized micro-survey data on family farms to explore a specific environmentally friendly behavior. Moreover, none of them has integrated non-agricultural management experience and green cognition into a unified analytical framework to fully assess the impact of specific environmental factors on family farms. This makes it difficult to determine the magnitude of the impact and the action path of eco-friendly behavior.

2.4. Theoretical Framework and Research Hypotheses

Based on the above literature review and analysis, farmers' non-agricultural management experience may influence environmentally friendly practices on family farms through multiple mechanisms. Figure 1 presents the theoretical analysis framework. First, such experience may leave an "Imprinting effect" on farmers, meaning that the behavioral habits, values, and management concepts formed in non-agricultural industries exert a lasting influence on their agricultural management practices. Second, non-agricultural management experience is often associated with higher economic returns, contributing to an "income enhancement effect" that strengthens farmers' financial capacity to adopt green agricultural practices. Moreover, the experience gained in external markets or corporate settings can improve farmers' awareness of risk prevention and their management capabilities, thereby increasing their sensitivity to environmental risks and resource constraints, and encouraging a more proactive adoption of eco-friendly practices.

At the same time, non-agricultural management experience can also enhance farmers' green cognition. With improved cognition, farmers are more likely to actively adopt green production technologies, reduce their reliance on chemical fertilizers and pesticides, and facilitate the green transformation of family farms. Therefore, green cognition may serve as a mediating factor between non-agricultural management experience and the adoption of environmentally friendly practices.

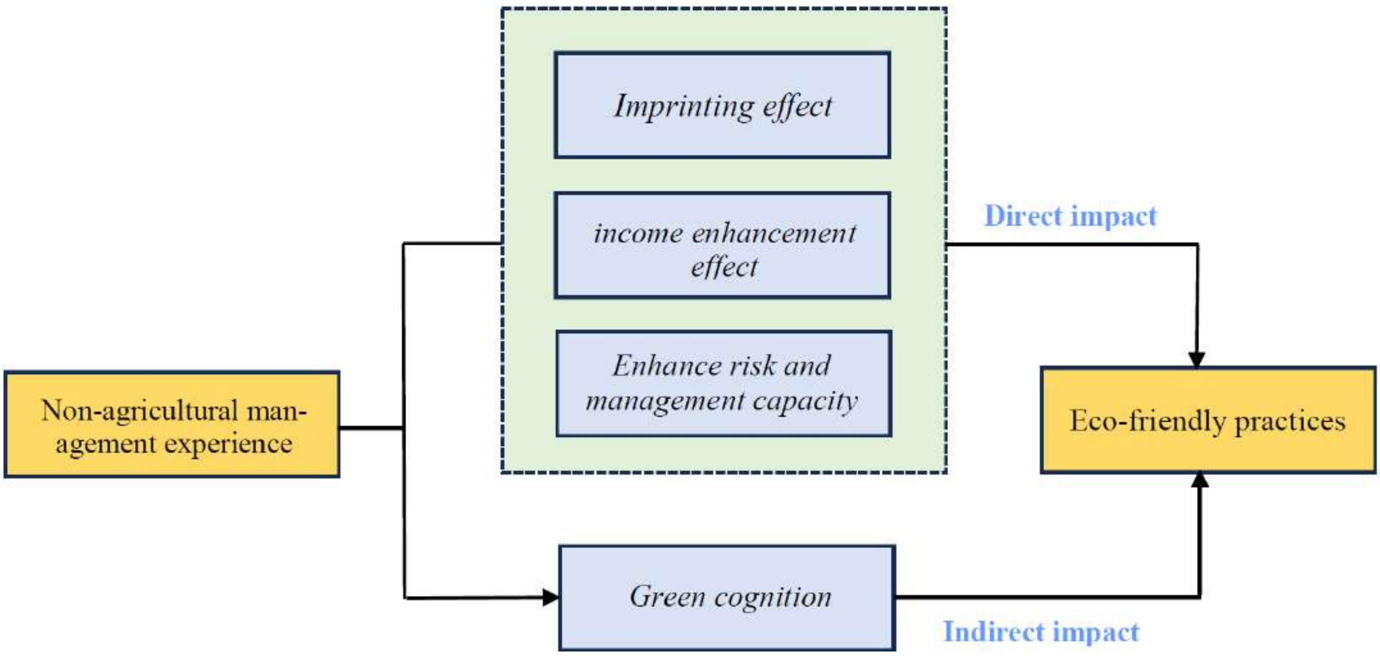


Figure 1. Theoretical framework.

Building on the above analysis, this study proposes the following hypotheses:

- H1: Non-agricultural management experience positively influences environmentally friendly practices on family farms.
- H2: Non-agricultural management experience enhances farmers' green cognition, thereby promoting environmentally friendly practices on family farms.

3. Material and Methods

3.1. Research Sample

Our study is based on a survey conducted by our team in Zhejiang, Anhui, Shandong, Hunan, and Sichuan provinces from July to October 2022. These five provinces were selected because they are geographically located in the eastern, central, and western regions of China, thereby capturing the diversity of agricultural conditions across the country. They differ significantly in terms of agricultural development levels, cropping systems, and the implementation of green agriculture-related policies. This regional diversity helps ensure the representativeness and generalizability of the research findings. We started by selecting representative family farms in prefecture-level cities, counties, and towns in each province using a random sampling method. The selected farmers were then invited to participate in training organized by the local agricultural management department. After the training, they filled in an online questionnaire that covered various aspects, including individual characteristics of the farmers (such as gender, age, education level, years of agricultural production, etc.), farm characteristics (such as farm type, operating income, operating scale, number of own labor force, etc.), environmental characteristics (such as loan difficulty, local government support for agricultural development, etc.), and awareness of green production. In the questionnaire, non-agricultural management experience is measured by whether the family farm operator has previously engaged in non-agricultural managerial work. Environmentally friendly practices are primarily assessed through the use of organic fertilizers, including whether organic fertilizers are applied and the intensity of their application. Organic fertilizer was chosen as the main indicator because it is a widely recognized and representative practice in green agriculture. Compared with other environmentally friendly measures, the use of organic fertilizer more directly reflects farmers' willingness to reduce chemical inputs and promote green and sustainable agricultural development.

This study focuses on the planting of family farms. After processing the survey data, we obtained a total of 433 samples of planting family farms. These farms are distributed as follows: 96 households in Zhejiang Province, accounting for 22.17%; 42 households in Anhui Province, accounting for 9.70%; 144 households in Shandong Province, accounting for 33.26%; 37 households in Hunan Province, accounting for 8.55%; and 114 households in Sichuan Province, accounting for 26.33%. The sample distribution is shown in Figure 2.

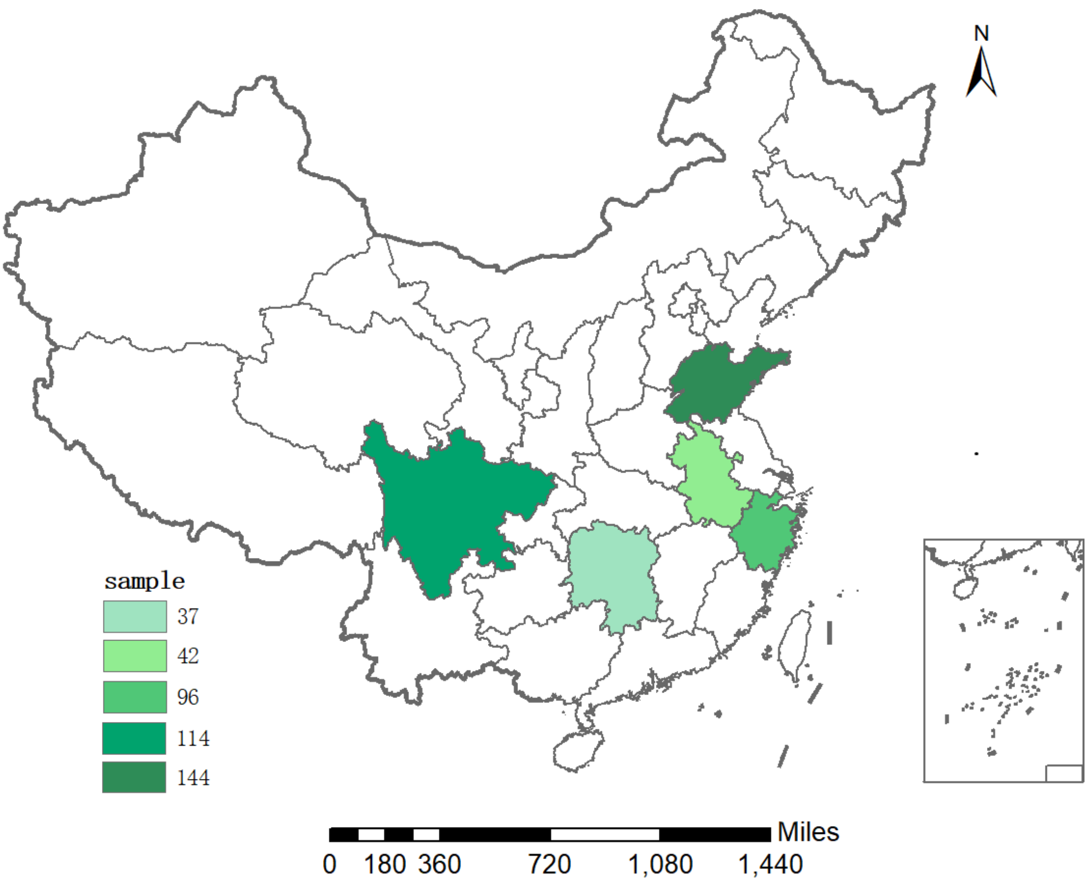


Figure 2. Research sample distribution in China.

3.2. Sample Description

Out of the 433 farms in the sample, 92.53% of the farmers are male, while only 7.47% are female. The proportion of farmers aged 35 or below is 12.47%, and the proportion of those aged over 55 is 14.07%. The majority of farmers, about 73.44%, fall between the ages of 36 to 55, indicating that most of them are in the prime of their lives. The proportion of farmers with a primary school education or below is only 2.08%, with 62.35% having completed junior high. Farmers with a college degree or above make up 35.57% of the total, highlighting that the educational level of family farm operators is generally not very high. More than half of the farmers have been engaged in agriculture for over 10 years. In addition, 51.04% of the farmers are members of the Communist Party. The proportion of farmers who have received technical training five times or fewer is 60.97%.

Most family farms have a land operation scale of between 3.33 and 33.33 hm^2, and the proportion of family farms with fewer than six employees is as high as 95.84%. In total, 66.05% of family farms are demonstration farms. The income level of most family farms falls between 60,000 and 500,000 CNY, accounting for 68.36% of the total. Most family farms have complete records of income and expenditure, as well as storage facilities. Additionally, 70.44% of the family farms have purchased agricultural insurance, highlighting that family farm operators have a strong awareness of risk prevention. 83.83% of family farms are located within 6 to 50 kilometers from the county seat, where the local government is relatively supportive of agricultural development. Only 22.86% of family farms believe that it is relatively difficult to obtain loans.

According to the study, the 433 family farms were divided into two groups based on the basis of whether the farmers had non-agricultural management experience. Figure 3 shows that out of the 185 family farms run by farmers without any non-agricultural management experience, 141 use organic fertilizers, which accounts for 76.22% of the total. On the other hand, out of 248 family farms run by farmers with non-agricultural management experience, 225 use organic fertilizer, which accounts for 90.73% of the total. The average organic fertilizer application rate of family farms run by farmers with non-agricultural management experience is 60.93%, which is higher than the average organic fertilizer application rate of family farms run by farmers without non-agricultural management experience. The latter has an average organic fertilizer application rate of 47.67%. This suggests that farmers with non-agricultural management experience are more inclined to apply organic fertilizers, and the intensity of organic fertilizer application is also higher.

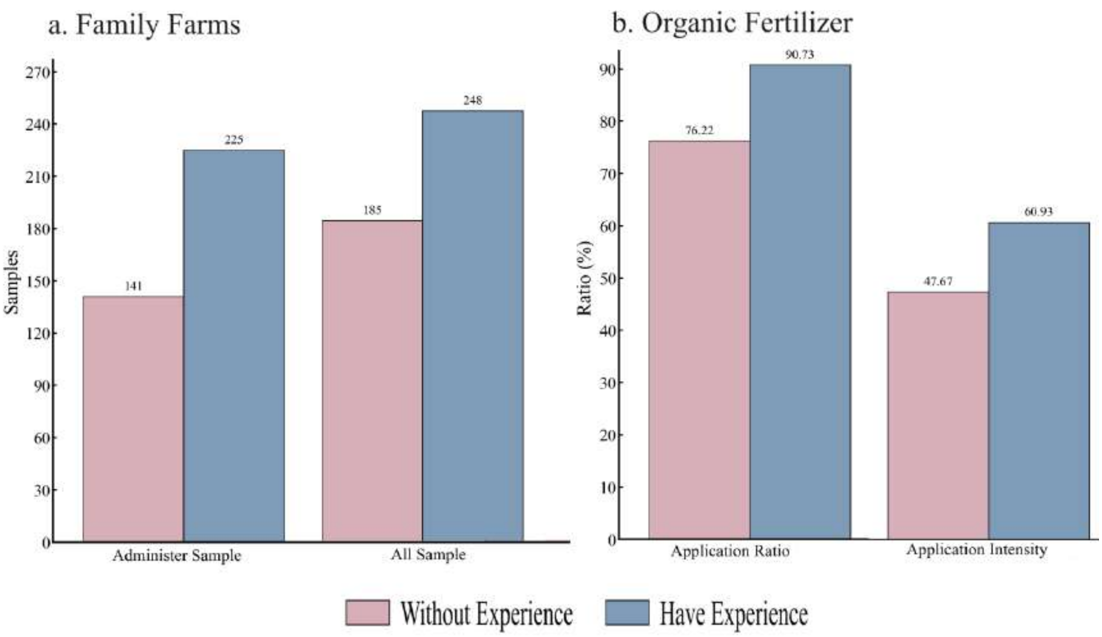


Figure 3. Non-agricultural management experience and organic fertilizer application behavior.

3.3. Model Specification

3.3.1. Baseline Model

This study employs Probit and OLS regression models to analyze the application of organic fertilizer on family farms. The Probit model is appropriate for analyzing binary outcomes, such as whether organic fertilizer is used, while the OLS model is suitable for examining continuous outcomes, such as the intensity of organic fertilizer application. These models were selected primarily to effectively capture both the adoption decision and the level of organic fertilizer use. The model specifications are as follows:

$$Y_i = Ln\frac{P_i}{(1-P_i)} = \beta_{0i} + \beta_{1i}X_1 + \beta_{2i}X_2 + ... + \beta_{ni}X_n + \lambda_{1i} + \lambda_{2i}Landform + \varepsilon_i \quad (1)$$

$$Z_i = \beta_{0i} + \beta_{1i}X_1 + \beta_{2i}X_2 + ... + \beta_{ni}X_n + \lambda_{1i}Dis + \lambda_{2i}Landform + \varepsilon_i \quad (2)$$

Y_i represents whether family farm *i* uses organic fertilizer (OF). If it is true, the value will be 1, otherwise it will be 0. *P* represents the probability of family farm applying organic fertilizer; Z_i represents the intensity of organic fertilizer application (OFA) in family farm *i*; X_1 checks whether farmers have non-agricultural managemental experience. $X_2 \sim X_n$ is a series of control variables that may affect the utilization of organic fertilizers in family farms; β_1 is the estimated coefficient of X_1 and $\beta_2 \sim \beta_n$ are the estimated coefficients of $X_2 \sim X_n$, respectively. *Dis* controls for location characteristics of family farm, while *Landform* are the family farm terrain variables. ε_i is the random disturbance term.

3.3.2. Propensity Score Matching (PSM) Model

It is worth noting that a farmer's decision to engage in non-agricultural management experience work is not arbitrary, but rather a deliberate choice based on their own needs and available resources. This creates a "selection bias" which can affect the results when estimating the impact of non-agricultural management experience on family farm organic fertilizer application behavior. To overcome this issue, this study proposes the use of propensity score matching, which involves building a "counterfactual inference model" to address the self-selection problem. This approach can lead to more accurate model estimation results. The model specification is set as follows:

$$P(T_i) = P_r(D_i = 1 | T_i) = \frac{\exp(\beta T_i)}{1 + \exp(\beta T_i)} \quad (3)$$

$P_r(D_i = 1 | T_i)$ is the propensity matching score value of the farmer's non-agricultural management experience; T_i is the matching variable, including farmer characteristics, farm characteristics, and environmental characteristics; β is the coefficient of the corresponding matching variable.

After analyzing the matching results, we can calculate the average effect of non-agricultural management experience on the application of organic fertilizers in family farms. The calculation formula is as follows:

$$ATT = E(y_{1i} | T_i = 1) - E(y_{0i} | T_i = 1) = E(y_{1i} - y_{0i} | T_i = 1) \quad (4)$$

Here, y_{1i} represents the application of organic fertilizer in the treatment group. y_{0i} indicates the application of organic fertilizer in the control group, and T_i represents the treatment variable.

3.3.3. Mediating Effect Model

In order to better understand the impact of non-agricultural management experience on the use of organic fertilizers in family farms, a mediation effect model was employed to analyze the mechanism behind it. The model's formula is as follows:

$$M = \beta_0 + aX_1 + \beta_1 X + \varepsilon_i \quad (5)$$

$$Y_1 = \beta_0 + c'X_1 + bM + \beta_2 X + \varepsilon_i \quad (6)$$

$$Y_2 = \beta_0 + c'X_1 + bM + \beta_3 X + \varepsilon_i \quad (7)$$

In the above formula, *M* is the intermediary variable that represents the farmer's green cognition. Y_1 indicates the utilization of organic fertilizer by family farms, and Y_2 shows the intensity of using organic fertilizer by family farms. X_1 checks whether farmers have non-agricultural management experience. Additionally, *X* is a series of control variables, including farmer characteristics, family farm characteristics, and environmental characteristics. Therefore, *a* represents the impact of farmers' non-agricultural management experience on their green cognition; *b* indicates the impact of farmer's green cognition on the utilization of organic fertilizer in the family farm. It is noted that c' shows the impact of the farmer's non-agricultural management experience on the behavior of utilizing organic fertilizer in the family farms. ε_i is the random disturbance term. As a result, we proceeded the mediating effect model with the following steps:

Firstly, we tested whether β_1 in the benchmark model, as shown in formulas (1) and (2), passes the significance test. If the significance test passes, a stepwise regression model will be used to test the mediation effect (as shown in formulas (5), (6), and (7)).

Secondly, we conducted a significance test to obtain the coefficients *a* and *b* by using the mediation effect model.

Thirdly, we tested the significance of coefficient c' if both coefficients *a* and *b* are significant. As a result, if c' is not significant, implying that there is a complete mediation effect; otherwise, there is a partial mediation effect.

3.3.4. Summary Statistics

This study focuses on the farmer's non-agricultural management experience (NAME) as the main explanatory variable, which refers to their past work experience in non-agricultural management. We also consider green cognition (GC) as a mediating variable that measures the farmer's willingness to adopt eco-friendly practices. The farmer's level of agreement with the statement "I believe that organic fertilizer should be used instead of chemical fertilizer" is evaluated on a scale of 1 to 5, with higher values indicating stronger green cognition.

Farmer characteristic variables are the personal traits of family farmers that can shape their attitudes and values toward environmental issues. This, in turn, can affect their adoption of eco-friendly practices (Adnan et al., 2020; A. Sarkar et al., 2022; Yu et al., 2023; Diallo & Abay, 2024). To get a better understanding of the individual characteristics of farmers, we have selected the following variables based on existing literature and data: (1) Gender (GEN); (2) Actual age (AGE); (3) Education level (EDU); (4) Agricultural tenure (APY), reflecting the number of years engaged in farming activities; (5) Membership in the Communist Party of China (CPC) is considered due to its potential influence on policy adherence and ideological alignment; (6) The frequency of agricultural technology training received within the past three years (ATTF).

Farm characteristic variables refer to basic attributes associated with family farms, which indicate the farm's resource status, economic capabilities, and management level. These variables significantly impact the farm's acceptance and implementation of environmental protection measures (Z. Chen et al., 2022; Hu et al., 2023; Zhou & Ding, 2022). In light of this, we considered the following variables relevant to farm characteristics (Table 1):

(1) Land operation scale (LAND), which denotes the extent of land under the farm's operation;
(2) Labor force (LABOR), represented by the number of year-round engaged laborers;
(3) Demonstration farm status (DF), designated by the government post-competitive selection, showcasing exemplary practices;
(4) Income level (INCOME), which reflects the farm's annual revenue;
(5) Expenditure records (ER), which document financial transactions;
(6) Availability of storage facilities (FAC), signifying essential infrastructure for preserving crop quality and ensuring food security.

Together, these variables describe the fundamental characteristics of family farms and profoundly influence their sustainability in the agricultural sector.

Environmental characteristic variables refer to the crucial factors that are associated with the farm's external influences and environmental context. These variables play a significant role in assessing the institutional support systems and external environmental conditions that may either facilitate or hinder the adoption of pro-environmental behaviors on family farms (Gholamrezai et al., 2021; Xie & Huang, 2021). The following are four factors that can impact a farm's environmental sustainability and risk management strategies:

(1) Agricultural insurance purchase (INS) – This factor reflects the farm's risk management strategies and resilience to potential environmental hazards or economic uncertainties.
(2) Distance from farm to county seat (DIST) – This indicates the farm's geographical proximity to administrative centers, which can influence access to markets, services, and policy support relevant to environmental sustainability.
(3) Loan accessibility difficulty (LOAN) – This factor reflects the financial constraints and challenges a farm may face in securing loans, which can impact investment in eco-friendly practices and infrastructure.
(4) Support for Local Agricultural Development (SUP) – This represents the level of government or community support for local agricultural development initiatives, which can impact the availability of resources, incentives, and technical assistance to implement environmentally sustainable practices.

Table 1. Descriptive statistic.

Variables	Obs.	Mean	Std. Dev.	Min	Max	Unit
NAME	433	0.57	0.50	0	1	-
GC	433	4.49	0.67	1	5	-
GEN	433	0.79	0.41	0	1	-
AGE	433	46.61	8.67	23	70	years
EDU	433	3.07	0.83	1	4	-
APY	433	15.57	10.16	1	55	years
CPC	433	0.36	0.48	0	1	-
ATTF	433	6.23	5.77	0	36	freq
LAND	433	21.22	26.87	0.33	142.93	hm^2
LABOR	433	3.50	1.74	1	11	person
DF	433	0.66	0.47	0	1	-
INCOME	433	34.99	47.74	0	368	10,000 CNY
ER	433	0.78	0.41	0	1	-
FAC	433	0.58	0.49	0	1	-
INS	433	0.70	0.46	0	1	-
DIST	433	22.66	15.98	1	90	km
LOAN	433	2.08	0.73	1	3	-
SUP	433	4.24	0.82	1	5	-

4. Results

4.1. Baseline Model Results

Table 2 shows the results of a regression analysis that examines the influence of non-agricultural management experience on the adoption of eco-friendly practices in family farms. The analysis reveals that non-agricultural management experience has a significant positive impact on the application of organic fertilizers. Farms with such experience are more willing to use organic fertilizers and apply them more intensively than those without. In terms of the impact of control variables on organic fertilizer usage in family farms, the study found that farmer characteristic variables have notable associations. GEN, representing gender, has a positive effect on organic fertilizer usage in family farms, but only at the 10% level. It does not significantly affect usage intensity. This suggests that male farmers are more inclined to use organic fertilizers, potentially due to their greater knowledge and willingness. However, gender does not seem to influence the intensity of application, which may vary due to individual personality traits.

Table 2. Baseline regression results.

Independent variables	*Probit* (1)	*OLS* (2)
	OF	*OFA*
NAME	0.624***	0.114***
	(0.176)	(0.036)
GEN	0.330*	0.005
	(0.194)	(0.042)
AGE	0.031	0.000
	(0.077)	(0.016)
*AGE*AGE*	−0.000	0.000
	(0.001)	(0.000)
EDU	0.259**	0.095***
	(0.109)	(0.024)
APY	0.028***	0.004*
	(0.010)	(0.002)
CPC	−0.021	−0.058
	(0.187)	(0.038)
ATTF	0.007	0.003
	(0.014)	(0.003)
LAND	0.000	−0.001*
	(0.004)	(0.001)
LABOR	0.016	−0.004
	(0.047)	(0.010)
DF	0.454**	0.110***
	(0.192)	(0.041)
INCOME	0.024	−0.002
	(0.078)	(0.016)
ER	−0.215	0.039
	(0.217)	(0.047)
FAC	0.048	0.016
	(0.179)	(0.037)
INS	−0.045	−0.089**
	(0.192)	(0.040)
DIST	0.008	−0.000
	(0.006)	(0.001)
LOAN	0.089	−0.029
	(0.119)	(0.025)
SUP	−0.079	0.013
	(0.108)	(0.022)
R^2	0.1573	0.1526
Observations	433	

Note: Standard errors are in parentheses; *, **, and *** represent significance at the 10%, 5%, and 1% statistical levels, respectively.

EDU, which indicates education level, significantly influences both usage likelihood and intensity, with higher education levels correlating with a greater inclination toward and intensity of organic fertilizer application. This may be attributed to more educated farmers having a clearer understanding of the benefits of organic fertilizers (Adator et al., 2023; Y. Chen et al., 2022). Additionally, APY, which indicates the length of time farmers have been engaged in agriculture, positively impacts both usage likelihood and intensity, being significant at the 1% and 10% levels, respectively. Longer engagement in agriculture correlates with a higher likelihood and intensity of organic fertilizer application, possibly due to accumulated experience enabling better market judgment and increased environmental awareness among farmers.

According to the analysis of farm characteristics, the size of the land does not have a statistically significant impact on whether family farms use organic fertilizers. However, it does have a negative effect on the intensity of usage, significant at a 10% level. This suggests that while the decision to use organic fertilizer is independent of the scale of land operations, larger farms tend to use it less intensively. This could be due to the farmers' preference for chemical fertilizers, which help maximize profits as the land area increases (Y. Chen et al., 2022; Li & Shen, 2021). On the other hand, the demonstration effect significantly impacts both the likelihood and intensity of usage, being significant at the 5% and 1% levels, respectively. This shows that compared to non-demonstration family farms, demonstration farms are more inclined to apply organic fertilizers, with higher application intensity. This may be because the demonstration farms exhibit better management and oversight, which leads to improved production behaviors.

When it comes to environmental factors, it appears that INS (Agricultural insurance purchase) does not have a significant impact on the adoption of organic fertilizers in family farms. However, it does appear to influence the intensity of usage, as evidenced by statistical significance at the 5% level. This implies that although agricultural insurance may not significantly affect the likelihood of organic fertilizer adoption, farms with insurance tend to use organic fertilizers less intensively than those without. This may be due to moral hazard, which can occur when individuals take more risks or behave less responsibly after purchasing insurance. Such behavior could potentially hinder long-term land investment and reduce the application of organic fertilizers.

4.2. Robustness Check

To enhance the reliability of the correlation between non-agricultural management experience and organic fertilizer application on family farms, this study employs a model substitution technique to test the robustness of the model's findings. As organic fertilizer application is a binary variable and its intensity ranges from zero to positive, both Logit and Tobit models are appropriate. The results in Table 3 indicate that non-agricultural management experience significantly impacts whether family farms use organic fertilizers, with a positive coefficient significant at the 1% level. Additionally, non-agricultural management experience also has a significant impact on the intensity of organic fertilizer application, again with a positive coefficient at the 1% significance level. These results are consistent with the main findings, indicating that the empirical analysis is reasonably robust.

Table 3. Robustness test results.

Independent variables	Logit	Tobit
	OF	OFA
NAME	1.155***	0.146***
	(0.322)	(0.042)
Farmer characteristic	Control	Control
Farm characteristic	Control	Control
Environmental characteristic	Control	Control
DIS	Control	Control
Landform	Control	Control
R^2	0.1594	0.1279
Observations	433	

Note: Standard errors are in parentheses; *, **, and *** represent significance at the 10%, 5%, and 1% statistical levels, respectively.

4.3. PSM Results

4.3.1. Commonly Support and Balance Tests

After analyzing the data, it has been found that farmers who have prior experience in non-agricultural management are more likely to adopt organic fertilizers in their family farms. However, it is important to note that such experience is usually a result of self-selection. This means that while estimating the impact of non-agricultural management experience on organic fertilizer application in family farms, there is a risk of biased parameter estimation results and reduced reliability. To address this issue, this study employs the propensity score matching (PSM) method to mitigate the self-selection problem and obtain more accurate regression estimation outcomes. The PSM model requires passing two fundamental tests: the common support domain test and the balance test of matching variables.

Figure 4 shows how similar the control group and treatment group are, before and after matching. In Figure 4a, before matching, the two groups differ greatly, as their distribution curves hardly overlap. After matching, shown in Figure 4b, the two curves overlap much more, indicating that the differences between the groups have been reduced. This means the matching worked well and the two groups are now comparable, which meets the basic requirement for analysis.

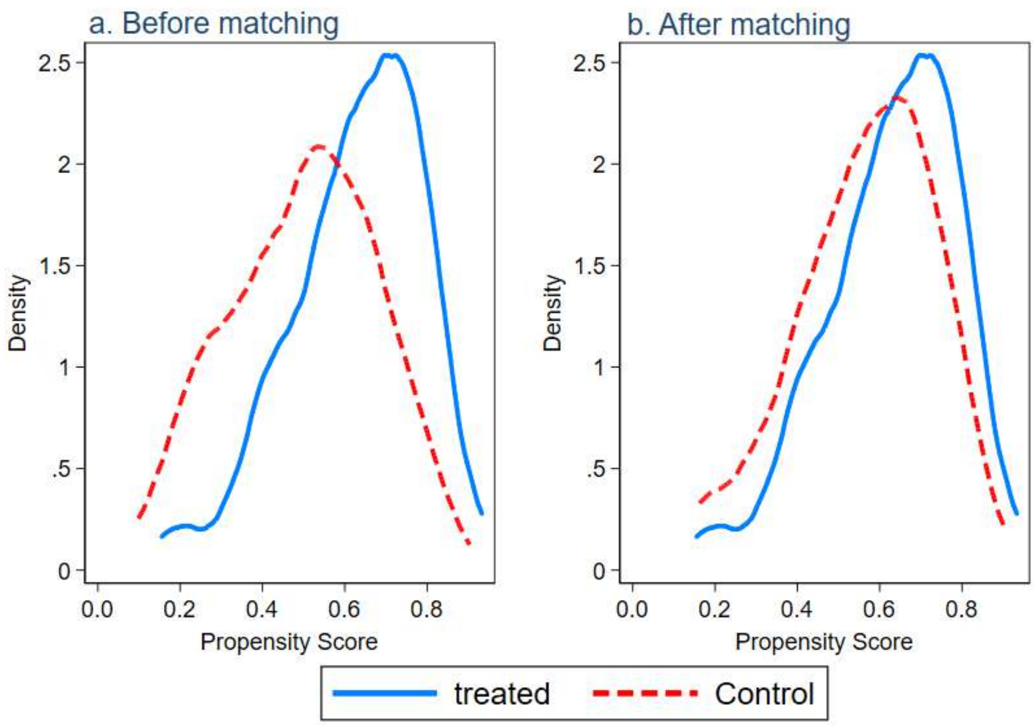


Figure 4. Probability dense distribution before and after matching.

The balance test mainly examines whether there is a significant difference in covariates between the control group and the experimental group. The hypothesis of the balance test was tested under nearest-neighbor matching, and the standard deviation of each covariate was substantially reduced. With the exception of age (5.4%) and loan (35.7%), which showed only slight reductions, the standard deviation of the other covariates decreased significantly. Overall, the reductions were large, and the sample means of the two groups were very close, with no significant differences. Therefore, the balance test was passed.

4.3.2. PSM Estimation

Table 4 presents the average treatment effect of farmers' non-agricultural management experience. As shown in the Table, there are significant differences between family farms managed by farmers without non-agricultural management experience and those managed by farmers with such experience. The average treatment effect values (ATT) for farms managed by farmers with non-agricultural management experience are 0.142 and 0.114, significant at the 5% and 10% levels, respectively. Robustness testing was conducted using nearest neighbor matching, radius matching, and kernel matching within a caliper. The ATT values obtained through these methods are 0.110, 0.119, 0.131 for one outcome, and 0.095, 0.102, 0.110 for the other, respectively. These results are significant at the 5%, 5%, 1%, and 10%, 5%, 1% levels, respectively, and are consistent with the findings from one-to-one nearest-neighbor matching. This indicates that, on the one hand, the estimated treatment effect of non-agricultural management experience remains robust after propensity score matching. On the other hand, non-agricultural management experience has a significant positive impact on the application of organic fertilizers on family farms.

Table 4. PSM results.

matching method	PSM			
	OF treated/control	ATT	*OFA* treated/control	ATT
K=1	181/246	0.142** (0.062)	181/246	0.114* (0.063)
K=4	160/232	0.110** (0.052)	160/232	0.095* (0.052)
R=0.01	160/232	0.119** (0.052)	160/232	0.102** (0.051)
Kernel	181/246	0.131*** (0.048)	181/246	0.110*** (0.043)

Note: Standard errors are in parentheses; *, **, and *** represent significance at the 10%, 5%, and 1% statistical levels, respectively.

4.4. Mediating Effect

The influence of non-agricultural management experience extends beyond its direct influence on the application of organic fertilizers in family farms. It may also have an indirect effect through green cognition, which acts as a mediating factor. Table 5 presents the results of the mediating effect model. Model 5 shows a positive correlation between non-agricultural management experience and farmers' green cognition, indicating that such experience enhances their levels of green cognition. Furthermore, models 6 and 7 demonstrate that when the green cognition variable is introduced, non-agricultural management experience significantly affects both the likelihood of organic fertilizer adoption and the intensity of application in family farms. Similarly, green cognition also significantly influences these behaviors. The mediation effect testing indicates that green cognition partially mediates the relationship between non-agricultural management experience and organic fertilizer application behavior in family farms. This is because past non-agricultural management experience allows farmers to access knowledge related to environmentally friendly practices, thereby enhancing their green cognition. As a result, this improved cognition translates into practical actions, making it easier for family farms to adopt organic fertilizers.

Table 5. Mediating effect results.

Independent variables	Model(5)	Model(6)	Model(7)
	GC	OF	OFA
NAME	0.113*	0.589***	0.099***
	(0.062)	(0.177)	(0.036)
GC		0.306**	0.139***
		(0.139)	(0.028)
Farmer characteristic	Control	Control	Control
Farm characteristic	Control	Control	Control
Environmental characteristic	Control	Control	Control
DIS	Control	Control	Control
Landform	Control	Control	Control
R^2	0.2679	0.1705	0.1992
Observations		433	

Note: Standard errors are in parentheses; *, **, and *** represent significance at the 10%, 5%, and 1% statistical levels, respectively.

5. Discussion

China's agricultural modernization is a crucial part of its overall modernization process. To achieve this objective and establish itself as an agricultural powerhouse, it is imperative to develop green agriculture that promotes high-quality growth in the sector. The promotion of family farms that adopt eco-friendly practices and the acceleration of the green transformation of agriculture is of utmost importance. This study analyzes data from 433 family farms in five provinces of China, namely Zhejiang, Anhui, Shandong, Hunan, and Sichuan, collected in 2022. An econometric model to empirically examine the impact of non-agricultural management experience on the adoption of eco-friendly practices in family farms.

The outcomes of our study demonstrate the significant impact of non-agricultural management experience on the application of organic fertilizers on family farms. Through the use of the propensity score matching method, we have found that family farms managed by farmers with non-agricultural management experience exhibit greater willingness and more intensive application of organic fertilizers. This finding aligns with previous studies by several scholars who have observed that farmers with non-agricultural backgrounds are more receptive to adopting environmentally friendly agricultural management practices (H. Li et al., 2023a; Zhang et al., 2018; Zhou et al., 2022), thus confirming the critical role of non-agricultural management experience in shaping family farm environmental behaviors. In comparison to earlier research, our study offers a more comprehensive understanding of the relationship between non-agricultural management experience and organic fertilizer application on family farms.

Our study has clearly identified educational level and years of farming experience as two significant control variables that influence the application of organic fertilizers on family farms. Our findings confirm and build upon previous research, which indicates that farmers with higher levels of education are more likely to adopt organic farming practices (Serebrennikov et al., 2020; Yazdanpanah et al., 2022), while those with more years of experience in agriculture are more willing to implement eco-friendly practices such as applying organic fertilizers (Adnan et al., 2020; Qi et al., 2021; Qiao et al., 2022).

Moreover, our study has also identified the effects of some new control variables on the use of organic fertilizers, such as farm demonstration effects and agricultural insurance. Our results show that demonstration farms are more likely to apply organic fertilizers due to their higher management level and better understanding of the importance of eco-friendly practices. Additionally, our study highlights that family farms that have purchased agricultural insurance tend to apply organic fertilizers less frequently, which we attribute to the challenges of long-term investment being hampered by moral hazard, thereby weakening willingness to apply organic fertilizers.

Our research has unequivocally demonstrated that off-farm management experience can indirectly influence the use of organic fertilizers on family farms by significantly boosting farmers' green cognition levels. This finding is entirely consistent with the results of previous research. Notably, some scholars have also found that green cognition plays an indispensable mediating role in environmental behavior (P. Liu et al., 2020; Ogiemwonyi et al., 2023; Tian et al., 2020). Although there may be some quantitative differences between our study and the existing literature, we are confident that they stem from differences in research samples, methods, or variable settings. Therefore, further research is warranted to verify these findings. These important findings provide a fresh, robust perspective for understanding the environmental behavior of family farms in depth. Furthermore, they provide invaluable guidance for formulating future policies that can effectively promote the sustainable development of family farms.

6. Conclusion and Policy Implications

Our study on the adoption of eco-friendly practices in family farms provides valuable insights for policy-making in China and other countries. Based on data collected from 433 family farms across five provinces in 2022, we employed an econometric model to analyze the impact of non-agricultural management experience on the use of organic fertilizers. The results indicate that such experience significantly promotes both the likelihood and the intensity of organic fertilizer application. In addition, green cognition plays a partial mediating role in this relationship, suggesting that farmers with experience in non-agricultural management tend to have stronger environmental awareness, which in turn encourages the adoption of eco-friendly farming practices. Other relevant influencing factors include gender, education level, years of farming, land operation scale, demonstration farm status, and agricultural insurance.

These findings highlight the need for a multi-level policy approach. At the central government level, efforts should focus on expanding the national carbon market and establishing long-term policy mechanisms that encourage sustainable agricultural practices. Local governments should provide targeted support based on regional characteristics, including technical training programs, the development of high-quality demonstration farms, and the supply of green agricultural inputs. Policies should also support individuals with non-agricultural management backgrounds who are entering the farming sector. Their skills in planning, organization, and resource management can help improve the operational efficiency of family farms and strengthen the implementation of green practices, particularly when accompanied by appropriate institutional support and training. In addition to fiscal and technical measures, both central and local governments should design agricultural programs that incorporate environmentally friendly principles and actively promote successful demonstration farms to encourage learning and replication among farmers. These strategies can help reinforce long-term eco-friendly practices on family farms by fostering an environment that strengthens green awareness and cultivates positive behavioral norms. A comprehensive approach that integrates economic incentives, behavior-oriented interventions, and a clear allocation of responsibilities between central and local authorities will be essential for advancing the ecological transformation and sustainable development of family farms. While we acknowledge some limitations in our study, such as not considering the impact of different types of non-agricultural management experience nor assessing the impact of current policies, we believe that our findings offer more specific and sustainable recommendations for family farms to better adopt environmentally friendly behaviors. We recommend that future research conduct comprehensive policy evaluations and analyze different types of non-agricultural management experiences to fill gaps in this area of research.

CRediT Author Statement: Jia Yue: Conceptualization, Methodology, and Writing – review & editing; **Siyao Chen:** Methodology and Writing – review & editing; **Zhixiong Weng:** Writing – review & editing; **Qiang Liu:** Formal analysis and Investigation.

Data Availability Statement: The data are available from the corresponding author upon reasonable request.

Funding: This work was supported by the Youth Project of the National Social Science Fund of China (NSSFC) (grant number: 21CGL028) and the Hunan Provincial Department of Education Scientific Research Outstanding Youth Project (grant number: 22B1061).

Conflicts of Interest: The authors declare no conflict of interest.

Acknowledgments: We would like to express our sincere gratitude to the Departments of Agriculture and Rural Affairs of Zhejiang, Anhui, Shandong, Hunan, and Sichuan provinces for their invaluable support and assistance during our research.

References

Adator, S. W., Wu, Q., Lambongang, M., Otoo, S. L., Bosah, C. P., & Nimako, K. O. (2023). Farmers' perception of the impact of gold mining on shrinking agricultural land and their livelihood in the Asutifi-North District. *Resources Policy*, *81*, 103379. https://doi.org/10.1016/j.resourpol.2023.103379

Adnan, N., Nordin, S. M., & Anwar, A. (2020). Transition pathways for Malaysian paddy farmers to sustainable agricultural practices: An integrated exhibiting tactics to adopt Green fertilizer. *Land Use Policy*, *90*, 104255. https://doi.org/10.1016/j.landusepol.2019.104255

Adnan, N., Nordin, S. M., Bahruddin, M. A., & Tareq, A. H. (2019). A state-of-the-art review on facilitating sustainable agriculture through green fertilizer technology adoption: Assessing farmers behavior. *Trends in Food Science & Technology*, *86*, 439–452. https://doi.org/10.1016/j.tifs.2019.02.040

Benyam, A., Soma, T., & Fraser, E. (2021). Digital agricultural technologies for food loss and waste prevention and reduction: Global trends, adoption opportunities and barriers. *Journal of Cleaner Production*, *323*, 129099. https://doi.org/10.1016/j.jclepro.2021.129099

Bhatt, A., & John, J. (2023). Including farmers' welfare in a government-led sector transition: The case of Sikkim's shift to organic agriculture. *Journal of Cleaner Production*, *411*, 137207. https://doi.org/10.1016/j.jclepro.2023.137207

Chen, Y., Fu, X., & Liu, Y. (2022). Effect of farmland scale on farmers' application behavior with organic fertilizer. *International Journal of Environmental Research and Public Health*, *19*(9), 4967. https://doi.org/10.3390/ijerph19094967

Chen, Z., Meng, Q., Yan, K., & Xu, R. (2022). The analysis of family farm efficiency and its influencing factors: Evidence from rural China. *Land*, *11*(4), 487. https://doi.org/10.3390/land11040487

Cheng, Z., Wang, L., & Zhang, Y. (2022). Does smart city policy promote urban green and low-carbon development? *Journal of Cleaner Production*, *379*, 134780. https://doi.org/10.1016/j.jclepro.2022.134780

Cui, Y., Khan, S. U., Sauer, J., & Zhao, M. (2022). Exploring the spatiotemporal heterogeneity and influencing factors of agricultural carbon footprint and carbon footprint intensity: Embodying carbon sink effect. *Science of The Total Environment*, *846*, 157507. https://doi.org/10.1016/j.scitotenv.2022.157507

de Moraes Sá, J. C., Lal, R., Cerri, C. C., Lorenz, K., Hungria, M., & de Faccio Carvalho, P. C. (2017). Low-carbon agriculture in South America to mitigate global climate change and advance food security. *Environment International*, *98*, 102–112. https://doi.org/10.1016/j.envint.2016.10.020

Diallo, T., & Abay, C. (2024). Malian farmers' perception of sustainable agriculture: A case of southern Mali farmers. *Agricultural & Rural Studies*, *2*(4), 0019. https://doi.org/10.59978/ar02040019

Dou, X. (2018). Low carbon agriculture and GHG emission reduction in China: An analysis of policy perspective. *Theoretical Economics Letters*, *8*(3), 538–556. https://doi.org/10.4236/tel.2018.83038

Durán-Lara, E. F., Valderrama, A., & Marican, A. (2020). Natural organic compounds for application in organic farming. *Agriculture*, *10*(2), 41. https://doi.org/10.3390/agriculture10020041

Elahi, E., Zhang, H., Lirong, X., Khalid, Z., & Xu, H. (2021). Understanding cognitive and socio-psychological factors determining farmers' intentions to use improved grassland: Implications of land use policy for sustainable pasture production. *Land Use Policy*, *102*, 105250. https://doi.org/10.1016/j.landusepol.2020.105250

Furtak, K., & Wolińska, A. (2023). The impact of extreme weather events as a consequence of climate change on the soil moisture and on the quality of the soil environment and agriculture–A review. *Catena*, *231*, 107378. https://doi.org/10.1016/j.catena.2023.107378

Gao, Y., Liu, B., Yu, L., Yang, H., & Yin, S. (2019). Social capital, land tenure and the adoption of green control techniques by family farms: Evidence from Shandong and Henan Provinces of China. *Land Use Policy*, *89*, 104250. https://doi.org/10.1016/j.landusepol.2019.104250

Gao, Y., Zhao, D., Yu, L., & Yang, H. (2020). Influence of a new agricultural technology extension mode on farmers' technology adoption behavior in China. *Journal of Rural Studies*, *76*, 173–183. https://doi.org/10.1016/j.jrurstud.2020.04.016

Geels, F. W. (2022). Conflicts between economic and low-carbon reorientation processes: Insights from a contextual analysis of evolving company strategies in the United Kingdom petrochemical industry (1970–2021). *Energy Research & Social Science*, *91*, 102729. https://doi.org/10.1016/j.erss.2022.102729

Gholamrezai, S., Aliabadi, V., & Ataei, P. (2021). Understanding the pro-environmental behavior among green poultry farmers: Application of behavioral theories. *Environment, Development and Sustainability*, *23*, 16100–16118. https://doi.org/10.1007/s10668-021-01331-1

Holka, M., Kowalska, J., & Jakubowska, M. (2022). Reducing carbon footprint of agriculture—Can organic farming help to mitigate climate change? *Agriculture*, *12*(9), 1383. https://doi.org/10.3390/agriculture12091383

Huang, X., Xu, X., Wang, Q., Zhang, L., Gao, X., & Chen, L. (2019). Assessment of agricultural carbon emissions and their spatiotemporal changes in China, 1997–2016. *International Journal of Environmental Research and Public Health*, *16*(17), 3105. https://doi.org/10.3390/ijerph16173105

Hu, G., Wang, J., Fahad, S., & Li, J. (2023). Influencing factors of farmers' land transfer, subjective well-being, and participation in agri-environment schemes in environmentally fragile areas of China. *Environmental Science and Pollution Research*, *30*, 4448–4461. https://doi.org/10.1007/s11356-022-22537-4

Johnstone, P., Rogge, K. S., Kivimaa, P., Fratini, C. F., & Primmer, E. (2021). Exploring the re-emergence of industrial policy: Perceptions regarding low-carbon energy transitions in Germany, the United Kingdom and Denmark. *Energy Research & Social Science*, *74*, 101889. https://doi.org/10.1016/j.erss.2020.101889

Ke, C., & Huang, S.-Z. (2023). The effect of environmental regulation and green subsidies on agricultural low-carbon production behavior: A survey of new agricultural management entities in Guangdong Province. *Environmental Research*, *242*, 117768. https://doi.org/10.1016/j.envres.2023.117768

Lee, C.-C., Feng, Y., & Peng, D. (2022). A green path towards sustainable development: The impact of low-carbon city pilot on energy transition. *Energy Economics*, *115*, 106343. https://doi.org/10.1016/j.eneco.2022.106343

Lei, S., Qiao, Q., Gao, X., Feng, J., Wen, Y., & Han, Y. (2023). Ecological awareness, policy perception, and green production behaviors of farmers living in or near protected areas. *Forests*, *14*(7), 1339. https://doi.org/10.3390/f14071339

Li, B., & Shen, Y. (2021). Effects of land transfer quality on the application of organic fertilizer by large-scale farmers in China. *Land Use Policy*, *100*, 105124. https://doi.org/10.1016/j.landusepol.2020.105124

Li, C., Li, X., & Jia, W. (2022). Non-farm employment experience, risk preferences, and low-carbon agricultural technology adoption: Evidence from 1843 grain farmers in 14 provinces in China. *Agriculture*, *13*(1), 24. https://doi.org/10.3390/agriculture13010024

Li, C., Shi, Y., Khan, S. U., & Zhao, M. (2021). Research on the impact of agricultural green production on farmers' technical efficiency: Evidence from China. *Environmental Science and Pollution Research*, *28*, 38535–38551. https://doi.org/10.1007/s11356-021-13417-4

Li, H., Liu, H., Chang, W.-Y., & Wang, C. (2023a). Factors affecting farmers' environment-friendly fertilization behavior in China: Synthesizing the evidence using meta-analysis. *Agriculture*, *13*(1), 150. https://doi.org/10.3390/agriculture13010150

Li, H., Wang, C., Chang, W.-Y., & Liu, H. (2023b). Factors affecting Chinese farmers' environment-friendly pesticide application behavior: A meta-analysis. *Journal of Cleaner Production*, *409*, 137277. https://doi.org/10.1016/j.jclepro.2023.137277

Li, X., Cifuentes-Faura, J., & Tan, Y. (2023). Analyzing the low carbon and pro-environment behavior of agricultural enterprises based on organizational commitment and role models' guidance. *Environmental Science and Pollution Research*. https://doi.org/10.1007/s11356-023-31302-0

Li, X., Liu, J., Liu, D., Fu, Q., Li, M., Faiz, M. A., Ali, S., Li, T., Cui, S., & Khan, M. I. (2021). Measurement and analysis of regional agricultural water and soil resource composite system harmony with an improved random forest model based on a dragonfly algorithm. *Journal of Cleaner Production*, *305*, 127217. https://doi.org/10.1016/j.jclepro.2021.127217

Liu, M., & Liu, H. (2024). Farmers' adoption of agriculture green production technologies: Perceived value or policy-driven? *Heliyon*, *10*(1), e23925. https://doi.org/10.1016/j.heliyon.2023.e23925

Liu, P., Teng, M., & Han, C. (2020). How does environmental knowledge translate into pro-environmental behaviors?: The mediating role of environmental attitudes and behavioral intentions. *Science of the Total Environment*, *728*, 138126. https://doi.org/10.1016/j.scitotenv.2020.138126

Liu, Y., Sun, D., Wang, H., Wang, X., Yu, G., & Zhao, X. (2020). An evaluation of China's agricultural green production: 1978–2017. *Journal of Cleaner Production*, *243*, 118483. https://doi.org/10.1016/j.jclepro.2019.118483

Lu, H. (2019). Impact of non-agricultural employment and environmental awareness on farmers' willingness to govern the heavy metal pollution of farmland: A case study of China. *Sustainability*, *11*(7), 2068. https://doi.org/10.3390/su11072068

Miao, X., Li, Z., Wang, M., Mei, J., & Chen, J. (2023). Measurement of cultivated land ecosystem resilience in black soil region of northeast China under the background of cultivated land protection policy in China: Case study of Qiqihar City. *Journal of Cleaner Production*, *434*, 140141. https://doi.org/10.1016/j.jclepro.2023.140141

Mora, C., McKenzie, T., Gaw, I. M., Dean, J. M., von Hammerstein, H., Knudson, T. A., Setter, R. O., Smith, C. Z., Webster, K. M., Patz, J. A., & Franklin, E. C. (2022). Over half of known human pathogenic diseases can be aggravated by climate change. *Nature Climate Change*, *12*, 869–875. https://doi.org/10.1038/s41558-022-01426-1

Northrup, D. L., Basso, B., Wang, M. Q., Morgan, C. L. S., & Benfey, P. N. (2021). Novel technologies for emission reduction complement conservation agriculture to achieve negative emissions from row-crop production. *Proceedings of the National Academy of Sciences*, *118*(28), e2022666118. https://doi.org/10.1073/pnas.2022666118

Ogiemwonyi, O., Alam, M. N., Alshareef, R., Alsolamy, M., Azizan, N. A., & Mat, N. (2023). Environmental factors affecting green purchase behaviors of the consumers: Mediating role of environmental attitude. *Cleaner Environmental Systems*, *10*, 100130. https://doi.org/10.1016/j.cesys.2023.100130

Qi, X., Liang, F., Yuan, W., Zhang, T., & Li, J. (2021). Factors influencing farmers' adoption of eco-friendly fertilization technology in grain production: An integrated spatial–econometric analysis in China. *Journal of Cleaner Production*, *310*, 127536. https://doi.org/10.1016/j.jclepro.2021.127536

Qiao, D., Li, N., Cao, L., Zhang, D., Zheng, Y., & Xu, T. (2022). How agricultural extension services improve farmers' organic fertilizer use in China? The perspective of neighborhood effect and ecological cognition. *Sustainability*, *14*(12), 7166. https://doi.org/10.3390/su14127166

Rana, S., Halim, M. A., Mohiuddin, M., Rahman, M. S., & Rana, M. M. (2024). Role of farmer information and advice center in technology transfer and farm business development of smallholder farmers: Insights from Bangladesh. *Agricultural & Rural Studies*, *2*(1), 0001. https://doi.org/10.59978/ar02010001

Ren, C., Liu, S., van Grinsven, H., Reis, S., Jin, S., Liu, H., & Gu, B. (2019). The impact of farm size on agricultural sustainability. *Journal of Cleaner Production*, *220*, 357–367. https://doi.org/10.1016/j.jclepro.2019.02.151

Sarkar, A., Wang, H., Rahman, A., Qian, L., & Memon, W. H. (2022). Evaluating the roles of the farmer's cooperative for fostering environmentally friendly production technologies-a case of kiwi-fruit farmers in Meixian, China. *Journal of Environmental Management*, *301*, 113858. https://doi.org/10.1016/j.jenvman.2021.113858

Sarkar, S., Skalicky, M., Hossain, A., Brestic, M., Saha, S., Garai, S., Ray, K., & Brahmachari, K. (2020). Management of crop residues for improving input use efficiency and agricultural sustainability. *Sustainability*, *12*(23), 9808. https://doi.org/10.3390/su12239808

Serebrennikov, D., Thorne, F., Kallas, Z., McCarthy, S. N. (2020). Factors influencing adoption of sustainable farming practices in Europe: A systemic review of empirical literature. *Sustainability*, *12*(22), 9719. https://doi.org/10.3390/su12229719

Shah, F., & Wu, W. (2019). Soil and crop management strategies to ensure higher crop productivity within sustainable environments. *Sustainability*, *11*(5), 1485. https://doi.org/10.3390/su11051485

Shang, L., Heckelei, T., Gerullis, M. K., Börner, J., & Rasch, S. (2021). Adoption and diffusion of digital farming technologies-integrating farm-level evidence and system interaction. *Agricultural Systems*, *190*, 103074. https://doi.org/10.1016/j.agsy.2021.103074

Slijper, T., Tensi, A. F., Ang, F., Ali, B. M., & van der Fels-Klerx, H. J. (2023). Investigating the relationship between knowledge and the adoption of sustainable agricultural practices: The case of Dutch arable farmers. *Journal of Cleaner Production*, *417*, 138011. https://doi.org/10.1016/j.jclepro.2023.138011

Song, M., Xie, Q., & Shen, Z. (2021). Impact of green credit on high-efficiency utilization of energy in China considering environmental constraints. *Energy Policy*, *153*, 112267. https://doi.org/10.1016/j.enpol.2021.112267

Sun, X., Lyu, J., & Ge, C. (2022). Knowledge and farmers' adoption of green production technologies: An empirical study on IPM adoption intention in major Indica-rice-producing areas in the Anhui Province of China. *International Journal of Environmental Research and Public Health*, *19*(21), 14292. https://doi.org/10.3390/ijerph192114292

Tian, H., Zhang, J., & Li, J. (2020). The relationship between pro-environmental attitude and employee green behavior: The role of motivational states and green work climate perceptions. *Environmental Science and Pollution Research*, *27*, 7341–7352. https://doi.org/10.1007/s11356-019-07393-z

Tong, S., Bambrick, H., Beggs, P. J., Chen, L., Hu, Y., Ma, W., Steffen, W., & Tan, J. (2022). Current and future threats to human health in the Anthropocene. *Environment International*, *158*, 106892. https://doi.org/10.1016/j.envint.2021.106892
Wang, H., Zhong, S., Guo, J., & Fu, Y. (2021). Factors affecting green agricultural production financing behavior in Heilongjiang family farms: A structural equation modeling approach. *Frontiers in Psychology*, *12*. https://doi.org/10.3389/fpsyg.2021.692140
Wang, L., Hu, Y., & Kong, R. (2023). The impact of bancassurance interaction on the adoption behavior of green production technology in family farms: Evidence from China. *Land*, *12*(5), 941. https://doi.org/10.3390/land12050941
Xie, H., & Huang, Y. (2021). Influencing factors of farmers' adoption of pro-environmental agricultural technologies in China: Meta-analysis. *Land Use Policy*, *109*, 105622. https://doi.org/10.1016/j.landusepol.2021.105622
Yang, H., Wang, X., & Bin, P. (2022). Agriculture carbon-emission reduction and changing factors behind agricultural eco-efficiency growth in China. *Journal of Cleaner Production*, *334*, 130193. https://doi.org/10.1016/j.jclepro.2021.130193
Yazdanpanah, M., Moghadam, M. T., Zobeidi, T., Turetta, A. P. D., Eufemia, L., & Sieber, S. (2022). What factors contribute to conversion to organic farming? Consideration of the Health Belief Model in relation to the uptake of organic farming by Iranian farmers. *Journal of Environmental Planning and Management*, *65*(5), 907–929. https://doi.org/10.1080/09640568.2021.1917348
Yeleliere, E., Antwi-Agyei, P., & Guodaar, L. (2023). Farmers response to climate variability and change in rainfed farming systems: Insight from lived experiences of farmers. *Heliyon*, *9*(9), e19656. https://doi.org/10.1016/j.heliyon.2023.e19656
Yu, L., Chen, C., Niu, Z., Gao, Y., Yang, H., & Xue, Z. (2021a). Risk aversion, cooperative membership and the adoption of green control techniques: Evidence from China. *Journal of Cleaner Production*, *279*, 123288. https://doi.org/10.1016/j.jclepro.2020.123288
Yu, L., Nilsson, J., Li, Y., & Guo, M. (2023). Cooperative membership and farmers' environment-friendly practices: Evidence from Fujian, China. *Heliyon*, *9*(10), e20819. https://doi.org/10.1016/j.heliyon.2023.e20819
Yu, L., Zhao, D., Gao, Y., Yang, H., Xu, W., & Zhao, K. (2021b). Spatial dependence of family farms' adoption behavior of green control techniques in China. *Agroecology and Sustainable Food Systems*, *45*(5), 767–789. https://doi.org/10.1080/21683565.2020.1841707
Yu, L., Zhao, D., Xue, Z., & Gao, Y. (2020). Research on the use of digital finance and the adoption of green control techniques by family farms in China. *Technology in Society*, *62*, 101323. https://doi.org/10.1016/j.techsoc.2020.101323
Yuan, J., Li, X., Sun, Z., & Ruan, J. (2021). Will the adoption of early fertigation techniques hinder famers' technology renewal? Evidence from fresh growers in Shaanxi, China. *Agriculture*, *11*(10), 913. https://doi.org/10.3390/agriculture11100913
Zhang, L., Li, X., Yu, J., & Yao, X. (2018). Toward cleaner production: What drives farmers to adopt eco-friendly agricultural production? *Journal of Cleaner Production*, *184*, 550–558. https://doi.org/10.1016/j.jclepro.2018.02.272
Zheng, S., Yin, K., & Yu, L. (2022). Factors influencing the farmer's chemical fertilizer reduction behavior from the perspective of farmer differentiation. *Heliyon*, *8*(12), e11918. https://doi.org/10.1016/j.heliyon.2022.e11918
Zheng, Y., & Zhuang, G. (2021). Systemic governance of mountains, rivers, forests, farmlands, lakes and grasslands: Theoretical framework and approaches. *Chinese Journal of Urban and Environmental Studies*, *9*(4), 2150021. https://doi.org/10.1142/S2345748121500214
Zhong, S., Li, J., Chen, X., & Wen, H. (2021). Research on the green total factor productivity of laying hens in China. *Journal of Cleaner Production*, *315*, 128150. https://doi.org/10.1016/j.jclepro.2021.128150
Zhou, X., & Ding, D. (2022). Factors influencing farmers' willingness and behaviors in organic agriculture development: An empirical analysis based on survey data of farmers in Anhui Province. *Sustainability*, *14*(22), 14945. https://doi.org/10.3390/su142214945
Zhou, Z., Zhang, Y., & Yan, Z. (2022). Will digital financial inclusion increase Chinese farmers' willingness to adopt agricultural technology? *Agriculture*, *12*(10), 1514. https://doi.org/10.3390/agriculture12101514

Agricultural & Rural Studies

Article

Investigating the Influence Mechanism of Douyin Live on the Sale of Traditional Handicrafts in China—Based on a Dual Perspective of Youth Participation

Linlin Li [1], Jiayan Chen [1], Dubin Dong [2], Jialu Chen [3] and Luhu Shuai [1,*]

1 Institute of Ecological Civilization, Zhejiang A&F University, Hangzhou 310007, China; 20140036@zafu.edu.cn (L.L.); 1661974114@qq.com (J.C.)
2 College of Tea Science and Tea Culture, Zhejiang A&F University, Hangzhou 310007, China; 812588636@qq.com
3 College of Economics and Management, Zhejiang A&F University, Hangzhou 310007, China; 2469388588@qq.com
* Correspondence: slh@zafu.edu.cn

Abstract: As an integral component of Chinese national culture, traditional handicrafts face dual challenges of being replaced by modern industrial products and market contraction. In the context of the digital economy, the youth demographic, serving as primary participants and innovators in live-streaming e-commerce, positions Douyin live as a pivotal avenue to explore new opportunities for traditional handicrafts in modern markets. This study focuses on Lin'an District, Hangzhou City, Zhejiang Province, employing questionnaire surveys and on-site interviews with 53 artisans to investigate the role of Douyin live in enhancing the sales of traditional handicrafts. The findings reveal that youth engagement drives the sales of traditional handicrafts through dual pathways of consumption support and cultural participation: young creators significantly improve the online visibility of handicrafts through content innovation; the Douyin platform facilitates the preservation of intangible cultural heritage, markedly boosting market sales; and policy support and resource integration facilitated by Douyin positively influence sales, with young livestream hosts demonstrating greater adaptability in leveraging policy resources. Based on empirical analysis, this study confirms the positive impact of Douyin live on traditional handicraft sales and proposes actionable strategies, including content innovation, brand building, and technological empowerment, to further promote sales and sustainable development. The results not only provide practical marketing strategies for artisans but also offer novel insights into the inheritance and innovative development of traditional handicrafts.

Keywords: Douyin live; traditional handicrafts; sale volume; youth; influence mechanism

Citation: Li, L., Chen, J., Dong, D., Chen, J., & Shuai, L. (2025). Investigating the Influence Mechanism of Douyin Live on the Sale of Traditional Handicrafts in China—Based on a Dual Perspective of Youth Participation. *Agricultural & Rural Studies*, *3*(2), 13. https://doi.org/10.59978/ar03020011

Received: 9 April 2025
Revised: 13 May 2025
Accepted: 16 May 2025
Published: 16 June 2025

1. Introduction

As a treasure of Chinese culture, traditional handicraft, which was the main mode of production in the pre-industrial era, carries abundant information about traditional culture and occupies an important position in both cultural and artistic activities. However, with the acceleration of modernization and the transformation of consumption concepts, traditional handicrafts have been greatly affected and are facing several unprecedented challenges nowadays. Two main issues currently affecting the sale of traditional handicrafts are revealed via an investigation through the visits and surveys of traditional handicraftsmen in China. On the one hand, handicraft products have been gradually replaced by modern craft products and have slowly lost their market share (Bao et al., 2023). In the presence of efficient industrial production, the traditional handicraft industry is unable to compete with the well-organized modern industry. A large number of handicraftsmen were struggling to survive or even abandon their business and move to the cities to earn income. Consequently, the traditional handicraft has been pushed to the side and several traditional crafting skills and techniques have been lost. But, on the other hand, many traditional handicrafts have unique charms, such as bamboo braiding, hand-knocking pecans, etc., and many people want to buy them but there is still a lack of smooth Business to Customer(B2C) sale channel (Sato et al., 2020). Many exquisite handicrafts have difficulty finding suitable market outlets, and this dilemma needs to be solved urgently. Hangzhou's Lin'an District boasts a rich traditional culture and is home to countless skilled artisans. The Lin'an District Trade Union has been innovatively implementing policies to promote the preservation of traditional culture and support artisans through new media platforms like Douyin. These efforts aim to boost the sales of traditional handicrafts and provide sustainable livelihoods for craftsmen. Given our strong interest in this initiative, this paper takes Lin'an District as a case study to analyze the impact mechanism of Douyin live streaming on the sales of handicrafts.

In the context of the information and networking era, the rise of new media platforms has provided new possibilities for the sale of traditional handicrafts. Douyin (Chinese version of TikTok), the most prominent short video and live broadcasting social platform in China, has emerged as one of the world's most popular social media platforms. Its unique content creation and sharing mechanisms have attracted a massive user base, particularly among youth demographics—data indicates that over half of Douyin live's user base comprises individuals under 35. This demographic's evolving demands for cultural consumption present unique opportunities for the marketing of traditional handicrafts. As indicated by data from QuestMobile (2023), the number of monthly active users of Douyin has reached 743 million, representing a year-on-year increase of 5.1%. The average daily usage time per person has increased from 108.4 minutes to 115.2 minutes in 2023, showing a high level of engagement and dependency on the platform among users. Moreover, the utilization of data analysis tools, such as the Douyin e-commerce compass, enables merchants to achieve the growth and optimization of business through data-driven insight. Consequently, investigating the impact of Douyin live on traditional handicraft sales from a youth perspective holds significant research value. It not only highlights the provision of a novel channel for product display and sales but also underscores how optimizing marketing strategies through youth-preferred content formats and interactive mechanisms enables businesses to deeply understand younger consumers' demands, thereby gaining a competitive edge in saturated markets. This mechanism offers critical insights into leveraging emerging social media platforms to enhance the market performance of traditional handicrafts.

Before the era of e-commerce live streaming, research on traditional handicrafts mainly focused on factors such as handicraft prices, brand value, consumers' habits, and social norms. With the rise and popularity of live streaming, live streaming has become a potential factor influencing consumers' decision to purchase traditional handicrafts. As a new form of e-commerce, although some studies have pointed out that live broadcast has the characteristics of real-time, interactivity, and convenience, there is still a lack of research on the relationship between traditional handicraft marketing and live broadcast utilization. In the international academic community, research on Douyin live to increase the sale of handicrafts has begun to attract attention. For example, Gao et al. (2021) in their 2021 study explored how live e-commerce viewers process persuasive information from the perspective of information processing and examined the moderating effect of mindfulness. This study provided a new perspective for understanding the psychology and behavior of consumers during live streaming, especially for goods such as handicrafts, which are highly dependent on personal experience and cultural value. Through a review of relevant literature, the study reveals that Douyin's live streaming functionality enhances the sales of traditional handicrafts by visually showcasing their production processes and artistic appeal through youth-oriented content. These youth-centric communication strategies—such as immersive craft demonstrations and real-time comment interactions—significantly strengthen young consumers' cultural identification and purchase intention, thereby promoting sales (Sheng et al., 2024). Although these studies provided us with valuable insights, there is still little research on how Douyin live specifically affects the sale of traditional handicrafts. Our research will fill this gap by providing empirical support for traditional craft marketing strategies through an in-depth analysis of the characteristics and consumer behavior of Douyin live. By combining domestic and international research, we are not only able to better understand the global trend of live-streaming e-commerce but also provide specific marketing strategy suggestions for the traditional handicraft industry to adapt to the market demand in the digital age.

In the absence of relevant research, this study aims to assess the effect of Douyin live on the sale of traditional handicrafts, so as to provide a theoretical basis for the development of live streaming of traditional handicrafts. Based on the data obtained from questionnaire surveys and field interviews with 53 craftsmen in Lin'an District, Hangzhou City, from July 2021 to March 2024, this study constructs a linear model with Douyin live as the core explanatory variable, and sale volume of traditional handicrafts as the explanatory variable, and rigorously analyzes the sale of traditional handicrafts. A linear model was constructed to rigorously estimate the mechanism of the influence of Douyin live on the sale of traditional handicrafts. Through the benchmark regression analysis (BRA) and mediated effects method, three aspects of the influence of Douyin live on the sale of traditional handicrafts are derived, and five suggestions are also put forward, in the hope that our study can provide craftsmen with effective marketing strategies, particularly the unique value of youth empowerment, and at the same time provide new ideas and directions for the inheritance and development of traditional handicrafts.

2. Literature Review

2.1. Related Research on Douyin Live

Concept Definition

Douyin is the Chinese version of TikTok. Douyin live is a real-time video interactive function provided by the Douyin platform, which allows users to broadcast live videos through mobile phones or professional equipment, and communicate and interact with the audience in real time. Many scholars have analyzed and explained the characteristics and functions of Douyin live. Some scholars pointed out in their research that as an important platform for live streaming, Douyin live has attracted the attention of a large number of young users by virtue of its unique short video content and social attributes, and its rich interactive functions have further enhanced the interaction and stickiness between users and anchors

2.2. Research on the Impact of Live E-Commerce on Product Sale

In recent years, with the rise of live-streaming e-commerce, many scholars have begun to conduct extensive research on live-streaming e-commerce and its impact on product sales. Zhang and Xu (2024) believed that brands can choose live streaming mode to create more value; We also studied the impact of different types of information on accurate sale forecasting (Xu & Ruan, 2023; Z. Zhang et al., 2023). G. Xu et al. (2024) used a comprehensive set of data to achieve the best performance among all evaluation metrics in e-commerce live streaming (Y. Xu et al., 2023; Lv et al., 2022). Chen et al. (2024) used structural equation modeling to reveal the important role of live streamers in shaping mobile commerce (Tran, 2021). Yang and Lee's (2024) research found that good live-streaming technology and experience quality can lead customers to discount their own information and imitate their peers. Customer conformity behavior has a positive impact on their purchase intention (Lu et al., 2023; Lu & Chen, 2021; Lyu et al., 2022). Luo et al. (2024) found that by enhancing our understanding of the information and emotional support obtained from streaming voice content, they have contributed to the existing literature on live-streaming commerce (Abarbanel & Johnson, 2020; Chen, 2023). Huang et al. (2024) found that social presence in live-streaming e-commerce has a significant positive impact on consumer happiness, thereby promoting product sales (Henderson et al., 2023). D. Zhang et al. (2024) studied some results that will help live-streaming business managers better understand consumers' psychological activities, enabling them to effectively design live-streaming interaction strategies for marketing activities (Giertz et al., 2021; Tian & Frank, 2024; Tan et al., 2018). Ma and Yang (2024) found that manufacturers' encroachment on live streaming channels can achieve a win-win situation for both manufacturers and e-commerce platforms (Fan et al., 2024).

Douyin Live on Product Sale

As new media platforms such as Douyin continue to set off a trend of live broadcasts and selling goods, many scholars have begun to focus on the research of Douyin live and product sales. Liu et al. (2022) explored the sustainable development of live broadcast and selling goods to help farmers in the 5G era. Taking the Douyin platform as an example, they analyzed the problems existing in the live broadcast and selling goods process, and put forward countermeasures and suggestions such as improving the live broadcast ability of anchors and developing short videos that are vertical to the Live broadcast content to promote the sustainable development of Live broadcast and selling goods to help farmers. Wang et al. (2010) analyzed that Douyin has a good delivery effect as a marketing activity platform and can increase consumers' purchasing intentions. Tang et al. (2021) pointed out that technological progress and 5G network applications will play a vital role in rural revitalization to increase the sale of agricultural products on Live broadcast platforms (Bansal, 2023). These studies revealed the potential of Douyin live in promoting product sales.

2.3. Research on the Sale of Traditional Handicrafts

In recent years, with the advent of modern production methods, market demands of global economic integration, and the mechanized era, exquisite traditional handicrafts are facing the dilemma of lack of market, loss of skills, and lack of successors.

Faced with such a dilemma, scholars at home and abroad have discussed new sale development directions for traditional handicrafts, mainly the combination of the traditional handicraft industry with e-commerce and the Internet. This transformative pathway is increasingly supported by cutting-edge empirical studies. These findings collectively suggest that the synergy of emerging technologies and traditional crafts can simultaneously address economic sustainability and cultural innovation.

However, a comprehensive review of existing literature reveals a paucity of research on Douyin's impact on traditional handicraft sales. Traditional handicrafts face persistent challenges in modern markets, including low visibility and stagnant sales, yet the mechanisms through which Douyin-a dominant social media platform in China-influences their commercialization remain underexplored. While existing literature acknowledges the dominant role of youth in e-commerce live streaming, their unique advantages in traditional craft dissemination remain underexplored. Young creators not only possess technological empowerment capabilities—such as employing green screen effects and 3D visualization techniques to showcase artisanal details—but also leverage social diffusion mechanisms like fan community operations and cross-platform traffic diversion to expand their reach, thereby forming a closed-loop system of "youth-produced content-youth-consumed content-youth-amplified content." Compared to middle-aged and elderly users, young creators demonstrate superior aptitude for integrating traditional craftsmanship with contemporary lifestyles—for instance, pairing intangible cultural heritage accessories with modern fashion or incorporating handcrafted furniture into minimalist home aesthetics—effectively lowering cultural consumption barriers and activating latent markets. Nevertheless, the full potential of young creators disseminating traditional crafts on Douyin remains underutilized and warrants further investigation. This study aims to address this research gap by systematically analyzing how Douyin's application affects the sales of traditional handicrafts, thereby proposing practical recommendations to alleviate the marketing difficulties inherent to these cultural products.

3. Data and Research Methods

3.1 Data Sources

The data for this study was gathered through a questionnaire survey and field visits to 53 craftsmen in Lin'an District, Hangzhou City, Zhejiang Province. Given the relatively novel perspective and micro-study focus on the local craftsmen in Lin'an, the total sample size is relatively limited. The distribution of the number of craftsmen in Lin'an District is shown in Figure 1. The sample was selected based on the following criteria:

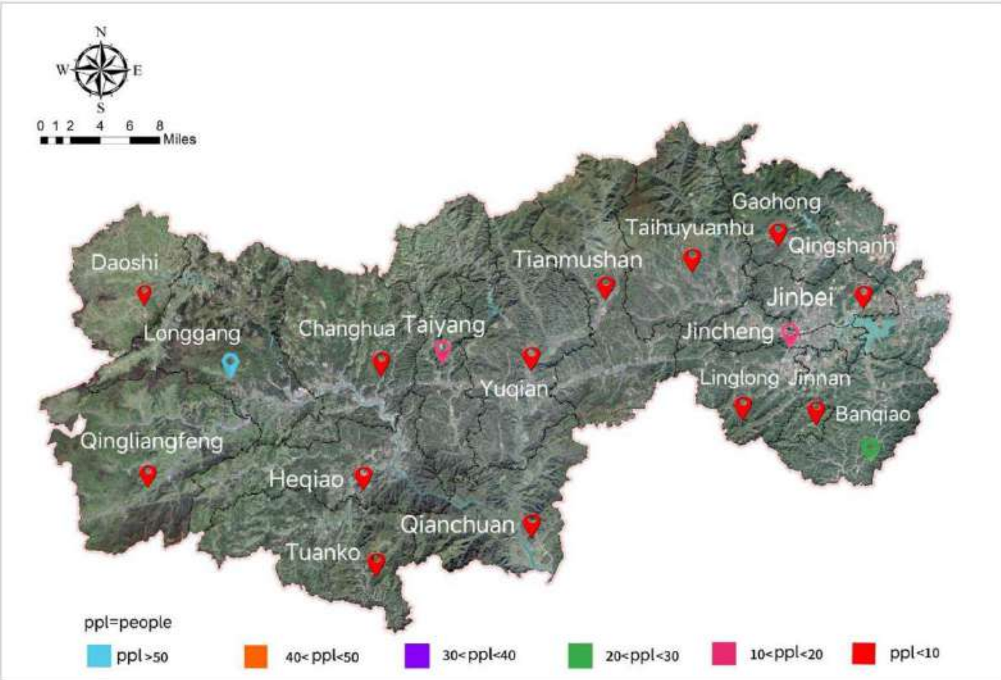


Figure 1. The distribution of traditional craftsmen in various towns in Lin'an District. Source: Authors.

(1) Industry representativeness: The interviewees represent a variety of traditional handicraft fields in Lin'an, including wood carving, bamboo weaving, paper cutting, and food processing, thereby ensuring comprehensive coverage of the research.
(2) Douyin live situation: To ensure the targeted nature of the research, all respondents have active accounts on the Douyin platform, which they make use of to display and sell their handicrafts. Meanwhile, there is a distinction between those who use Live broadcasts and those who do not, allowing us to conduct a comparative analysis.
(3) Diversity of experience: The respondents exhibited a wide range of experience in using the Douyin platform, from novice to senior. This allows us for an investigation into the impact of different experience levels on handicraft sales.

Research object case:

(1) Official case: Lin'an District Federation of Trade Unions established and registered an official Douyin account "Tianmu Searching Craftsmen." This has attracted considerable attention in a relatively short time and become a prototype for promoting the spirit of artisans through the flow of new media. One approach is to systematically create a series of short videos of traditional craftsmen in Lin'an. Through a process of comparison and selection, the District Federation of Trade Unions identified three professional Douyin short video copywriting, planning, and shooting units as cooperation units, as well as five "Internet + traditional craft" incubation projects such as Qingke bamboo flute, Qingke bird cage, and Tianmu Stone carving. As of the time of writing, there have been a total of 151,000 followers. Another approach is the professional management of the official TikTok account "Tianmu Searching Craftsmen," where the Federation of Trade Unions and the selected cooperation units work together to set up a professional operation team for utilizing high-quality videos and live broadcasting and other techniques to shunt the pipelines.

(2) Artisan case: Jiang Yunpan is a post-80s entrepreneur and the founder of "Xiao Junsu Di," who is proficient in bamboo flute making technology. He learned from Xu Zhaoyi, a master of folk craft skills inheriting talent in Hubei Province and once learned bamboo flute manufacturing technology in Tongling Bridge, "the hometown of bamboo flute in China." After completing his studies, he returned to his hometown Qingke village in Lin'an District to make flute and initiated a business venture. His expertise enabled him to quickly produce high-quality flutes with excellent timbres and pitches. However, to ensure the sustainability of his enterprise, he recognized the necessity to not only manufacture these instruments but also to effectively market and sell them. Later, with the support of the "Tianmu Searching Craftsmen" project in Lin'an District, he created a Douyin account and released short videos about the process of making the flute. Up to now, his Douyin account "Xiao Junsudi" has released 180 works, received 127,000 likes, and gained 27,000 followers. By the end of 2022, sales from Jiang Yunpan's live broadcast had exceeded 150,000 in just half a month, with the highest single-session sales reaching nearly 40,000 yuan. Since 2022, Jiang Yunpan's team has broadcast daily with a notable increase in sales from more than 80,000 yuan per month to about 200,000 yuan now. This has resulted in total sales exceeding 2 million.

The data collection process followed these steps:

(1) Questionnaire design: The questionnaire was designed mainly to investigate the usage of the Douyin platform, sale data of handicrafts, and the specific impact of Douyin on sales.

(2) Pre-test: Before the formal survey, the questionnaire was pre-tested to ensure its scientific rigor and operational efficacy.

(3) Field interviews: Members of the research team personally visited handicraft practitioners in the Lin'an area and collected first-hand data through face-to-face interviews, ensuring the authenticity and depth of the data.

This article is based on first-hand data combined with questionnaire surveys and on-site visits, which provide a comprehensive understanding of the role and influence of the Douyin platform in the sale of traditional handicrafts. The research results aim to provide empirical support for understanding the transformation and development of the traditional handicraft industry in the context of new media.

3.2. Mechanism Analysis and Hypotheses

Through its e-commerce and live broadcast functions, Douyin platform provides a new channel and display window for the sale of traditional handicrafts, effectively promoting the marketing and cultural inheritance of handicrafts while significantly enhancing the market exposure of traditional handicrafts. As well, the popularity and sale of traditional handicrafts have also contributed to the inheritance and promotion of intangible cultural heritage.

(1) Improve visibility and market access:

Douyin platform provides small and medium-sized craftsmen the opportunity to gain exposure through its live video broadcast and intelligent distribution capabilities. The traditional model of handicraft production has been dominated by individual studios, which have been lacking in effective marketing and promotion capabilities. The low barrier to entry and user-friendly character of Douyin provide an accessible platform for craftsmen to showcase their crafts and products, thereby increasing the visibility of their work. Pan Chunxiang, a carver skilled in tooth carving, wood carving, horn carving, and other carving techniques, earns his income mainly by processing and carving finished products for other people's materials. Because he was deaf and dumb, and because few people knew about his carvings, his income could not support his life for a while. Until April 2023, the Lin'an District Labor Union "Tianmu Searching Craftsmen" Group found him and sent a professional team for Pan Chunxiang to open a Douyin live account and training guide, so that his craft was found by more people, and greatly increased his account clout and the development of the fan economy. Up to now, his Douyin account "stone teeth antlers walnut obsessed (Tianmu Seeking Craftsmen)" has gained 4033 fans and received 24,000 likes, of which the highest number of views of the short video had reached 200,000, through the Douyin live effectively increase the number of orders, the monthly income from the previous 3,000 yuan to the current 10,000 yuan or so. Furthermore, Douyin also attracts young people to learn flute-making skills, thereby driving local employment and common prosperity. This case fully demonstrates the effective way for craftsmen to use Douyin platform to enhance brand awareness, cultivate traditional handicraft inheritors, and expand sale channels.

(2) Increase sale channels:

The Douyin e-commerce plan, well known as "Seeing Crafts," is designed to help craftsmen to enhance their income through various measures, such as traffic support, fee discounts, official training, exclusive operating activities, and live broadcast base services. Douyin's live e-commerce function enables craftsmen to showcase their crafts and products and interact with consumers in real time through live broadcast. This model increases the immediacy and interactivity of sales and thereby increases consumers' willingness to purchase. Youth entrepreneur Su Guanghui, through operating the Douyin account "Chao Ba Agritourism," has successfully expanded online sales channels for agricultural products, emerging as a benchmark case of digital economy-driven rural revitalization. By integrating the traditional culinary culture of Lin'an Changhua with short videos and live streaming promotions, he has effectively enhanced brand awareness and boosted sales of local agricultural products. With the assistance of the "Tianmu Searching Craftsmen" project, he not only achieved an increase in the viewership of his personal Douyin account but also helped local farmers increase their income through live broadcasts for charity. This plan led to the creation of employment for nearly 80 farmers and an annual income of 20 million for the village collective. His Douyin account published 1,065 works, received 1.023 million likes, and gained 121,000 followers. In 2022, it achieved more than 2.8 million agricultural products sales and B&B revenue of 1.5 million, significantly promoting common prosperity.

Combining (1) and (2), we propose the following hypothesis:

H1: The Douyin application has a positive effect on the sale of traditional handicrafts.

(3) Cultural inheritance and innovation:

The short video format of the Douyin platform provides traditional handicrafts an opportunity to display their cultural values and craft history. Strikingly, the combination of cultural inheritance and innovation has attracted the attention and support of a growing number of young consumers. The Douyin platform facilitates access to traditional handicrafts with the younger generation and thus stimulates their interest in traditional culture and handicrafts. Jiang Sihai, an expert in the field of bloodstone in Lin'an, has utilized the Douyin platform as a means to inherit and innovate the cultural values associated with the bloodstone. By combining traditional crafts with the Douyin application, he has released 799 works and attracted 22,000 fans, thereby significantly enhancing cultural visibility. His account "Jiang Sihai·One Yin per Person" maintains a regular live broadcast about 1–2 hours each day and has launched a "Daily Yin" gift link that is very popular among Douyin fans, greatly improving the fan viscosity and activity in the live broadcast room. It not only demonstrates the traditional charm of bloodstone, but also innovatively attracts the interest of the younger generation. The combination of traditional and modern communication methods enhances the cultural experience while providing new ideas for the innovative dissemination of traditional culture. Furthermore, it promotes widespread dissemination and innovative development of chicken blood stone culture.

(4) Assisting in the inheritance of intangible cultural heritage:

A new approach to the transmission of intangible cultural heritage has been facilitated by the extensive coverage and in-depth promotion of the Douyin platform. A considerable number of projects pertaining to intangible cultural heritage have experienced a resurgence of vitality. For example, a revolutionary change has been done by the "Tuanyuan People" in the inheritance of the intangible cultural heritage of hand-knocking pecans. During the period of the epidemic, the traditional sales model was dreadfully constrained and there is a rapid growth in the use of online shopping. As a consequence of the successful digital transformation of Douyin, the "Tuanyuan People" have not only broadened their sales channels but also greatly increased brand awareness. Through the form of short videos, the "Tuanyuan People" intuitively demonstrate the unique charm of pecan hand-stripping skills, capturing the attention of the public especially the youth. This, in turn, enhances the dissemination and influence of intangible cultural heritage and lets the world see Lin'an pecans.

Based on (3) and (4), we propose the following hypothesis: H2:

The Douyin app drives employment and sale of traditional handicrafts through cultural heritage.

(5) Policy support and resource integration:

The data analysis of the Douyin platform identifies potential craftsmen, thus enabling the government to accurately capture potential craftsmen. These selected craftsmen are awarded the title of “Common Prosperity Workshop” and get the government’s policy inclination and resource investment. Specially, we display the “Tianmu Searching Craftsmen” project established by the Lin’an District Federation of Trade Unions. In this project, the selected craftsmen are guided on how to live broadcast and introduce their goods on the Douyin platform, and multiple resources are provided to promote the dissemination of traditional handicraft culture. Combined with new media, the traditional handicraft industry is promoted, thereby stimulating employment and income growth for low-income groups.

Based on (5), the hypothesis is proposed: H3:
The Douyin app enhances the sales of traditional handicrafts by leveraging precise targeting to attract policy support, and youth-led livestream accounts exhibit significant advantages in accessing policy resources.

3.3. Model Building

The objective of this study is to examine the potential impact of Douyin live streams on the sales of traditional handicrafts. To this end, a preliminary model has been formulated to test the hypothesis that such broadcasts can stimulate sales of these traditional products. The model is as follows:

$$xl_i = \alpha_0 + \beta_1 zb_i + \gamma_1 sk_i + \gamma_2 ls_i + \gamma_3 jp_i + \theta_i + \mu_i \tag{1}$$

Among them, i is an individual index, xl_i is the explained variable of traditional handicraft sale volume, α_0 represents the intercept term, and β_1 represents the regression coefficient of the explanatory variable. Here zb_i is the core explanation of whether it is Douyin live, γ_1 to γ_3 is the regression index of the control variable, sk_i, ls_i, and jp_i represent external teaching promotion, brand history, and the number of competing products in the market, respectively. θ_i represents the individual fixed effect and μ_i is a random disturbance term.

Based on Jiang Ting’s operational proposals on mediation effect analysis, the traditional three-step method of mediating variables was improved to construct the following mediation effect model:

$$M_i = \alpha_0 + \beta_1 zb_i + \gamma_1 sk_i + \gamma_2 ls_i + \gamma_3 jp_i + \theta_i + \mu_i \tag{2}$$

As above, the variable i, as an individual, serves as the mediating factor that influences both the number of employed individuals and their eligibility for participation in the “Common Wealth Workshop.” α_0 denotes the intercept term, β_1 denotes the regression coefficient of the explanatory variable, zb_i is the core explanatory variable whether or not the person is doing Douyin live, γ_1 to γ_3 is the regression index of the control variable, sk_i, ls_i, and jp_i denote the number of out-of-home lectures and publicity, the history of the brand, and the number of competing products in the market, respectively, θ_i denotes an individual fixed effect, and μ_i is a random perturbation term.

3.4. Variable and Data Selection

(1) Core explanatory variables

The core explanatory variable in this article is whether the craftsmen engage in Douyin lives. The data obtained from the questionnaire, denoted by *zb*, is set as a binary variable, who conducts Douyin lives is set to 1, and who does not is 0.

(2) Explained variable

In this paper, the explained variable is the sale volume of traditional handicrafts (xl), the sale which was obtained from the questionnaires within one year are obtained through questionnaires, denoted as xl.

(3) Mediating variables

In order to ascertain whether there is an indirect impact between Douyin live streams and traditional handicrafts, this paper selects the number of people employed and the company’s designation as a “Common Wealth Workshop” as mediating variables. The number of people employed (jy) is used as a signal for the positive impact of Douyin live streams on stimulating employment. Meanwhile, the company’s designation as a “Common Wealth Workshop” (gf) is employed as a proxy for the promotion of common prosperity and the sale of traditional handicrafts by breaking down sale barriers and developing remote shopping.

In Zhejiang, the “Common Wealth Workshop” has become an important carrier for the advancement of common prosperity. By providing a variety of resources and technical support, it effectively absorbs surplus rural labor and low-income farmers, increases the village collective economic income, and promotes the common prosperity of farmers. Here we note that the "Common Wealth Workshop" in this article mainly refers to the one established by the Lin'an District Federation of Trade Unions. The Lin'an District Labor Union has designated the establishment of the "Tianmu Common Wealth Workshop" as a key area for financial support and has so far arranged a total of 1 million yuan in incentive funds. The workshops are classified into three levels (one-star, two-star, and three-star) based on several criteria, including the number of low-income groups employed by the workshop, the number of online live broadcasts, and the number of followers on the workshop's Douyin account.

(4) Control variables

In this study, the external teaching promotion, brand history, and the number of competing products in the market are identified as control variables. Through questionnaires, the number of external teaching promotions, the years of brand existence, and the number of competing products in the market evaluated subjectively by individuals on a 1–10 scoring system are obtained to control the factors other than Douyin live streams that affect the sale volume of handicrafts in that year, which are recorded as sk, ls, and jp, respectively.

The various types of variables set in this paper are shown in Table 1.

Table 1. Variables.

Variable Types	Variable Name	Variable Symbols	Variable Source
Core explanatory variables	Whether to live broadcast on Douyin	zb	Questionnaire results
Explained variable	The sale of traditional handicrafts	xl	Questionnaire results
Mediating variables	Driving employment	jy	Questionnaire results
	Whether or not to be awarded the Common Wealth Workshop	gf	Questionnaire results
Control variables	Out-of-town teaching promotion	sk	Questionnaire results
	Brand history	ls	Questionnaire results
	Number of competing products in the market	jp	Questionnaire results

4. Results and Analysis

4.1. Descriptive Statistics

Descriptive statistics are performed on the 53 individuals involved in this study, and the results are collected in Table 2. Firstly, the core explanatory variable as a 0/1 variable, shows that among the interviewees, people who have initiated a Douyin live is slightly less than the craftsmen who have not yet. Forward, the maximum value of the explained variable is 40 million yuan, the minimum value is 40,000 yuan, and the average income is 2.39 million yuan, indicating that Lin'an traditional handicrafts have a relatively complete sale system and good market prospects. As an important control variable, the average employment is 17.92 but with a large gap. The maximum value of people employed is up to 78, while the minimum is just two. According to the mediating variable "gf," we uncovered that the "Common Wealth Workshop" project is accessible to handicraftsmen and most of them have been awarded and supported by this project. The control variable "ls" has a high degree of variability, reflecting that the Lin'an handicraft industry has a long history, and the variable "jp" suggests that the local market is growing rapidly, and has a good development driving force.

Table 2. Descriptive statistics of variables.

Descriptive Statistics	N	Scope	Minimum	Maximum	Average value	Standard Deviation	Variance
zb	53	1	0	1	0.42	0.497	0.247
x	53	3996	4	4000	239.21	731.588	535221.245
jy	53	76	2	78	17.92	18.952	359.187
gf	53	1	0	1	0.51	0.505	0.255
sk	53	99	1	100	13.3	16.899	285.561
ls	53	59	1	60	15.28	12.196	148.745
jp	53	91	5	96	53.94	25.449	647.67

4.2. Benchmark Regression

After model selection, this paper uses a single fixed effect model to conduct a regression analysis of the impact of Douyin live on the sale of traditional handicrafts. The analysis results are shown in Table 3.

Table 3. Single fixed effect regression results.

Dependent Variable	Independent Variable	Beta	t	R^2	F
The sale of traditional handicrafts	Whether to live broadcast on Douyin	0.318	3.030***	0.856	78.569***
	Out-of-town teaching promotion	0.314	2.971***		
	Brand history	1.205	4.805***		
	Number of competing products in the market	0.406	2.024*		

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Four core explanatory variables of Douyin live are well analyzed and the results indicate that there is a significant promoting effect on the sale of traditional handicrafts. As the most important element, the use of Douyin live in the handicraft industry can effectively promote the sale of traditional handicrafts. The online sale model has the additional benefits of reducing marketing costs and expanding the audience, while also enabling the production of goods according to pre-made orders, which in turn reduces order losses. The promotion of out-of-town teaching has a significant positive impact on the sale of traditional handicrafts at the 1 % level. This demonstrates that the promotion of out-of-town teaching can promote the popularity of traditional handicrafts and attract a great number of handicraft inheritors to enter the traditional handicraft industry offline. Instructional professors are able to more intuitively demonstrate the beauty of craftsmanship that cannot be replicated by machines. Moreover, they also allow the public to get close to traditional handicrafts through personal experiential learning. The brand history of a product has a significant positive influence on the sale of traditional handicrafts at the statistical 1 % level. In light of traditional Chinese concepts, this study will be more inclined to conclude that the brands and industries with a long history have been refined by the market over the years and are now still able to gain high popularity and support in the face of adversity. Moreover, brand history serves as a "living business card," that attracts customers and sells products by word-of-mouth.

Interestingly, we found that the number of competing products in the market also has a positive effect on the sale of traditional handicrafts with an estimated impact of 10 % level. It can be observed that among all variables, the impact of the number of competing products on the market on the sale of traditional handicrafts is the least significant. This is due to the fact that the scope of the study is limited in Lin'an District, which is relatively small compared to the entire sale market. Why we still can observe the impact is that the traditional Handicrafts themselves have regional characteristics and have a larger audience in the region. With the development of digitalization, the sales market has gradually expanded.

4.3. Mediating Effect Model

The fixed effects regression results are shown in Table 4. It can be seen that at the 5% significance level, there is a significant positive correlation between the number of driven jobs and whether to live broadcast on Douyin. That is to say, as the use of Douyin live increases, there is a significant increase in handicraft employees. Naturally, as employment opportunities increase and people's income levels increase, the demand for cultural products also increases, which in turn promotes the development of the handicraft market. In-depth research on the influence of job creation through the sale of traditional handicrafts has been conducted in previous literature. In addition, the expansion of employment has also led to the growth of related industrial chains, thereby providing impetus for innovation and diversification within the handicrafts-producing region. These studies not only provided theoretical support for understanding the dynamics of the handicraft market but also offer practical guidance for promoting the development of cultural industries and employment growth.

Table 4. Intermediation effect regression results.

Mediating variable	Independent variable	Beta	t	R^2	F
Number of people led to employment	Whether to live broadcast on Douyin	0.530	4.459***	0.266	19.886***
Whether or not to be awarded the Common Wealth Workshop		0.827	10.492***	0.677	110.083***

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

From Table 4, the impact of being awarded as a "Common Wealth Workshop" is positive and at a 5% significance level. Specifically, the number of employees has increased significantly with the granting of the "Common Wealth Workshop." As a new industrial poverty alleviation model, the impact of the "Common Wealth Workshop" project on the sale of traditional handicrafts has gained widespread attention from academic researchers. It's shown that the "Common Wealth Workshop" has significantly improved the production efficiency and quality of handicrafts. This has been achieved by providing professional training, technical support, and market channels, thereby enhancing the market competitiveness of its products. In addition, the "Common Wealth Workshop" also increased the purchasing power of handicrafts by fostering local employment and growing residents' income, thus driving sales growth. These studies provided an important perspective for understanding the role of the "Common Wealth Workshop" in the development of the traditional handicraft industry, and also provide a theoretical basis for the formulation of relevant policy.

4.4. Results Analysis

Based on the data from 53 craftsmen in Lin'an District, Hangzhou City, Zhejiang Province, this study investigates and analyzes the situation of traditional craftsmen using Douyin to increase the sale of handicrafts. We consider whether Douyin live as the core explanatory variable and construct a model with the sale volume of traditional handicrafts as the explained variable. The results of benchmark regression analysis and mediation effect model lead to the following conclusions:

(1) Douyin increases sales of traditional handicrafts in various ways:

Empirical research indicated that, firstly, Douyin expands the visibility and market access of traditional craftsmen and their craftsmanship through live broadcasts and short video promotions. At the same time, Douyin's e-commerce activities such as the "Seeing Craftsmanship" program supported by the big data technique, have actively expanded the audience of traditional handicrafts, and traditional craftsmen and craftsmanship have been effectively showcased. Secondly, Douyin's low threshold and operability also facilitate the development of online sales channels for traditional handicraftsmen. The use of short videos enables the display of handicrafts anytime and anywhere, thereby increasing the consumers' willingness to purchase the goods. Moreover, live broadcasts facilitate face-to-face interaction between the consumers and handicraftsmen. The Explanation of product interaction for the promotion of consumption has significantly increased the market sale of traditional handicrafts. Douyin live streaming fosters a bidirectional driving mechanism—"craft visualization-cultural identity construction-consumption conversion"—through content production by young creators and interactive engagement from young consumers. Youth creators excel at deconstructing traditional crafts into shareable "cultural symbols," such as using slow live streams to showcase the artisan spirit behind woodworking joinery, employing close-up shots in short videos to highlight the aesthetic details of embroidery color matching, or designing interactive "handicraft workshop" sessions during broadcasts to allow young consumers to directly appreciate the value of craftsmanship. Simultaneously, as "social dissemination nodes," young users amplify reach through sharing livestream links, participating in hashtag challenges, and creating secondary derivative content, thereby activating a social diffusion loop of "product seeding-instant purchasing-repeat buying." This operational model, grounded in the behavioral logic of digital natives, significantly enhances both the dissemination efficiency and commercial conversion rates of traditional handicrafts.

(2) Douyin drives employment and sale of traditional handicrafts through cultural heritage:

The Douyin app provides a platform for traditional handicrafts to demonstrate their unique cultural value and historical craft traditions through the user-friendly and interactive form of short videos, attracting considerable interest from younger audiences. This innovation in cultural inheritance not only revitalizes traditional handicrafts but also inspires younger consumers to engage with traditional culture and participate in the handicraft industry, stimulating the sale of handicrafts and promoting the inheritance of traditional culture. Meanwhile, the promotion of the Douyin platform provides additional employment opportunities for low-income people. Through skills training and policy support, craftsmen can expand their online sales channels and encourage surrounding villagers to participate in the production and sale of handicrafts. Remarkably, the Douyin platform has successfully achieved the dual objectives of cultural inheritance and employment promotion, thereby providing a robust foundation for the sustainable development of traditional handicrafts.

(3) Douyin platform gains policy support through adopting a precise positioning strategy that promotes the sale of traditional handicrafts:

The data analysis and user behavior tracking functions of the Douyin platform provide the government with a way to accurately identify and locate traditional craftsmen with development potential. Through the platform's big data analysis, the government can identify those craftsmen who are active on Douyin and popular with users, and then award them the title of "Common Wealth Workshop" as a recognition of their craftsmanship and market potential. Craftsmen who receive the title will receive government policy support and resource support, including but not limited to the investment of human resources, capital, technology, and other factors. This policy support helps craftsmen expand their production scale and improve their craftsmanship, while also promoting the sustainable development and innovation of traditional handicrafts. Through the effective combination of the Douyin platform and government resources, the marketization and modernization of traditional handicrafts can be further promoted, achieving a win-win situation for cultural heritage and economic development. Young livestream hosts demonstrate stronger adaptability in policy and resource coordination compared to middle-aged and elderly artisans, with their unique advantages manifesting in three key aspects. First, their technological proficiency enables them to quickly master data analytics tools such as Douyin's E-Commerce Compass, allowing for precise user targeting—for instance, by refining product designs based on audience demographics. Second, their content innovation bridges traditional craftsmanship and contemporary trends, such as combining classical handicrafts with "Hanfu" fashion or integrating intangible cultural heritage (ICH) paper-cutting into Chinese products, thereby appealing to younger consumers. Third, their social media engagement strategies—including community management and interactive livestream techniques like "exclusive fan perks" and "limited-time customization"—effectively enhance user retention. A notable example is young artisan Su Guanghui, who operates the "Chao Ba Agritourism" account. By transforming traditional Changhua food-making processes into engaging short videos and supplementing livestreams with behind-the-scenes narratives, his account achieved significantly higher follower growth and product sales than those run by older artisans, serving as a prime case of youth-driven revitalization of traditional crafts.

5. Conclusion and Discussion

The utilization of the Douyin platform's video and live broadcasting functions has resulted in a favorable impact on the sales of conventional handicrafts. However, this has also given rise to a number of challenges and shortcomings. For example, the promotion of handicrafts on the Douyin platform may encounter some problems such as content homogeneity, user aesthetic fatigue, and obstacles for craftsmen in the use of Douyin functions. Therefore, in order to further promote the sales and development of traditional handicrafts, this study proposes the following countermeasures and suggestions:

(1) Brand building and sustainable development: It's recommended that efforts should be made to enhance the brand awareness of traditional handicrafts and improve brand influence and

market competitiveness. This may be achieved through the utilization of storytelling marketing and brand history inheritance. For the realization of the sustainable development of the handicraft industry, we should balance the relationship between traditional craft protection and market innovation, and ensure the long-term development of the handicraft industry.

(2) Cooperative operation model: It's possible for handicraftsmen to cooperate with professional social media operation companies, utilizing the knowledge and experience of their professional teams to effectively manage and optimize their Douyin accounts. These operation companies usually possess professional capabilities, including market analysis, content planning, video production, and account promotion. These capabilities assist the handicraftsmen showcase the unique value and process of their handicrafts more effectively, and improve the creativity and attractiveness of the content.

(3) Utilize platform tools and resources: Handicraftsmen are encouraged to make full use of the various tools and resources provided by the Douyin platform. These include data analysis tools such as the Douyin e-commerce compass system, which can assist the users to better understand the target audience and market trends. In addition, handicraftsmen can participate in various trainings and seminars held by the Douyin platform. In those lectures, they may learn how to utilize the platform's marketing functions, including challenges, hashtags, advertising, etc., and finally improve their brand awareness and sale conversion rate on Douyin.

(4) Strengthen the creation and promotion of intangible cultural heritage content: We should encourage and support intangible cultural heritage inheritors and related organizations to publish high-quality intangible cultural heritage content on Douyin. To attract the interest of younger audiences, this can be presented in the form of short videos that showcase the craftsmanship process, cultural background, and artistic value. Cross-border cooperation and brand collaboration should be pursued. We should promote the cooperation between intangible cultural heritage and modern brands, and combine intangible cultural heritage with modern aesthetics through joint products, special activities, and other forms. The aim of this is to broaden the audience base of intangible cultural heritage.

(5) Technical training and policy support: Governments and relevant departments should introduce more support policies to provide financial assistance and policy guidance for preserving and developing traditional handicrafts. According to Douyin's 2023 Intangible Cultural Heritage Data Report, among the top 100 intangible cultural heritage inheritors with the highest e-commerce sales on the platform in 2023, 37% were post-90s generation, highlighting the rise of young artisans and underscoring the critical need for targeted youth-oriented policy support and technical training. To empower this demographic, it is essential to provide comprehensive training in new media operations and e-commerce sales, particularly for young artisans. Initiatives such as advancing the "Youth Douyin Livestream" platform development can enhance their ability to leverage digital tools for effective market promotion. Simultaneously, specialized workshops on contemporary marketing strategies should be offered to help artisans better utilize online platforms for commercial success.

CRediT Author Statement: Linlin Li: Conceptualization, Investigation, Resources, and Supervision; **Jiayan Chen:** Writing – original draft and Writing – review & editing; **Dubin Dong:** Methodology, Resources, and Supervision; **Jialu Chen:** Formal analysis and Validation; **Luhu Shuai:** Methodology and Project administration.

Data Availability Statement: The data for this study is available upon request

Funding: This research was funded by Special Project on "Basic Research Funds for Colleges and Universities" of Philosophy and Social Science Planning of Zhejiang Province in 2025, Grant Number 25NDJC108YBMS

Conflicts of Interest: The authors declare no conflict of interest.

Acknowledgments: Not applicable

References

Abarbanel, B., & Johnson, M. R. (2020). Gambling engagement mechanisms in Twitch live streaming. *International Gambling Studies*, *20*(3), 393–413. https://doi.org/10.1080/14459795.2020.1766097

Bansal, G. (2023). Contract farming, capital and state: Corporatisation of Indian agriculture. *The Journal of Peasant Studies*, *50*(5), 2116–2119. https://doi.org/10.1080/03066150.2022.2137629

Bao, N., Liu, J., Liu, Y., & Yang, J. (2023). Exploring the development path of traditional culture handicraft industry under the background of digital economy – A case study of Jingdezhen. In C. T. Dang, J. Cifuentes-Faura, & X. Li (Eds.), *Proceedings of the 2nd International Conference on Business and Policy Studies* (pp. 1383–1397). Springer, Singapore. https://doi.org/10.1007/978-981-99-6441-3_125

Chen, C.-P. (2023). Hardcore viewer engagement and social exchange with streamers and their digital live streaming communities. *Qualitative Market Research*, *26*(1), 37–57. https://doi.org/10.1108/QMR-06-2021-0074

Chen, X., Wu, M., & Yang, Y. (2024). Determining the role of live streamers in mobile commerce: Psychological effect of social presence and risk preference. *Current Psychology*, *43*, 22781–22796. https://doi.org/10.1007/s12144-024-05939-0

Fan, X., Zhang, L., Guo, X., & Zhao, W. (2024). The impact of live-streaming interactivity on live-streaming sale mode based on game-theoretic analysis. *Journal of Retailing and Consumer Services*, *81*, 103981. https://doi.org/10.1016/j.jretconser.2024.103981

Gao, X., Xu, X.-Y., Tayyab, S. M. U., & Li, Q. (2021). How the live streaming commerce viewers process the persuasive message: An ELM perspective and the moderating effect of mindfulness. *Electronic Commerce Research and Applications*, *49*, 101087. https://doi.org/10.1016/j.elerap.2021.101087

Giertz, J. N., Weiger, W. H., Törhönen, M., & Hamari, J. (2021). Content versus community focus in live streaming services: How to drive engagement in synchronous social media. *Journal of Service Management*, *33*(1), 33–58. https://doi.org/10.1108/JOSM-12-2020-0439

Henderson, I. L., Avis, M., Tsui, W. H. K., Ngo, T., & Gilbey, A. (2023). Compound brands and the multi-creation of brand associations: Evidence from airports and shopping malls. *Sustainability*, *15*(2), 1450. https://doi.org/10.3390/su15021450

Huang, Z., Yan, X., & Deng, J. (2024). How social presence influences consumer well-being in live video commerce: The mediating role of shopping enjoyment and the moderating role of familiarity. *Journal of Theoretical and Applied Electronic Commerce Research*, *19*(2), 725–742. https://doi.org/10.3390/jtaer19020039

Liu, H., Si, J., Yang, Y., Zhang, X., & Zeng, Y. (2022). Research on the sustainable development of Live broadcast to help farmers in the 5G era. *Sustainable Development*, *12*(2), 396–401. https://www.oalib.com/research/6771713

Lu, B., & Chen, B. (2021). Live streaming commerce and consumers' purchase intention: An uncertainty reduction perspective. *Information & Management*, *58*(7), 103509. https://doi.org/10.1016/j.im.2021.103509

Lu, Y., He, Y., & Ke, Y. (2023). The influence of e-commerce live streaming affordance on consumer's gift-giving and purchase intention. *Data Science and Management*, *6*(1), 13–20. https://doi.org/10.1016/j.dsm.2022.10.002

Luo, L., Xu, M., & Zheng, Y. (2024). Informative or affective? Exploring the effects of streamers' topic types on user engagement in live streaming commerce. *Journal of Retailing and Consumer Services*, *79*, 103799. https://doi.org/10.1016/j.jretconser.2024.103799

Lv, J., Yao, W., Wang, Y., Wang, Z., & Yu, J. (2022). A game model for information dissemination in live streaming e-commerce environment. *International Journal of Communication Systems*, *35*(1), e5010. https://doi.org/10.1002/dac.5010

Lyu, W., Qi, Y., & Liu, J. (2022). Proliferation in live streaming commerce, and key opinion leader selection. *Electronic Commerce Research*, *24*, 1153–1186. https://doi.org/10.1007/s10660-022-09605-0

Ma, R., & Yang, T. (2024). Manufacturer's channel strategy in live streaming E-commerce supply chain. *Managerial and Decision Economics*, *45*(4), 2087–2107. https://doi.org/10.1002/mde.4102

QuestMobile. (2023, November 24). *New media ecosystem insights: Industry user base reaches 1.088 billion, user migration and diversion enter a new phase, platforms pursue growth and monetization through two main channels*. 36 Kr. https://www.36kr.com/p/2527404954035973

Sato, D., Ikeda, Y., Kawai, S., & Schich, M. (2020). The sustainability and the survivability of Kyoto's traditional craft industry revealed from supplier-customer network. *PloS one*, *15*(11), e0240618. https://doi.org/10.1371/journal.pone.0240618

Sheng, J., Gao, X., Diao, M., & Gerasimova, K. (2024). Discussion of consumers' preference for food product traceability information: Beijing traceable tomato case study. *Agricultural & Rural Studies*, *2*(3), 0017. https://doi.org/10.59978/ar02030017

Tang, Y., Dananjayan, S., Hou, C., Guo, Q., Luo, S., & He, Y. (2021). A survey on the 5G network and its impact on agriculture: Challenges and opportunities. *Computers and Electronics in Agriculture*, *180*, 105895. https://doi.org/10.1016/j.compag.2020.105895

Tan, X., Guo, Y., Orgun, M. A., Xue, L., & Chen, Y. (2018). An engagement model based on user interest and QoS in video streaming systems. *Wireless Communications and Mobile Computing*, *2018*(1), 1398958. https://doi.org/10.1155/2018/1398958

Tian, Y., & Frank, B. (2024). Optimizing live streaming features to enhance customer immersion and engagement: A comparative study of live streaming genres in China. *Journal of Retailing and Consumer Services*, *81*, 103974. https://doi.org/10.1016/j.jretconser.2024.103974

Tran, L. T. T. (2021). Managing the effectiveness of e-commerce platforms in a pandemic. *Journal of Retailing and Consumer Services*, 58, 102287. https://doi.org/10.1016/j.jretconser.2020.102287

Wang, K.-Y., Liang, M., & Peracchio, A. L. (2010). Strategies to offset dissatisfactory product performance: The role of post-purchase marketing. *Journal of Business Research*, *64*(8), 809–815. https://doi.org/10.1016/j.jbusres.2010.10.006

Xu, G., Ren, M., Wang, Z., & Li, G. (2024). MEMF: Multi-entity multimodal fusion framework for sale prediction in live streaming commerce. *Decision Support Systems*, *184*, 114277. https://doi.org/10.1016/j.dss.2024.114277

Xu, Y., Kapitan, S., & Phillips, M. (2023).The commercial impact of live streaming: A systematic literature review and future research agenda. *International Journal of Consumer Studies*, *47*(6), 2495–2527. https://doi.org/10.1111/ijcs.12960

Xu, Y., & Ruan, Y. (2023). AI and human broadcasters: Relative impact on consumer engagement in live streaming commerce. *Electronic Commerce Research and Applications*, *62*, 101335. https://doi.org/10.1016/j.elerap.2023.101335

Yang, Q., & Lee, Y.-L. (2024). The effect of live streaming commerce quality on customers' purchase intention: Extending the elaboration likelihood model with herd behaviour. *Behaviour & Information Technology*, *43*(5), 907–928. https://doi.org/10.1080/0144929X.2023.2196355

Zhang, D., Fu, L., Ma, J., & Chen, C. (2024). Social-oriented versus task-oriented streamer interaction styles on live streaming e-commerce: Empirical research in China. *Journal of Consumer Behaviour*, *23*(4), 1995–2008. https://doi.org/10.1002/cb.2320

Zhang, Y., & Xu, Q. (2024). Consumer engagement in live streaming commerce: Value co-creation and incentive mechanisms. *Journal of Retailing and Consumer Services*, *81*, 103987. https://doi.org/10.1016/j.jretconser.2024.103987

Zhang, Z., Chen, Z., Wan, M., & Zhang, Z. (2023). Dynamic quality management of live streaming e-commerce supply chain considering streamer type. *Computers & Industrial Engineering*, *182*, 109357. https://doi.org/10.1016/j.cie.2023.109357

Agricultural & Rural Studies

Article

Spatial Modeling of Child Malnutrition and Farming Methods in Rural Sub-Sahara Africa

Brent Lloyd [1]

1 Nez Perce Tribe, Land Services Department, Lapwai, ID 83540, United States; brentl@nezperce.org

Abstract: Food security in rural sub-Saharan Africa is dependent on crop yields grown on subsistence rainfed farms. Yields for rain-fed farms in Africa are often affected by the high variability in precipitation during the growing season. Low crop yields in many communities in developing regions affect the physical and mental growth of children by reducing their caloric intake. Water harvesting farms provide a way to capture water for agricultural purposes and increase crop yield. This study aimed to determine whether the prevalence of water harvesting farm techniques is spatially correlated with malnutrition. Multilevel regression models at the within-household and geographic levels were used to evaluate the correlation between water harvesting farms and stunting, a measurement of malnutrition, among children aged 1 to 5 years. The results suggest that the use of water harvesting farm methods is correlated with stunting and offers the potential to reduce malnutrition in rural subsistence farming communities in Africa.

Keywords: spatial analysis; malnutrition; multilevel regression; water harvesting farms; demographic health surveys; rural health; developing countries; health demand; stunting

1. Introduction

The ability of a country to achieve economic growth, structural transformation, and poverty reduction relies on stable production of agricultural crop yields (Barrett et al., 2017; Enongene, 2024). Communities in developing countries of sub-Saharan Africa (SSA) struggle, in some years, to be food secure throughout the year because of low crop yields. Food security was defined by the World Food Summit in 1996 as "when all people, at all times, have physical and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life." The Food and Agriculture Organization (FAO) defined four pillars of food security in 2006: food availability, food access, utilization, and stability (Alexandratos & Bruinsma, 2006). The stability of crop yields has been highly variable in many areas of SSA over the past 40 years and is projected to be so in the future because of factors such as drought, flooding, pests, population growth, and economic instability (Alimagham et al., 2024; Noort et al., 2022; Rojas et al., 2011). Low crop yields restrict the daily caloric intake of individuals and increase local food market prices (Grace et al., 2014). Food insecurity due to low crop yields in many communities in developing regions affects the physical and mental health and well-being of families (Nanama & Frongillo, 2012). High variability in climate, compounded with other problems, such as low soil fertility and crop diseases, can cause low per capita food production (Chakraborty & Newton, 2011; Richard et al., 2022). This is the result of the breakdown of conventional practices, and policymakers have given low priority to farming communities (Feder & Savastano, 2017; Sanchez, 1987). Crop yields provide an important economic measurement of food security (Godfray et al., 2010), while malnutrition in children provides an important anthropometric measurement of food security (FAO, 2014).

Child malnutrition is prevalent in many developing SSA countries (de Sherbinin, 2011; Godfray & Garnett, 2014; Grace et al., 2012). Malnutrition lacks adequate energy, protein, and micronutrients to meet the basic requirements of body maintenance, growth, and development (FAO, 2014). Malnutrition affects all groups of people; however, infants and children are more vulnerable because of their higher nutritional requirements for growth and development (Blössner & de Onis, 2005; Morales et al., 2023). Malnutrition in children is routinely measured as wasting or stunting. Wasting is < -2 standard deviations for weight-for-age, and stunting is < -2 standard deviations for height-for-age. Stunting is commonly used as an indicator of malnourishment because wasting can vary throughout the year depending on food availability, whereas stunting outcomes occur as a result of chronic exposure to inadequate calories or nutritional inputs

Citation: Lloyd, B. (2025). Spatial Modeling of Child Malnutrition and Farming Methods in Rural Sub-Sahara Africa. *Agricultural & Rural Studies*, *3*(2), 13. https://doi.org/10.59978/ar03020012

Received: 1 April 2025
Revised: 29 April 2025
Accepted: 7 May 2025
Published: 10 June 2025

(Frongillo, 2022). Stunting in children has been associated with behavioral problems, cognitive deficits, and an increased risk of hypertension and cardiovascular diseases (Black et al., 2013). As of 2012, approximately 165 million children under 5 years of age worldwide were considered stunted (de Onis et al., 2012).

Multiple studies have been conducted using demographic and health survey (DHS) data to monitor malnutrition in children in SSA (e.g., Beni et al., 2024; Grace et al., 2012). Many developing countries outside SSA have seen a decrease in malnutrition and an increase in agricultural production in the past 40 years, but overall, countries in SSA have seen a much lower agriculture production rate compared to other developing countries in the world; in addition, the malnutrition rate in some SSA countries has increased (Kanamori & Pullum, 2013).

Production from small farm plots is important for the food security of people in areas of low population density in SSA. Villagers rely primarily on what they produce. Low crop yields have caused malnutrition in many parts of SSA (i.e., stunted growth, impaired mental development, and impeded physical growth; Slingerland et al., 2006). The intake of nutrients from crop yields in rural areas of SSA has been shown to positively affect health outcomes (Beyene, 2023; Reij et al., 2009; Slingerland et al., 2006).

The farming techniques used in SSA affect crop yields (Barbier et al., 2009; Lloyd & Dennison, 2018; Sidibé, 2005). Conventional farming practices in SSA usually consist of farmers plowing or hoeing fields without modifying the landscape. Conventional agricultural farming can lead to soil leeching of nutrients and a low water-holding capacity. Water harvesting systems may be defined as "methods of collecting and concentrating various forms of runoff (rooftop, runoff, overland flow, stream flow, etc.) from various sources (precipitation, dew, etc.) and for various purposes" (Reij et al., 1988, p. 4). The adoption of water harvesting techniques, such as macrocatchments, helps to maintain soil erosion by slowing the rate of water flow. Water harvesting can be practiced within, around, and outside areas used for farming (Reij et al., 2009). Water harvesting farms help maintain nutrients and organic matter in the soil and increase the water productivity of farms.

While the literature has focused on the relationship between children's health and other variables, such as climate (Dos Santos & Henry, 2008; Grace et al., 2012), socio-economics (Balk et al., 2005; Pérez-Mesa et al., 2022), and geophysical variables (de Sherbinin, 2011), no study has evaluated farming techniques applied to children's health. This analysis examines the relationship between stunted growth and local farming practices in rural Burkina Faso. The research questions for this study are as follows: 1) What areas in Burkina Faso have high concentrations of water harvesting farms? 2) Does the concentration of water harvesting farms within the DHS cluster areas correlate with child stunting in Burkina Faso? 3) Does the proportion of farms within each DHS cluster area correlate with child stunting in Burkina Faso? 4) What land uses besides farms can be correlated with stunting? 5) How do water harvesting farm practices spatially relate to stunting in Burkina Faso? A unique contribution of this analysis is the use of land-use data in combination with household- and community-level DHS data, using a multilevel regression model. The significance of this study is that it provides an understanding of whether investment in water harvesting farms may contribute to the overall health of children and overall communities. In addition, this study provides insights into the determinants of health within-household along with geographic factors related to the stunting of children.

2. Methods

Land-use data were collected around DHS cluster locations to identify the types of farming techniques and other land-use classifications that are correlated with stunting. A 1.6 x 1.6 km square was overlaid on high-resolution imagery from Google Earth for three random farming communities within 5 km of each DHS cluster location. The size of the overlaid square and number of points were chosen based on the average area around the villages used for agricultural purposes. The majority of farming communities in Burkina Faso consist of fewer than 200 people (WorldPop, n.d.), with agricultural farms spread around the center of the community at an average 0.8 km in each direction. Within each randomly positioned square, 50 randomly selected points were used for land-use identification. The land use underlying each point was classified into one of ten land-use types (Table 1). Land use was assigned to points if images with pan-sharpened spatial resolution less than or equal to 1 m were available within four years of 2010. Land-use data in this study were compared to a land cover classification image produced by GlobeLand30-2010 (GLC30). GLC30 has a multispectral 30 m resolution image with 10 classified land cover types for most of the Earth's surface, with an overall accuracy of 80.33% (Office for Outer Space Affairs UN-SPIDER Knowledge Portal, 2016).

Table 1. Image interpretation description of land use types; Adapted from Anderson et al., 1976.

Land-use Type	Description
Conventional farm	Distinctive areas of geometric shape and pattern (usually square or round) that have been cultivated for the production of food and fiber
Water harvesting farm	Same description as conventional farms including the use natural or man-made barriers to collect or store water for the use of crops
Road	Linear features interconnected with each other and bare of vegetation
Urban	Built-up land comprised of areas of intensive use with structures
Water	Areas or linear features within a land mass covered with water
Rangeland	Area where natural vegetation is predominantly grasses, grass-like plants, forbs, or shrubs
Forestland	Area of land having a tree-crown area density of 10% or more
Barren land	Area of land limited to less than one-third vegetation or another land cover (usually an area of thin soil, sand, or rocks)
Intermittent stream	Ephemeral riverbed that contains water only during times of heavy rain

2.1. Study Area

Burkina Faso lies within the Sahel region of Africa on the fringe of the Sahara Desert. The terrain is mostly flat, with dissected plains and plateaus. The elevation of the country ranges from 200 to 750 m. Approximately 70% of Burkinabes live in rural areas (World Bank, 2015). More than 90% of the workforce is employed in agriculture and is dominated by small-scale farms of less than 5 ha (FAO, 2014). The main crops grown in the region are millet, sorghum, and cotton. Most farmers practice dryland farming to grow crops during the monsoon season.

2.2. DHS Data

In 2010, the DHS collected over 17,000 household surveys, including information on the health of children, clustered into 540 spatially referenced locations within Burkina Faso (Figure 1). The spatially referenced DHS cluster locations are randomly shifted 0–2 km in urban areas, 0–5 km in rural areas, with 1% of rural cluster locations displaced 0–10 km, to protect the privacy of respondents (DHS, n.d.). Stunted growth collected for this study was obtained from each of the DHS survey cluster locations, and land-use data were collected in proximity to each DHS survey cluster location. The displacement of the cluster points was restricted within each provincial boundary.

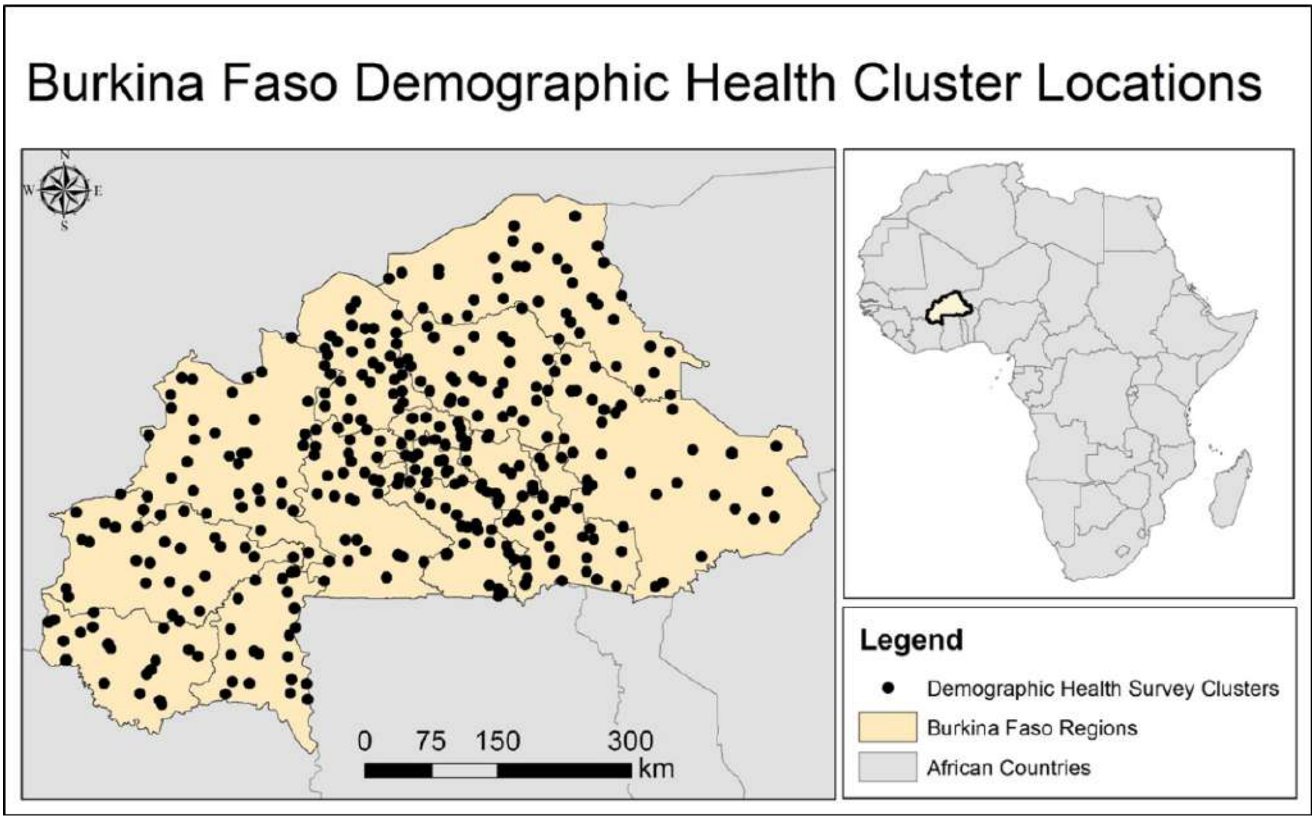


Figure 1. Rural DHS cluster locations within Burkina Faso.

The DHS surveys provide measures of children's anthropometric health and well-being, including indicators of malnutrition. Burkina Faso is among the countries in SSA that suffer from the highest malnutrition rates. In 2011, the National Nutritional Survey estimated that 35% of Burkinabé children under 5 are affected by stunted growth (United Nations International Children's Fund [UNICEF], 2013).

Data collected by the DHS aids in explaining where major problems of malnutrition occur, as it relates to the measurement of children's height and weight (Nanama & Frongillo, 2012). The survey data cover information about health, lifestyle, personal information, and the surrounding environment for each applicant; 4,870 households with children under five were surveyed throughout Burkina Faso. Seventy-six percent (3,696) of the surveys were conducted in rural areas. One of the objectives of the DHS survey data is to collect information on the growth of children under five. Physical measurements based on height and weight were compared with the World Health Organization (WHO) global database on child growth and malnutrition (WHO & UNICEF, 2009). The physical measurements of children under 5 were collected and recorded at DHS cluster locations; however, it should be noted that it is unknown how long each of the children lived in a certain location. Several studies using DHS data have been conducted in Burkina Faso to monitor malnutrition and its effects on individuals and households (Beiersmann et al., 2007; Grace et al., 2017; Maxwell, 1996; Wuehler et al., 2011). Malnutrition affects all regions of Burkina Faso (Institut National de la Statistique et de la Démographie & ICF International, 2012). Some explanations for the high rate of malnutrition as related to farming within the country include low soil fertility, variable precipitation, unsustainable farming management strategies, and low-quality seeds (Ikazaki et al., 2011; Miller & Welch, 2013).

2.3. Land-Use Data

Land-use data were collected around DHS cluster locations to identify what types of farming techniques and other land-use classifications are correlated to stunting. A 1.6 x 1.6 km square was overlaid on high-resolution imagery from Google Earth for three random farming communities within 5 km of each DHS cluster location. The size of the overlaid square and the number of points were chosen based upon the average area around villages used for agricultural purposes. The majority of farming communities in Burkina Faso consist of less than 200 people (WorldPop, n.d.), with agricultural farms spread around the center of the community on average 0.8 km in each direction. Within each randomly positioned square, 50 randomly selected points were used for land-use identification. Land use underlying each point was classified into one of ten land-use types

(Table 1). Land use was assigned to points if images with pan-sharpened spatial resolution less than or equal to 1 m were available within 4 years of 2010. Land-use data in this study were compared to a land cover classification image produced by GlobeLand30-2010 (GLC30). GLC30 has a multispectral 30 m resolution image with 10 classified land cover types for most of the surface of the earth, with an assessed overall accuracy of 80.33% (Office for Outer Space Affairs UN-SPIDER Knowledge Portal, 2016).

2.4. Multilevel Regression Modeling

A multilevel regression model was created to test whether the stunting of children at the within-household level was highly impacted by water harvesting farming. Multilevel modeling analyzes the data in a hierarchical structure, allowing for residual components at each level in the structure. The dependent variable in this study is the height-for-age Z-scores (HAZ) of children between 1 and 5 years old. HAZ is a standard measurement for chronic childhood malnutrition (Frongillo & Nanama, 2006; Grace et al., 2012). The child growth standards provided by the WHO were used to calculate Z-scores for child stunting (WHO & UNICEF, 2009). The independent variables selected for this study have been used in other studies to assess malnutrition in children (Grace et al., 2012; Balk et al., 2005; de Sherbinin, 2011). The model uses two hierarchical levels categorized as within-household and geographic (Table 2). Within-household determinants include children's age, child's size at birth, child's sex, mother's age, mother's height, mother's education, number of small children, child body mass index, floor material, mosquito nets, approved water sources, and scooters or motorcycles. The within-household variables were retrieved from the 2010 DHS data (DHS, n.d.). Geographic determinants include soil type, population density, province, percentage of water harvesting farms, and percentage of total farm area. The soil type data have a resolution of 100 km and were collected by the Joint Research Centre- European Soil Data Centre in 2013 (JRC-ESDAC, 2013). The population density data have a resolution of 30 seconds and were created by the Center for International Earth Science Information Network (CIESIN) for the year 2000 (CIESIN, 2016).

Table 2. List of variables and a description of how each variable is categorized for each child respondent under 5.

Determinants	
Within-household	**Geographic**
1. Child Age	13. Soil Type
2. Child Size at Birth	14. Population Density
3. Child Sex	15. Province
4. Mother's Age	16. Water Harvesting Farms %
5. Mother's Height	17. Total Farm Area
6. Mother's Education	
7. Small Children	
8. Floor Material	
9. BMI	
10. Mosquito Bed Net(s)	
11. Approved Water Source	
12. Scooter/Motorcycle	

The multilevel regression accounts for associations among observations within levels to make efficient and valid inferences. The multilevel model equation is as follows (Bafumi & Gelman, 2006):

$$yi = \alpha_{s[i]} + \beta x_i + \epsilon_i \tag{1}$$

where s[i] is the group's containing unit i

$$\alpha_j = \alpha_0 + \eta_s \tag{2}$$

Equation (1) shows where yi is the score of a variable on the dependent variable and is being predicted by modeling varying intercepts α_s and a predictor x_i. The error in the model is denoted by ϵ_i. Equation (2) displays the hierarchal level equation that estimates the mean of the varying intercepts α_0 and the hierarchal level error η_s. The method of using a multilevel structure regression model over other regression models has proven to be a more reliable model estimate between response and independent variables when data could be nested at different geographic scales (Curtis & Rees Jones, 1998). Multicollinearity was assessed between each variable.

2.5. Moran's I Index

In addition to multilevel analysis, an ordinary least squares (OLS) regression model using spatial filtering regression with eigenvectors analyzed how farm types are spatially correlated with stunting. Regression models using spatial data may contain spatially autocorrelated residuals causing a misspecification error. Moran's I methodology tests for global spatial autocorrelation and corrects for misspecification errors (Moran, 1950). Moran's I was used in this study to measure farm land-use and water harvesting farms clustering in Burkina Faso and is based on the cross-products of the deviations from the mean and is calculated for n observations on a variable x at locations *i*, and *j* as:

$$\mathrm{I} = \frac{N}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij} \left(X_i - \bar{X}\right)\left(X_j - \bar{X}\right)}{\sum_i \left(X_i - \bar{X}\right)^2}. \quad (3)$$

where $\bar{x}$ the mean of the x variable and w_{ij} are the elements of the weight matrix. Moran's I uses eigenvectors with OLS regression accounting for spatial autocorrelation during the statistical modeling of the spatial data using an inverse distance spatial relationship (Griffith, 2000). Moran's I is similar to a correlation coefficient varying from −1 to 1. Values toward 1 indicate clustering while values toward −1 indicate dispersion.

2.6. Geographic Weighted Regression

Geographic weighted regression (GWR) is a relatively new local statistical technique that analyzes spatial relationships between a dependent variable and one or more independent variables (Fotheringham et al., 2002). The GWR is a local regression model used to examine spatial heterogeneity across a study area. The GWR equation is based on the OLS regression by constructing an equation for every location in the dataset and is as follows (Charlton & Fotheringham, 2009):

$$y_i(u) = \beta_{0i}(u) + \beta_{1i}(u)x_{1i} + \beta_{2i}(u)x_{2i} \ldots \beta_{mi}(u)x_{mI} \quad (4)$$

where y_i is the dependent variable, and u is an observation at a specific location, while x is an independent variable. The notation $\beta_{0i}(u)$ is a parameter that describes a relationship around a location (u) and is specific to that location. The parameters set for this analysis included using a fixed kernel type and an AIC bandwidth. The output of running a GWR provides a table delineating where and how much variation is present between the dependent and independent variable(s) at each location.

2.7. Interpolation

The distribution of water harvesting farms and stunting in Burkina Faso were mapped using a process called empirical Bayesian kriging (EBK). EBK is a common geostatistical interpolation algorithm for scattered point data and has been used in multiple DHS data studies (Gemperli et al., 2004; Gosoniu et al., 2010; 2012). The EBK method uses an intrinsic random function accounting for the error introduced by estimating the underlying semivariogram model (Krivoruchko, 2012). The parameters chosen for the EBK model include using a k-Bessel semivariogram model with a maximum search neighborhood parameter of 10. The parameters provide a way to identify local trends from the inserted DHS data while providing prediction surfaces from the interpolated values. The stunted growth survey data collected at each clustered location were averaged at each of the 540 geolocated point locations. Water harvesting farm data were collected at three farming communities around each DHS clustered location and averaged. Due to the nature and distribution of the cluster points, EBK was a suitable method for deriving an interpolated surface of the study area. The random shift in the geolocated DHS cluster areas should have little effect on predicting cell values as the offset is minimal and the interpolation method accounts for multiple surrounding values.

3. Results

Over 50,000 land-use sample points were collected from farming communities around DHS cluster locations in Burkina Faso. Table 3 displays the average and standard deviation of the percentage of land-use for each land-use type. Conventional farms and rangeland comprised the majority of land-use types around farming communities, consisting of 75% of total land usage while water harvesting farms averaged 12.6% of land usage. Roads, urban areas, water areas, forestland, barren land, and intermittent stream combine for a minority portion of land-usage sample data at 12.4%

Table 3. Descriptive statistics of land use types for farming communities in Burkina Faso.

Land-use Types	Average Percentage of Land Use	Standard Deviation Percentage of Land Use
Water	1.0%	2.2%
Forestland	1.0%	3.8%
Barren land	1.6%	4.9%
Intermittent Stream	2.0%	2.9%
Road	2.8%	3.2%
Urban	4.0%	6.6%
Water Harvesting Farms	12.6%	13.4%
Rangeland	33.2%	18.2%
Conventional Farms	41.8%	19.3%

Results from Moran's I test show areas of clustering, as shown in Figure 2a for the total farm area and Figure 2b for water harvesting farms. Areas of high-high clustering indicate the concentration of total farm area per land-use. There was significant clustering of the percentage of total farm area per land use in Burkina Faso, with a Moran's index of 0.97 and a Z-score of 81.97. The concentration of the percentage of the total farm area is prevalent in the central areas of the country near the capital of Ouagadougou, but there are other regions throughout the country with high clustering. Areas of low-low clustering are areas where there is little farming. Most water harvesting farms are located in the north-central part of the country. Water harvesting averages, where high-high clustering occurred, averaged 62% of the land usage. The majority of areas with low-low clustering had no water harvesting farms. The spatial analysis of the clustering of water harvesting farms had a Moran's index of 0.96 and a Z-score of 80.51, indicating significant clustering of water harvesting farms in the country.

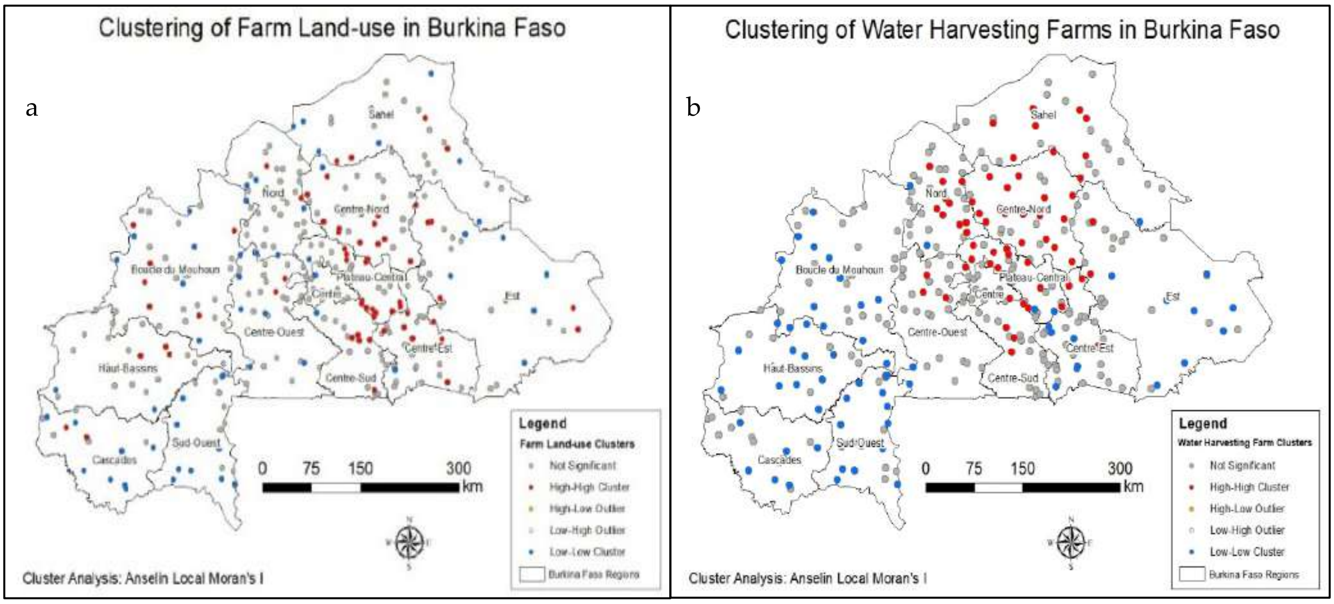


Figure 2. The concentration of percentage of total farm area (a) and percentage of water harvesting farms (b) in Burkina Faso using Moran's index.

The results in Table 4 show the significant factors for each hierarchal level related to stunting. Within-household variables in this analysis are similar to those seen in other studies modeling malnutrition in SSA (de Sherbinin, 2011; Grace et al., 2012; Henry & Dos Santos, 2013; Sandler & Sun, 2024). The mother's influence is an important factor in the health of their children. Mother's height, education, and maternal age were all negatively correlated with the stunting of their children.

Table 4. Significant variables related to stunting at the within-household and geographic hierarchal levels.

Dependent Variable: Stunting				
Significant Values	p < 0.001	0.001< p < 0.01	0.01 < p <0.05	0.05 < p < 0.1
Within-household Variables	Mother's Height (−) Mother's Education: Secondary (−)	Population Density (−)	Natural Floor Material (+) Mother's Education: Primary (−) Sex – Male (+)	Maternal Age (−)
Geographic Variables	Comoé Province (+) Water Harvesting Farms (−)	Ioba Province (+) Kadiogo Province (+)	Bazèga Province (+) Kompienga Province (+) Kouritenga Province (+) Kourwéogo Province (+) Léraba Province (+) Poni Province (+) Tapoa Province (+) Tuy Province (+) Ziro Province (+)	Banwa Province (+) Boulkiemdé Province (+) Gourma Province (+) Houet Province (+) Koulpélogo (+) Zoundwéogo (+) Roads (−)

The geographic variables in this study included soil types, population density, provinces, the percentage of water harvesting farmland, and the percentage of total farm area. Only the percentage of water harvesting farms and certain provinces indicated a correlation with malnutrition rates based on the DHS 2010 Survey. Provinces that positively correlated with stunting in this analysis include Ganzourgou, Kadiogo, Banwa, Kompienga, Tapoa, Poni, Tuy, Gourm, and Bazega; these provinces are distributed throughout central and southern areas of Burkina Faso.

The distribution of land designated for farming based on sample data is significantly clustered. The average percentage of the land used for the total farming area was 60.6%, with areas of high clustering averaging 78%. There is no significant correlation between total farmland and stunting in Burkina Faso in this study. Besides water harvesting farms, the only other land-use type that showed correlation were roads, which were negatively correlated with stunting ($p < 0.05$).

Figures 3a and 3b display an interpolated distribution of water harvesting farms and stunting in Burkina Faso. The highest concentration of water harvesting farms is in the central and north-central parts of Burkina Faso, with total land use over 44.8%. Child stunting is also clustered in Burkina Faso but varies throughout the country. The highest areas of stunting occur away from the center of the country with pockets of low stunting scattered throughout the country.

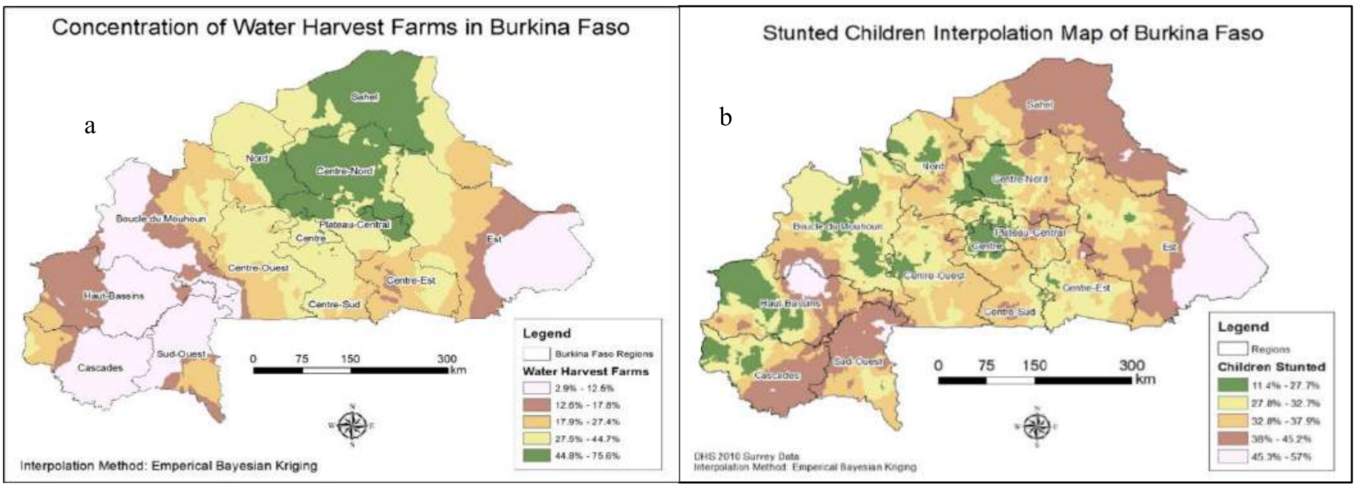


Figure 3. Interpolation of water harvesting farms based upon collections of land cover data around DHS survey locations (a) and Interpolation of stunted children data based upon DHS 2010 Survey data cluster locations (b).

GWR analysis was performed at each DHS survey cluster point to explain the local variance. Figure 4 displays the GWR map of the standard regression of water harvesting farms to stunting.

The standard regression residuals provide information for understanding where water harvesting farms, the locally weighted regression coefficient to stunting, move away from their global values. Standard regression areas close to zero were predicted to indicate a strong relationship between water harvesting and stunting. Areas with a higher standard regression away from zero will have a weaker correlation between water harvesting farms and stunting. Areas with a high standard regression imply that other key explanatory variables are missing from this spatial model to explain spatial variance. Areas in red (high standard regression) are relatively low in stunting and have a high percentage of land-use appropriated for water harvesting farms. Areas in blue (low standard regression) were high in stunting and low in water harvesting farms.

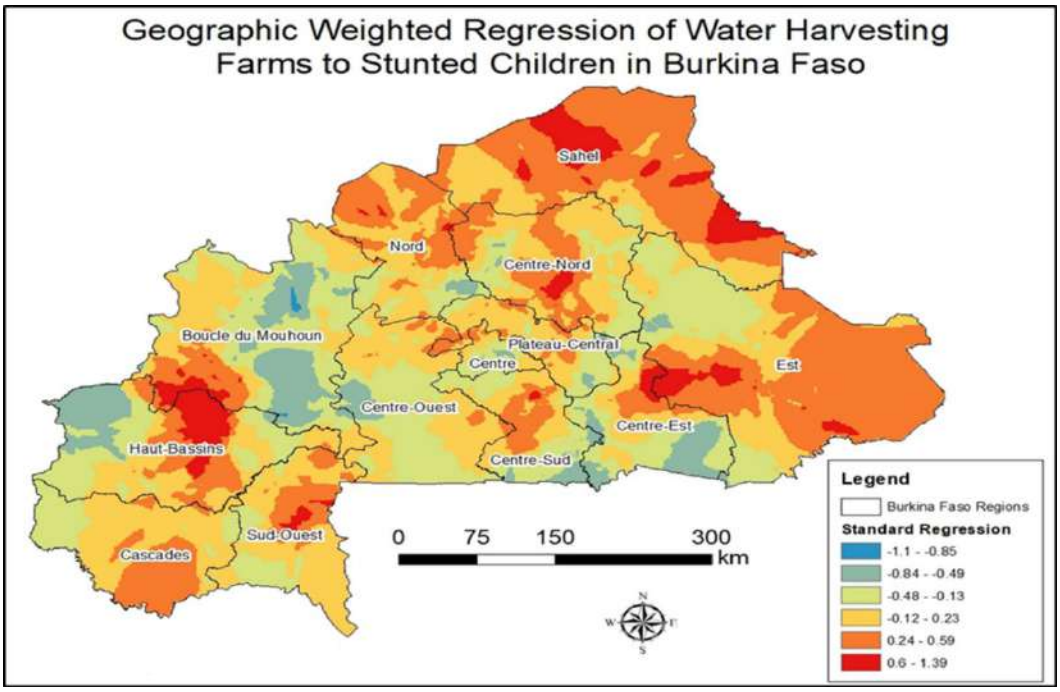


Figure 4. Displays the GWR interpolation map of the percentage of stunting from DHS 2010 surveys and data collected on water harvesting farms per land use in farming communities around the survey locations.

4. Discussion

The production of crops from small farm plots is critical to the food security of people in areas with low population density in SSA. Low investments in land improvement and fertilizer use have caused long-term deterioration in soil fertility and crop productivity, affecting the nutritional requirements for productive crops to be met (Dimkpa et al., 2023). As the population increases and more arable land is being used for farming, water harvesting farms can be an important investment for rural households that rely on farming. Water harvesting farms provide a sustainable solution to produce higher crop yields by replenishing fertility and water productivity for agricultural use, with little management costs for small-scale farmers. DHS cluster locations where communities invest in water harvesting farming techniques correlate with lower rates of stunting. The ability of an area to invest in land rehabilitation using water harvesting techniques can aid the health of households by increasing nutrients in the soil, providing stable production in seasons with high climate variability. Households that do invest in water harvesting farming techniques come from government or non-government organizations projects or from farmers that understand soil conservation strategies, have resources, and the money to implement water harvesting techniques (Bunclark, 2015).

Correlations between within-household factors and stunting in this analysis were similar to those found in other studies modeling malnutrition in SSA (Bain et al., 2013; Grace et al., 2012; Sandler & Sun, 2024). Mothers' influence is an important factor in the health of their children. The mother's height, education, and maternal age were all important within-household variables that were negatively correlated with the stunting of their children. This study, along with other studies, reflects the importance of mothers' well-being in raising healthy children.

In addition to water harvest farms being a significant geographic determinant of stunting, the distance of stunted children from major roads was negatively correlated. Another study found a significant relationship between transportation infrastructure and crop production (Dorosh et al., 2010). Road density is a major factor in cash income from agricultural sales (Briceño-Garmendia

& Domínguez, 2011). The proximity to roads also helps decrease travel time to healthcare facilities, which has been shown to be an important indicator of children's health (Rutherford et al., 2010).

Local, national, and international agencies began to successfully implement water harvesting techniques in the 1980s in the north-central region of Burkina Faso. These projects have helped subsistence farmers achieve more stable crop production. Agencies and local farmers who have invested in such techniques have been, on average, able to produce higher crop yields (Barbier et al., 2009; Lloyd & Dennison, 2018). Examining the spatial distribution of water harvesting farms to stunting helps to better understand regional variations in the GWR model.

This study provides a unique perspective in accounting not only for information related to a child's immediate care but also for a spatial, environmental, and agricultural perspective in relation to the stunting of children. Understanding spatial components is crucial for providing aid to those who have less access to nutritious food and clean water. In the case of stunting, practicing water harvesting methods for farmers who rely on what they produce can influence a child's health.

There are many areas in the GWR model where there is varying standard regression, implying that other key variables are needed to explain spatial variance. Key variables such as those related to the mother in this study and in other studies can have an impact on some of these areas. Some areas with high spatial variance may also have been influenced by variables that were not used in this study. Local areas can also have factors that affect malnutrition that are not prevalent in other communities. An influencing variable that could affect the growth of children in a local area could be prolonged illness from malaria, which could reduce their nutrition and growth over time.

Future research on farming practices in relation to health in developing countries can help local government agencies and other stakeholders determine how to meet future food security requirements. This includes knowing the best methods to grow crops where there is high variability in climate. This study was conducted in a small area of SSA; further investigation is needed to understand how water harvesting techniques affect the health of people in other areas of SSA where rainfed crops dominate. Long-term studies of farming practices and health within Burkina Faso would allow for a more in-depth exploration of the interactions between the different factors affecting crop yields and stunting in this region.

5. Conclusion

Food security will continue to be a major issue in developing countries because of climate variability, population growth, and economic instability. This study examined the concentration of water harvesting farms and their spatial correlation with stunting in Burkina Faso. This study found that mothers' height, education, and age strongly influenced stunting within households, similar to other studies. Water harvesting farms were significantly clustered in Burkina Faso and spatially correlated with stunting in certain areas of Burkina Faso. Water harvesting farms were correlated with stunting; however, the amount of land use dedicated to farming in farming communities did not correlate with stunting, indicating that investment in soil and water conservation techniques is important to the livelihood of people in rural areas of Burkina Faso. These findings indicate that simply adding more farmland or expanding it to more marginal land may not improve stunting. However, this research suggests that investing in existing agricultural land to develop water conservation techniques could lead to reductions in stunting. Google Earth's high-resolution historical imagery provides a cost-effective way to sample land use, especially in remote parts of the world, and Google Earth data for other regions can be used to examine land-use variables correlated with global malnutrition.

CRediT Author Statement: This is a single author paper and the author was solely responsible for the content, including the concept, design, analysis, writing, and revision of the manuscript.

Data Availability Statement: Data available in a publicly accessible repository. https://dhsprogram.com/data/

Funding: This research received no external funding.

Conflicts of Interest: The author declares no conflict of interest.

Acknowledgments: Not applicable.

References

Alexandratos, N., & Bruinsma, J. (2006). *World agriculture: Towards 2030/2050: The 2012 revisions*. Food and Agriculture Organization. http://www.fao.org/3/a-ap106e.pdf

Alimagham, S., van Loon, M. P., Ramirez-Villegas, J., Adjei-Nsiah, S., Baijukya, F., Bala, A., Chikowo, R., Silva, J. V., Soulé, A. M., Taulya, G., Tenorio, F. A., Tesfaye, K., & van Ittersum, M. K. (2024). Climate change impact and adaptation of rainfed cereal crops in sub-Saharan Africa. *European Journal of Agronomy*, *155*, 127137. https://doi.org/10.1016/j.eja.2024.127137

Anderson, J. R., Hardy, E. E., Roach, J. T., & Witmer, R. E. (1976). *A land use and land cover classification system for use with remote sensor data*. U. S. Geological Survey. https://doi.org/10.3133/pp964

Barbier, B., Yacouba, H., Karambiri, H., Zoromé, M., & Somé, B. (2009). Human vulnerability to climate variability in the Sahel: Farmers' adaptation strategies in northern Burkina Faso. *Environmental Management*, *43*, 790–803. https://doi.org/10.1007/s00267-008-9237-9

Beiersmann, C., Sanou, A., Wladarsch, E., De Allegri, M., Kouyaté, B., & Müller, O. (2007). Malaria in rural Burkina Faso: Local illness concepts, patterns of traditional treatment and influence on health-seeking behaviour. *Malaria Journal*, *6*, 106. https://doi.org/10.1186/1475-2875-6-106

Bafumi, J., & Gelman, A. (2006). Fitting multilevel models when predictors and group effects correlate. SSRN. https://doi.org/10.2139/ssrn.1010095

Bain, L. E., Awah, P. K., Geraldine, N., Kindong, N. P., Sigal, Y., Bernard, N., & Tanjeko, A. T. (2013). Malnutrition in sub–Saharan Africa: Burden, causes and prospects. *Pan African Medical Journal*, *15*, 120. https://doi.org/10.11604/pamj.2013.15.120.2535

Balk, D., Storeygard, A., Levy, M., Gaskell, J., Sharma, M., & Flor, R. (2005). Child hunger in the developing world: An analysis of environmental and social correlates. *Food Policy*, *30*(5–6), 584–611. https://doi.org/10.1016/j.foodpol.2005.10.007

Barrett, C. B., Christian, P., & Shiferaw, B. A. (2017). The structural transformation of African agriculture and rural spaces: Introduction to a special section. *Agricultural Economics*, *48*(S1), 5–10. https://doi.org/10.1111/agec.12382

Beni, R., Ramroop, S., & Habyarimana, F. (2024). Analyzing childhood (0-59 months) malnutrition determinants in five West African Countries of Gabon, Gambia, Liberia, Mauritania, and Nigeria using survey logistic regression-insights from DHS data. *Archives of Public Health*, *82*, 147. https://doi.org/10.1186/s13690-024-01374-6

Beyene, S. D. (2023). The impact of food insecurity on health outcomes: Empirical evidence from sub-Saharan African countries. *BMC Public Health*, *23*, 338. https://doi.org/10.1186/s12889-023-15244-3

Black, R. E., Victora, C. G., Walker, S. P., Bhutta, Z. A., Christian, P., de Onis, M., Ezzati, M., Grantham-McGregor, S., Katz, J., Martorell, R., & Uauy, R. (2013). Maternal and child undernutrition and overweight in low-income and middle-income countries. *The Lancet*, *382*(9890), 427–451. https://doi.org/10.1016/S0140-6736(13)60937-X

Blössner, M., & de Onis, M. (2005). *Malnutrition: Quantifying the health impact at national and local levels*. WHO Nutrition for Health and Development. https://iris.who.int/bitstream/handle/10665/43120/9?sequence=1

Briceño-Garmendia, C., & Domínguez-Torres, C. (2011). *Burkina Faso's infrastructure. A continental perspective*. World Bank Group. https://doi.org/10.1596/1813-9450-5818

Bunclark, L. A. (2015). Water harvesting for crop production: Exploring adoption and use in Burkina Faso from a livelihood's perspectives [Doctoral thesis, Newcastle University]. Duraspace. http://hdl.handle.net/10443/3126

Center for International Earth Science Information Network. (2025, April 10). *SEDAC data catalog* [Data catalog]. Columbia Climate School. https://ciesin.climate.columbia.edu/content/data

Chakraborty, S., & Newton, A. C. (2011). Climate change, plant diseases and food security: An overview. *Plant Pathology*, *60*(1), 2–14. https://doi.org/10.1111/j.1365-3059.2010.02411.x

Charlton, M., & Fotheringham, A. S. (2009). *Geographically weighted regression: White paper*. National Centre for Geocomputation. https://www.geos.ed.ac.uk/~gisteac/fspat/gwr/gwr_arcgis/GWR_WhitePaper.pdf

Curtis, S., & Rees Jones, I. (1998). Is there a place for geography in the analysis of health inequality? *Sociology of Health & Illness*, *20*(5), 645–672. https://doi.org/10.1111/1467-9566.00123

Demograph & Health Surveys. (n.d.). *DHS Methodology.* Retrieved December 12, 2017, from http://dhsprogram.com/What-We-Do/Survey-Types/DHS-Methodology.cfm

de Onis, M., Brown, D., Blössner, M., & Borghi, E. (2012). *Levels & trends in child malnutrition: UNICEF–WHO–The World Bank Joint Child Malnutrition Estimates*. United Nations Children's Fund, World Health Organization, & World Bank. https://cdn.who.int/media/docs/default-source/child-growth/jme-brochure2012.pdf?sfvrsn=ca20d895_2

de Sherbinin, A. (2011). The biophysical and geographical correlates of child malnutrition in Africa. *Population, Space and Place*, *17*(1), 27–46. https://doi.org/10.1002/psp.599

Dimkpa, C., Adzawla, W., Pandey, R., Atakora, W. K., Kouame, A. K., Jemo, M., & Bindraban, P. S. (2023). Fertilizers for food and nutrition security in sub-Saharan Africa: An overview of soil health implications. *Frontiers in Soil Science*, *3*. https://doi.org/10.3389/fsoil.2023.1123931

Dorosh, P., Wang, H.-G., You, L., & Schmidt, E. (2010). *Crop production and road connectivity in sub-Saharan Africa: A spatial analysis*. The World Bank Africa Region Sustainable Development Division. http://documents.worldbank.org/curated/en/319731468006253963/pdf/WPS5835.pdf

Dos Santos, S., & Henry, S. (2008). Rainfall variation as a factor in child survival in rural Burkina Faso: The benefit of an event-history analysis. *Population, Space and Place*, *14*(1), 1–20. https://doi.org/10.1002/psp.470

Enongene, B. E. (2024). Structural transformation and poverty alleviation in Sub-Saharan Africa countries: Sectoral value-added analysis. *Journal of Business and Socio-economic Development*, *4*(4), 326–339. https://doi.org/10.1108/JBSED-12-2022-0128

Feder, G., & Savastano, S. (2017). Modern agricultural technology adoption in sub-Saharan Africa: A four-country analysis. In P. Pingali, & G. Feder (Eds.), *Agriculture and rural development in a globalizing world* (pp. 11–25). Routledge. https://doi.org/10.4324/9781315314051-2

Food and Agriculture Organization. (2014). *Food and agriculture policy decision analysis country fact sheet on food and agriculture policy trends: Burkina Faso*. http://www.fao.org/3/i3760e/i3760e.pdf

Fotheringham, A. S., Brunsdon, C., & Charlton, M. (2002). *Geographically weighted regression: The analysis of spatially varying relationships*. John Wiley & Sons. https://www.researchgate.net/publication/27246972_Geographically_Weighted_Regression_The_Analysis_of_Spatially_Varying_Relationships

Frongillo, E. A. (2022). Validity and cross-context equivalence of experience-based measures of food insecurity. *Global Food Security*, *32*, 100599. https://doi.org/10.1016/j.gfs.2021.100599

Frongillo, E. A., & Nanama, S. (2006). Development and validation of an experience-based measure of household food insecurity within and across seasons in northern Burkina Faso. *The Journal of Nutrition*, *136*(5), 1409S–1419S. https://doi.org/10.1093/jn/136.5.1409S

Gemperli, A., Vounatsou, P., Kleinschmidt, I., Bagayoko, M., Lengeler, C., & Smith, T. (2004). Spatial patterns of infant mortality in Mali: The effect of malaria endemicity. *American Journal of Epidemiology*, *159*(1), 64–72. https://doi.org/10.1093/aje/kwh001

Godfray, H. C. J., Beddington, J. R., Crute, I. R., Haddad, L., Lawrence, D., Muir, J. F., Pretty, J., Robinson, S., Thomas, S. M., & Toulmin, C. (2010). Food security: The challenge of feeding 9 billion people. *Science*, *327*(5967), 812–818. https://www.science.org/doi/10.1126/science.1185383

Godfray, H. C. J., & Garnett, T. (2014). Food security and sustainable intensification. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *369*(1639), 20120273. https://doi.org/10.1098/rstb.2012.0273

Gosoniu, L., Veta, A. M., & Vounatsou, P. (2010). Bayesian geostatistical modeling of malaria indicator survey data in Angola. *PLoS One*, *5*(3), e9322. https://doi.org/10.1371/journal.pone.0009322

Gosoniu, L., Msengwa, A., Lengeler, C., & Vounatsou, P. (2012). Spatially explicit burden estimates of malaria in Tanzania: Bayesian geostatistical modeling of the malaria indicator survey data. *PLoS One*, *7*(5), e23966. https://doi.org/10.1371/journal.pone.0023966

Grace, K., Davenport, F., Funk, C., & Lerner, A. M. (2012). Child malnutrition and climate in sub-Saharan Africa: An analysis of recent trends in Kenya. *Applied Geography*, *35*(1–2), 405–413. https://doi.org/10.1016/j.apgeog.2012.06.017

Grace, K., Frederick, L., Brown, M. E., Boukerrou, L., & Lloyd, B. (2017). Investigating important interactions between water and food security for child health in Burkina Faso. *Population and Environment*, *39*, 26–46. https://link.springer.com/article/10.1007/s11111-017-0270-6

Grace, K., Husak, G., & Bogle, S. (2014). Estimating agricultural production in marginal and food insecure areas in Kenya using very high resolution remotely sensed imagery. *Applied Geography*, *55*, 257–265. https://doi.org/10.1016/j.apgeog.2014.08.014

Griffith, D. A. (2000). A linear regression solution to the spatial autocorrelation problem. *Journal of Geographical Systems*, *2*, 141–156. https://link.springer.com/article/10.1007/PL00011451

Henry, S. J. F., & Dos Santos, S. (2013). Rainfall variations and child mortality in the Sahel: Results from a comparative event history analysis in Burkina Faso and Mali. *Population and Environment*, *34*, 431–459. https://doi.org/10.1007/s11111-012-0174-4

Ikazaki, K., Shinjo, H., Tanaka, U., Tobita, S., Funakawa, S., & Kosaki, T. (2011). "Fallow Band System," a land management practice for controlling desertification and improving crop production in the Sahel, West Africa. 1. Effectiveness in desertification control and soil fertility improvement. *Soil Science and Plant Nutrition*, *57*(4), 573–586. https://doi.org/10.1080/00380768.2011.593155

Institut National de la Statistique et de la Démographie & ICF International. (2012). *Enquête démographique et de santé et à indicateurs multiples du Burkina Faso 2010* [Burkina Faso Demographic and Health Survey 2010]. https://www.dhsprogram.com/pubs/pdf/FR256/FR256.pdf

Joint Research Centre- European Soil Data Centre. (2013). European Soil Database Derived data [Data set]. https://esdac.jrc.ec.europa.eu/content/european-soil-database-derived-data#tabs-0-description=0

Kanamori, M. J., & Pullum, T. (2013). *Indicators of child deprivation in sub-Saharan Africa: Levels and trends from the demographic and health surveys*. United States Agency for International Development. https://www.dhsprogram.com/pubs/pdf/CR32/CR32.pdf

Krivoruchko, K. (2012). *Empirical Bayesian kriging*. ESRI. https://www.esri.com/news/arcuser/1012/empirical-byesian-kriging.html

Lloyd, B. J., & Dennison, P. E. (2018). Evaluating the response of conventional and water harvesting farms to environmental variables using remote sensing. *Agriculture, Ecosystems & Environment*, *262*, 11–17. https://doi.org/10.1016/j.agee.2018.04.009

Maxwell, D. G. (1996). Measuring food insecurity: The frequency and severity of "coping strategies." *Food Policy*, *21*(3), 291–303. https://doi.org/10.1016/0306-9192(96)00005-X

Miller, D. D., & Welch, R. M. (2013). Food system strategies for preventing micronutrient malnutrition. *Food Policy*, *42*, 115–128. https://doi.org/10.1016/j.foodpol.2013.06.008

Morales, F., Montserrat-de la Paz, S., Leon, M. J., & Rivero-Pino, F. (2023). Effects of malnutrition on the immune system and infection and the role of nutritional strategies regarding improvements in children's health status: A literature review. *Nutrients*, *16*(1), 1. https://doi.org/10.3390/nu16010001

Moran, P. A. P. (1950). A test for the serial independence of residuals. *Biometrika*, *37*(1–2), 178–181. https://doi.org/10.1093/biomet/37.1-2.178

Nanama, S., & Frongillo, E. A. (2012). Altered social cohesion and adverse psychological experiences with chronic food insecurity in the non-market economy and complex households of Burkina Faso. *Social Science & Medicine*, *74*(3), 444–451. https://doi.org/10.1016/j.socscimed.2011.11.009

Noort, M. W. J., Renzetti, S., Linderhof, V., du Rand, G. E., Marx-Pienaar, N. J. M. M., de Kock, H. L., Magano, N., & Taylor, J. R. N. (2022). Towards sustainable shifts to healthy diets and food security in sub-Saharan Africa with climate-resilient crops in bread-type products: A food system analysis. *Foods*, *11*(2), 135. https://doi.org/10.3390/foods11020135

Office for Outer Space Affairs UN-SPIDER Knowledge Portal. (2016). *Land Cover Map (GlobeLand 30 - NGCC)*. United Nations. Retrieved July 26, 2016, from http://www.un-spider.org/links-and-resources/data-sources/land-cover-map-globeland-30-ngcc

Pérez-Mesa, D., Marrero, G. A., & Darias-Curvo, S. (2022). Child health inequality in Sub-Saharan Africa. *Economics & Human Biology*, *47*, 101176. https://doi.org/10.1016/j.ehb.2022.101176

Reij, C., Mulder, P. & Begemann, L. (1988). *Water harvesting for plant production.* World Bank Group.

Reij, C., Tappan, G., & Smale, M. (2009). *Agroenvironmental transformation in the Sahel: Another kind of "Green Revolution"*. International Food Policy Research Institute. https://www.researchgate.net/publication/239807425

Richard, B., Qi, A., & Fitt, B. D. L. (2022). Control of crop diseases through Integrated Crop Management to deliver climate-smart farming systems for low-and high-input crop production. *Plant Pathology*, *71*(1), 187–206. https://doi.org/10.1111/ppa.13493

Rojas, O., Vrieling, A., & Rembold, F. (2011). Assessing drought probability for agricultural areas in Africa with coarse resolution remote sensing imagery. *Remote Sensing of Environment*, *115*(2), 343–352. https://doi.org/10.1016/j.rse.2010.09.006

Rutherford, M. E., Mulholland, K., & Hill, P. C. (2010). How access to health care relates to under-five mortality in sub-Saharan Africa: Systematic review. *Tropical Medicine & International Health*, *15*(5), 508–519. https://doi.org/10.1111/j.1365-3156.2010.02497.x

Sanchez, P. A. (1987). Soil productivity and sustainability in agroforestry systems. In H. A. Steppler, & P. K. R. Nair (Eds.), *Agroforestry: A decade of development* (pp. 205–223). International Council for Research in Agroforestry. https://www.doc-developpement-durable.org/file/Culture/Fertilisation-des-Terres-et-des-Sols/agroforestrie/Agroforestry_a_decade_of_development.pdf#page=214

Sandler, A., & Sun, L. (2024). The socio-environmental determinants of childhood malnutrition: A spatial and hierarchical analysis. *Nutrients*, *16*(13), 2014. https://doi.org/10.3390/nu16132014

Sidibé, A. (2005). Farm-level adoption of soil and water conservation techniques in northern Burkina Faso. *Agricultural Water Management*, *71*(3), 211–224. https://doi.org/10.1016/j.agwat.2004.09.002

Slingerland, M. A., Traore, K., Kayodé, A. P. P. & Mitchikpe, C. E. S. (2006). Fighting Fe deficiency malnutrition in West Africa: An interdisciplinary programme on a food chain approach. *NJAS: Wageningen Journal of Life Sciences*, *53*(3–4), 253–279. https://doi.org/10.1016/S1573-5214(06)80009-6

United Nations International Children's Fund. (2013). Improving child nutrition: The achievable imperative for global progress [Data set]. https://data.unicef.org/resources/improving-child-nutrition-the-achievable-imperative-for-global-progress/

World Health Organization & United Nations International Children's Fund. (2009). *WHO child growth standards and the identification of severe acute malnutrition in infants and children: A joint statement*. https://www.who.int/publications/i/item/9789241598163

World Bank. (2015). *Data: Burkina Faso*. Retrieved July 24, 2017, from http://data.worldbank.org/country/burkina-faso

WorldPop. (n.d.). *WorldPop open population repository*. https://wopr.worldpop.org/?BFA/

Wuehler, S. E., Hess, S. Y. & Brown, K. H. (2011). Accelerating improvement in nutritional and health status of young children in the Sahel region of sub-Saharan Africa: Review of international guidelines on infant and young child feeding and nutrition. *Maternal & Child Nutrition*, *7*(s1), 6–34. https://doi.org/10.1111/j.1740-8709.2010.00306.x

Open Call for Papers

Bridging disciplines such as economics, sociology, and human geography, Agricultural & Rural Studies (**A&R, ISSN 2959-9784**) is a double-blind peer-reviewed international journal that fosters high-impact research connecting theoretical innovation with empirical depth, ultimately supporting evidence-based solutions for sustainable and equitable futures in agriculture and rural communities worldwide.

Aims

A&R seeks to:

- Foster critical dialogue on contemporary challenges and opportunities in agriculture and rural contexts, from local to global scales.
- Promote methodologically robust research—encompassing quantitative, qualitative, and mixed approaches—that generates actionable insights for academia, policymakers, and practitioners.
- Highlight interdisciplinary perspectives to address complex issues at the intersection of agrarian systems, rural societies, and policy frameworks.
- Amplify diverse voices, ensuring representation of marginalized regions, communities, and stakeholders in scholarly discourse.

Scope

A&R prioritizes, but is not confined to, research that engages with the following thematic areas:

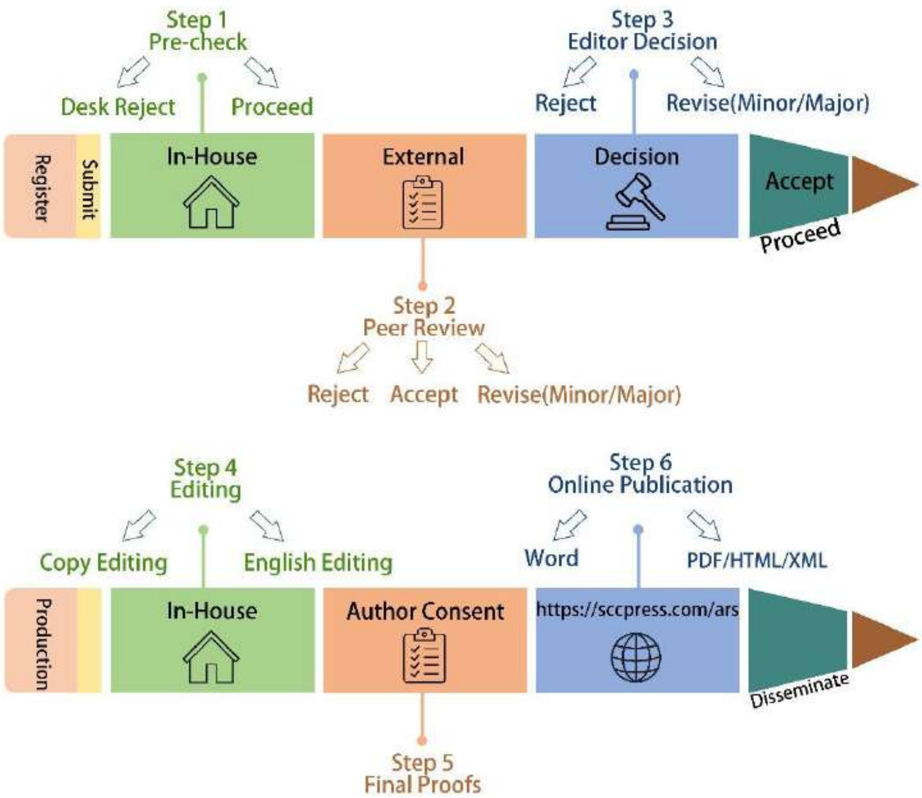
- Agricultural Systems & Sustainability: Studies on sustainable farming practices, agroecology, climate resilience, and the environmental, social, and economic dimensions of agricultural production and food systems.
- Rural Development & Livelihoods: Analyses of rural economic transformations, poverty alleviation strategies, rural-urban linkages, and the socio-cultural dynamics of rural communities.
- Farmer Well-being & Equity: Investigations into farmer agency, gender and social inclusion, labor dynamics, and the impacts of policies on rural households and vulnerable groups.
- AI Innovation & Technology: Research on smart agriculture, precision farming, rural e-commerce, and the socio-institutional implications of AI tools for agricultural and rural development.
- Policy & Governance: Evaluations of agricultural and rural policy frameworks, institutional arrangements, and regulatory mechanisms, with attention to their

effectiveness, equity, and adaptability across contexts.

- Emergent Challenges & Opportunities: Explorations of transformative trends—from biotechnological advancements to climate adaptation—to understand their potential to reshape agricultural and rural futures.

A&R prioritizes empirical research that connects localized insights to broader theoretical or policy debates, as well as critical reviews, case studies, and methodological innovations. All submissions undergo rigorous peer review to ensure scholarly excellence, relevance, and clarity. By bridging discipline boundaries and fostering global dialogue, **A&R** aims to be a cornerstone of interdisciplinary scholarship in agricultural and rural studies.

We cordially invite authors to submit original, previously unpublished manuscripts for consideration in **A&R**. All submissions should be made via our online submission system at https://sccpress.com/ars.



To Be

a Leading Academic Journal at the Nexus of Agricultural Sustainability, Rural Revitalization & Farmer Well-Being.

Agricultural & Rural Studies

Abstracted & Indexed in: Crossref; Dimensions; Google Scholar; J-Gate.

Publisher
SCC PRESS, Unit 811, Beverley Commercial Centre, 87-105 Chatham Road South, Tsim Sha Tsui, Kowloon, Hong Kong S.A.R., China.

Editorial Office
Rural Revitalization Academy of Zhejiang Province, Zhejiang A&F University, Hangzhou, Zhejiang, 311300, China.

Editorial Assistants
Travis Malone (travismalone@sccpress.com)
Grace Li (grace@sccpress.com)
Rui Zhang (ruizhang@sccpress.com)

Photographer
Zhaoping Ying

Layouter
Jiaru Zheng

SCC PRESS
Academic OA Publishing
Began in 2023